Financial Contagion from the US Structured Finance Market: Evidence from International Markets and Asset Pricing Perspectives

by

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A Thesis Submitted in Partial Fulfilment of the Requirements for the Degree of Doctor of Philosophy of Cardiff University

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Abstract

Given the growing importance of securitisation to financial stability, it is surprising that empirical studies on the role of the US structured finance market in the recent crisis have been relatively sparse. To fill this gap, this thesis studies the US structured finance market (tracked by the ABX indices) and addresses various important research questions specific to the recent 2007 to 2009 financial crisis. First, I contribute to the contagion literature by extending Longstaff's (2010) investigation to an international market perspective. Evidence of contagion from the ABX indices to the G5 international equity and government bond markets via the funding illiquidity and credit risk channels during the subprime crisis is documented. Second, I formulate a multifactor model with crisis interaction effects and document significant increases in the ABX AAA factor loadings during the subprime crisis, which is consistent with contagion. My cross-sectional pricing tests show that the ABX AAA factor significantly explains the cross-section of expected returns during the subprime crisis; that is, the impact of contagion on the US equity market was reasonably systematic. I compute a simple statistic that gauges the degree of the stocks' exposure to the ABX innovations in each month and find that the exposure spiked in February, July and October 2007 and in February, July and November 2008. Third, I investigate whether the US bank holding companies' fundamental characteristics determine bank equity risks during the recent crisis. I depart from prior studies and consider bank equity risks relating to the banks' exposure to the ABX innovations, the asset-backed money market and the market wide default risk in a variance decomposition. My study establishes the link between the banks' fundamental and equity risks, and shows that banks' regulatory capital requirement is an effective means to limit banks' exposure to systemic risks in relation to funding illiquidity. Lastly, I document compelling evidence of quarterly bank stock return predictability based on variables relating to banks' profitability, loan asset credit quality, capital adequacy and equity risks over the 2006 to 2011 period. By studying the turnover ratios and order flows, I show that bank stocks with weaker fundamentals and smaller size were traded more intensely in the following quarter while the higher trading activity was dominated by selling pressure. The evidence lends support to my 'fire sale' or 'flight-to-safety' hypothesis and reveals that the banks' fundamental variables and size were the major criteria used by investors in formulating their 'flight' decisions during the recent crisis.

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Chapter 1

Introduction

1.1 Background and context

This thesis studies the role of the US structured finance market in the financial contagion that spread during the recent 2007 to 2009 financial crisis. My focus will be on an empirical identification of contagion as it travelled from the structured finance market to major international developed markets. I will also investigate the validity of a few widely-acknowledged transmission channels, examine the impact of the spillovers of shocks from the structured finance market on the US equity market, and I will also study of the role played by the US bank holding companies (BHC) during the recent crisis. The aim of this thesis is to contribute to the literature of contagion and asset pricing.

Despite widespread disagreement, financial contagion can be defined as the phenomenon of significant increases in market co-movements that are conditional on a crisis event (Dornbusch et al., 2000; Forbes and Rigobon, 2002; Bekaert et al., 2005, 2011). Empirical contagion research can be broadly organised into two themes. The first theme refers to studies that primarily test for the existence of contagion (see, for example, Eichengreen et al., 1996; Dungey and Martin, 2001; Forbes and Rigobon, 2002; Bekaert et al., 2005; Corsetti et al., 2005; Chiang et al., 2007; Longstaff, 2010) while the second theme refers to the examination of the validity of contagion transmission channels and on the dynamics of shock transmission (see, for example, Kaminsky and Reinhart, 2000; Caramazza et al., 2000, 2004; Forbes, 2004; Longstaff, 2010). This empirical study is closely related to the first theme but also sheds light on the transmission channels and provides insight into how contagion propagated during the crises.

The recent 2007 to 2009 financial crisis was remarkable in its scope and severity. However, it represents an invaluable opportunity for researchers to investigate the role of funding illiquidity and of the impact of 'toxic' structured finance securities on financial stability and market integration. As pointed out by various researchers, the rapid expansion of the structured finance market and the growing popularity of securitisation in the US financial system are at least in part responsible for the severity of the recent financial crisis (see, for example, Benmelech and Dlugosz, 2009; Brunnermeier, 2009; Longstaff, 2010; Mählmann, 2013). Over the past decade, the subprime mortgage market grew rapidly and the securitisation of subprime mortgage loans became enormously popular (see Chapter 2). Underpinning this fast-growing financial innovation was the invention of various complex and opaque pass-through and tranched fixed income instruments, such as residential mortgage-backed securities (RMBS), asset-backed securities (ABS), collateralised debt obligations (CDOs) and many more. These structured finance securities suffered severe rating downgrades and sharp declines in prices as the subprime crisis unfolded and went global. In particular, 64% of the rating downgrades of structured finance securities in 2007 and 2008 were tied to securities with residential mortgages or first mortgages as collateral and 42% of the total mark-to-market losses in financial institutions worldwide were associated with CDOs backed by ABS (see Benmelech and Dlugosz, 2009). The troubles in the structured finance market quickly translated into widespread concern for insolvencies amongst financial institutions and resulted in severe market wide funding and market illiquidity, which is commonly referred to as the 'credit crunch'.

Given the growing importance of the structured finance market on financial stability, the understanding of its impact and relation to other asset markets is of the utmost importance to effective portfolio management, risk management and policy making during extreme market conditions. Consequently, this study uses various widely-acknowledged empirical methods to address these issues and discuss the major implications.

1.2 Motivation

The ABX indices, which track the static portfolios of 20 subprime RMBS, have been widely-referenced as an important class of stress barometers during the subprime crisis. In early 2007, the ABX indices started to decline sharply when the delinquency rates of the subprime mortgages increased and the number of rating downgrades of the structured finance securities heightened. To the best of my knowledge, despite the growing interest in the structured finance market performance, empirical studies that examine its role in the recent crisis in the context of contagion and asset pricing have been relatively sparse. One of the first papers is Longstaff (2010) which tests for contagion from the ABX indices travelling to a number of major US financial markets. Longstaff (2010) documents evidence of significant predictive power in the past returns of the ABX indices over the returns of US domestic markets. Fender and Scheicher (2009) showed that the declining ABX prices reflected substantial market illiquidity risks and increasing risk aversion amongst investors in the US financial system. This thesis builds on these studies and comprehensively studies the contagion specifically from the US structured finance market over a sample period that covers the recent 2007 to 2009 financial crisis.

This study follows three main research directions. The first research direction is to investigate contagion from the US structured finance market within an international market perspective and to extend Longstaff's (2010) study to cover a number of developed equity and government bond markets. The contention of international shock transmission is motivated from the fact that numerous financial institutions that suffered tremendous mark-to-market losses in their subprime mortgage businesses and from holding 'toxic' structured finance securities during the crisis operate with cross-market functionality. Idiosyncratic shocks from the structured finance market might have transmitted across markets via fundamental shocks on the financial institutions' balance sheets. In addition, cross-market comovements may also arise from the heightening risk aversion (Eichengreen et al., 2009), herding (Calvo and Mendoza, 2000), funding and market illiquidity (Allen and Gale, 2000; Brunnermeier and Pedersen, 2009), possible 'flights-to-safety' (Longstaff, 2004; Baur and McDermott, 2010), and portfolio rebalancing or deleveraging (Longstaff, 2010; Ben-David et al., 2012) by fund managers for risk management purposes.

The second research direction refers to the examination of market dynamics in relation to the possible asset 'fire sale', or 'flight-to-safety', phenomena during the crisis. A 'fire sale' is defined as a forced sale in which the seller liquidates their assets to repay the creditors during financial distress. Evidence of a 'fire sale' by hedge funds and mutual funds, commercial banks, and financial institutions has been documented (see Chapter 7) during the recent crisis while evidence of possible 'flight-to-safety' has also been noted by Longstaff (2010), who points out that the severely impaired financial stocks were traded more intensely relative to the market during the crisis. While assets sold at 'fire sale' prices and possible 'flight-to-safety' phenomenon have had considerable impact on stock returns (Coval and Stafford, 2007), apart from investors' concern about market illiquidity (Anand et al., 2013), relatively little is known as to how investors formulate their investment or 'flight' decisions and how relevant fundamental characteristics were to their investment decision making during the crisis. For example, did the investors tend to sell the assets with the worse fundamentals in a 'fire sale'? And, did the investors fly from stocks with weaker fundamentals to other assets? An improved understanding of how investors formulated their 'flight' decision during a market failure provides important insights to investors in evaluating future stock performance and, thus, helps in achieving superior investment performance during a period characterised by contagion and heightening macroeconomic risk and uncertainty.

The third research direction is related to the argument of Fender and Scheicher (2009) in that asset pricing models that do not account for the increasing market illiquidity risks and heightening risk aversion as reflected by the falling prices of the ABX indices are inappropriate. I will formulate an asset pricing framework to test this conjecture and seek to quantify the individual stocks' exposure to the unexpected shocks from the US structured finance market over the 2006 to 2011 period. This study departs from the majority of contagion studies in the literature, and instead of focusing on the aggregate market variables as units of analysis, will utilise firm-level information to investigate the impact of contagion on the US equity market and the industry sectors. This study includes all available individual stocks from the major US Exchanges in its empirical analysis and reveals the time evolution of the US equity market's exposure to the structured finance market, based on novel and simple statistics of exposure to the ABX indices. In addition, from an investor's perspective, I aim to identify the major fundamental characteristics that contribute to the individual stock's vulnerability to shocks from the structured finance market.

1.3 Organisational structure and content overview

Chapter 2 reviews the contexts, causes, and chronological development of the subprime and subsequent global financial crises. It also reviews and discusses a few of the major issues with regard to the process of securitisation, the role of the subprime mortgage market, and the reinforcing liquidity spiral between funding and market illiquidity. Chapter 3 reviews the contagion literature, it also explains the major theoretical aspects of contagion. It will then survey a set of widely-acknowledged empirical methods, which is followed by a summary of empirical findings. Chapters 4, 5, 6 and 7 are individual self-contained working papers. Chapter 4 tests for contagion, from the US structured finance market to the equity and government bond markets in the G5 countries, and examines the validity of a few contagion transmission channels. Chapter 5 closely examines the US equity market and tests for evidence of contagion using asset-pricing models, which is augmented with crisis related factors and all available individual stocks on US Exchanges. Chapter 6 focuses on the US bank holding companies (BHCs) and seeks to identify the determinants of bank equity risks using a number of the banks' fundamental and market variables. Chapter 7 tests for quarterly bank stock return predictability using a number of bank-specific fundamental variables as predictors, and reveals how the return predictability pertains to investors' asset 'fire sale' or 'flight-to-safety' phenomenon by examining the bank-level turnover ratios and order flows. Chapter 8 concludes this thesis and makes a number of recommendations for future research.

In Chapter 4, following Longstaff (2010), I will use vector autoregressive (VAR) models to test for contagion, from the US structured finance market (tracked by the ABX indices) to the broad equity, financial equity and government bond markets in the G5 countries. While the US findings are consistent with Longstaff (2010), I document reasonably strong evidence of contagion, from the ABX indices to the G5 financial markets, during the subprime and global crisis subperiods. In addition, I show that idiosyncratic shocks in the ABX indices are translated into higher trading intensity in financial stocks (US, UK and France), widening of interest rate spreads (all G5 countries), and increased comovements between domestic equity and government bonds (all G5 countries except Germany) in support of the risk premia transmission channel and possible 'flight-to-safety' phenomenon. I will then depart from Longstaff (2010) and proceed to investigate the 'short-lived' contagion using higher frequency data (daily) and document strong evidence of 'short-lived' contagion in international markets. To account for simultaneous spillovers of shocks from other major US markets to the international markets, I augment the set of exogenous variables to include a few major US market variables and find that the significant predictive power of the lagged ABX index returns remains highly significant. In addition, I demonstrate that past US S&P 500 composite index returns, changes in the US Treasury yield spreads, corporate bond yield spreads and asset-backed commercial papers (ABCPs) yield spreads possess significant predictive ability over international market returns, a result that is reflective of the relatively integrated nature of international and US markets.

In the first part of Chapter 5, I aim to test for contagion travelling from the structured finance market to the US equity market using an asset pricing framework and all available individual stock data from the three major US Exchanges. First, I will follow Bekaert et al. (2011) and formulate my contagion tests within a two-factor model framework (a market risk factor augmented with an orthogonalised ABX factor) with crisis dummy variables that allow for shift changes in the intercepts and factor loadings across crisis subperiods. As a preview to my findings, I document a significant increase in the ABX AAA factor loading during the subprime crisis and lower ABX AAA factor loading during the global crisis subperiod in support of the conjecture that the ABX AAA index was an important source of risk during the subprime crisis (Fender and Scheicher, 2009). My industry subsample results are qualitatively similar in that the ABX shocks were considerably systematic across industries.[1] I further interact the factor loadings with a few widely-acknowledged contagion variables related to market wide default risks and funding illiquidity. A significant and positive relation between the changes in ABCP yield spreads and the ABX factor loadings during the crisis subperiods has been identified, suggesting that the time variations in the ABX risk were closely related to funding illiquidity. I will then proceed to test whether the ABX factors explain the cross-section of expected returns. Using a two-pass regression framework and Generalized Least Squares (GLS) approach on 25 Fama-French (1993) size and book-to-market ratios sorted portfolios (daily data), I find that the Carhart (1997) four-factor model augmented with the orthogonalised ABX AAA factor holds with insignificant pricing error statistics during the subprime crisis subperiod.[2] In summary, my empirical findings show that the contagion effects from the US structured finance market were considerably systematic and can explain the cross-sectional variations in expected daily returns during the subprime crisis.

After contagion has been identified, I will seek to reveal how the individual stock's exposure to the ABX innovations evolved over the sample period. To this end, I will create a novel and simple measure of time-varying exposure to the ABX innovations, denoted as $\kappa_{ABX,t}$, which is computed as the proportion of stocks with significant ABX factor loadings to the total number of

[1] The 12-industry classification code is obtained from Kenneth R. French's web site, accessed via: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[2] The Carhart (1997) four-factor model refers to the Fama-French (1993) three-factor model with the addition of the Carhart (1997) momentum factor.

available stocks in my sample based on three asset pricing model specifications. The underlying intuition is that, when contagion took place, the significant increases in cross-market linkages between the US equity and structured finance market should be reflected by a larger proportion of stocks with significant ABX factor loadings. Significant time-variations have been observed in the $\kappa_{ABX,t}$ with occasional spikes, especially in February, July and October 2007 during the subprime crisis, and in February, July and November 2008 during the global crisis, which is consistent with previous findings documented in Chapter 4. Additionally, the results of my Granger-causality tests show that the level of the stocks' exposure to the ABX AAA innovations was driven by average market illiquidity, LIBOR-OIS spreads (funding illiquidity) and the value-weighted average idiosyncratic volatilities. In the last section of Chapter 5, I will seek to identify the determinants of individual stock's exposure to the ABX risk using logistic, multinomial logistic and multivariate OLS regressions. My findings show that idiosyncratic volatilities, total return volatilities, market systematic risks, log turnover, and book-to-market ratios significantly determine the exposure to the ABX indices. Overall, I find little evidence of explanatory power in the firm-specific fundamental variables over the ABX risk exposure.

In Chapter 6, I will focus on the role of the US BHCs in the recent crisis and examine whether their fundamental characteristics determine their equity risks during the crisis. This analysis centers on the notion that bank equity risk is a timely measure of the banks' risks (Stiroh, 2006) and seeks to identify their major determinants using a diverse set of fundamental variables pertaining to the banks' profitability, loan portfolio asset quality, capital adequacy and asset composition. Following the variance decomposition approach of Anderson and Fraser (2000), I will depart from previous studies by taking into account the individual banks' exposure to the troubled structured finance market (the ABX AAA innovations), asset-backed money markets (the ABCP innovations), and market wide default spreads (the Moody's default spread innovations). My empirical approach involves orthogonalising the factors so that the decomposed equity risk can be interpreted as the bank's exposure to factor variations unexplained by all other factors. I will then use pooled weighted least squares (WLS) regressions with two-way fixed effects and robust standard errors clustered by both firm and time dimensions to test for the determinants of each component of equity risks. Four main results emerge: (1) banks with lower earnings and capital ratios have higher equity risks; (2) the positive impact of non-performing loans on equity risks increased by threefold during the crisis; (3) banks with a larger buffer of Tier 1 capital were less exposed to the idiosyncratic shocks from the structured finance market and the asset-backed money market; and, (4) the riskiness in banks' opaque investments was not accurately priced. From an investor's perspective, this chapter empirically establishes the linkage between the bank's fundamental and equity risks while from a supervisory perspective, the evidence advances that proper management of bank's regulatory capital requirement represents an effective means to hedge against systemic bank failures in times of systematic funding illiquidity.

In Chapter 7, using the same sample of US BHCs as in Chapter 6, I will further test whether the banks' fundamental characteristics predict the one-quarter ahead bank stock returns over 2006 to 2011. The evidence shows that the banks' profitability, loan portfolio credit quality and capital adequacy predict significantly (with positive relation) the banks' future stock returns, which is robust to both univariate and multivariate tests. The main contribution of this study is that it presents strong evidence of linkages between the quarterly bank stock return predictability and the investors' asset 'fire sale' or 'flight-to-safety' phenomena during the recent crisis. This is the first study to discover that the bank stocks' future turnover were significantly predicted by the banks' fundamental variables. More precisely, banks with worse profitability, loan portfolio credit quality or a smaller buffer of Tier 1 capital have had lower average one-quarter ahead returns, higher trading intensity, and relatively stronger sell pressure in the next quarter, which is robust to both two-way sort portfolio and multivariate analysis. The disproportionately stronger sell pressure on bank stocks with weak fundamentals is consistent with the asset 'fire sale' or 'flight-to-safety' phenomena and leads me to conclude that banks' fundamental performance is the most relevant criteria used by investors in formulating their 'flight' decisions. In addition, I propose ex ante investable strategies and demonstrate how investors can generate economically significant profits.

Chapter 2

An Overview of the Recent Subprime and Global Financial Crises

2.1 Introduction

The subprime crisis was allegedly triggered by the bursting of the US housing bubble and the subsequent threat of massive waves of subprime mortgages delinquencies in 2007. It was shortly followed by sharp declines in the market values of various types of structured finance securities, such as the ABS portfolios that were held by a number of financial institutions (Longstaff, 2010). The majority of these complex structured instruments, which were usually issued in off-balance sheet conduits, were written down by a number of financial institutions around the world; for example, the Bank of America, Royal Bank of Scotland, Credit Suisse, Citigroup and Deutsche Bank (BBC News), and many more. The widespread concern about the insolvency risks of these financial institutions along with the lack of transparency in the credit derivatives markets quickly translated into severe funding illiquidity (McSweeney, 2009). Market makers and speculators (e.g. traders and hedge funds), when faced with increasing margin requirements and funding illiquidity, failed to provide sufficient liquidity to the markets and, as a result, both funding and market liquidity plunged. The further declines in asset prices reinforced even higher funding illiquidity, forcing traders and hedge funds to quickly delever and liquidate assets at 'fire-sale' prices to meet redemptions and contingent liabilities. The result was a 'liquidity spiral' that in part explains the 'credit crunch' (Brunnermeier and Pedersen, 2009; Boyson et al., 2010; Ben-David et al., 2012).

During 2008, the subprime crisis quickly evolved into a global and catastrophic context. A number of international financial markets were adversely affected and this resulted in systematic flights into safer assets (e.g. Treasuries and gold market[3]). A number of giant financial institutions collapsed and filed for bankruptcy protection, including Lehman Brothers, Merrill Lynch, Washington Mutual, AIG, Fannie Mae, Freddie Mac, and many more. Concerns regarding the financial viability of the US Treasury and Central banks heightened and were echoed in a number of economies outside of North America. The Treasury bill-Eurodollar spread (TED spread), which indicates the perceived credit risk and funding illiquidity in the wholesale market, which soared from 2007 onwards and peaked at 463 basis points on 10 October 2008 (Kenc and Dibooglu, 2010). Credit default swaps (CDS) on the US Treasury were traded at spreads as high as 100 basis points in late 2008, reflecting the surging credit risks, and market and funding illiquidity. In 2009, the market was not yet free from shocks and volatilities since a number of financial institutions still faced financial difficulties as a result of continuing losses related to their subprime mortgage related businesses. The negative consequences of the financial crises were protracted.[4]

In this chapter I will provide a detailed discussion of the contexts and causes of the subprime crisis, and the subsequent global crisis based on facts and empirical evidence documented in the literature. The main objective is to facilitate a broad and in-depth understanding of the important role played by the structured finance market in the recent crises.

2.2 The context of the subprime crisis

2.2.1 The US housing boom over the past two decades

The underlying cause of the subprime crisis dates back to the 1970s when the savings and loan industry in the US, which was based primarily on short-term borrowing and long-term re-lending, collapsed. With high inflation and interest rates, credit markets were in trouble and access to funding became severely restricted resulting in substantial funding illiquidity. During the Savings and Loan crisis in the 1980s, the whole home financing system was bailed out. As the credit terms

[3]Baur and McDermott (2010) find evidence that gold was a safe haven for most developed markets during the recent 2007 to 2009 financial crisis.

[4]Some researchers assert that the continual financial weakness in the economy and financial systems, as a result of the subprime and global crisis, are the prerequisites and fundamental causes of the recent European Sovereign Debt Crisis of 2010 to 2012.

became restrictive, the incentive for home owning as well as the residential construction spending decreased. This was a time that the bankers referred to as the regulatory reign of terror before which the mortgage market stabilised and normal credit conditions re-emerged. This was thought to be the start of the current mortgage credit cycle (Lindsey, 2007). Meanwhile, to boost the declining mortgage loan and housing markets, regulators and financial markets facilitated the enactment of the FIRREA[5] and the FDICIA in 1991 to restructure the industry. The restructuring encouraged the borrowing of variable rate mortgages and hedging on long-term loans. It also allowed financial institutions to free up their balance sheets by transferring their mortgage loans and risk exposure to institutions (underwriters) that were more diversified through securitisation. The overall result was the development of a nationwide mortgage securities market.

A significant development that came along with the restructuring was the increasing numbers of financial institutions that specialised in originating loans, packaging them into pools, and then selling the claims to the mortgage cash flows as mortgage-backed securities (MBSs). This process was called the securitisation of mortgage loans. The aggregated pools of mortgages then became national in scope and they were less subject to individual default risks and prepayment risks. These MBSs were then bought by financial institutions for diversification and risk management purposes. Two of the most important MBS issuers were the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac), which are government sponsored associations. Fannie Mae and the Freddie Mac are backed and guaranteed by the Federal Government. which enables them to borrow from the US Treasury. The guarantees greatly increased the investors confidence and the liquidity available for issuers to make new loans increased substantially.

In 1995, a new set of regulations under the Community Reinvestment Act were implemented, which incorporated a soft quota on lending to areas and neighborhoods with low to moderate income levels. Meanwhile, regulators also largely lowered the requirements for borrowing mortgage loans, such as loosening the loan-to-value requirements. This led to an increase in housing demand

[5]The Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) was signed on 9th August 1989 in an attempt to stabilise the savings and loans markets. Under the Act, two deposit insurance funds were established, namely the Savings Association Insurance Fund (SAIF) and the Bank Insurance Fund (BIF). In addition, the Resolution Trust Corporation (RTC), a new government agency, was established to close insolvent thrifts, resell their Savings and Loan assets, and use the proceeds to provide insurance to depositors. In addition, the credit appraisal methods have also been modified. For details of the Act, please refer to the Federal Deposit Insurance Corporation web site: http://www.fdic.gov/regulations/laws/rules/8000-3100.html

and this supported the subsequent increases in housing prices. House owners sold their homes to new buyers and reaped capital gains. Consequently, the default rates dropped significantly. The lenders of mortgages began to realise the potential profitability in these mortgage loans and they were willing to pay a higher price for mortgages by accepting a lower yield (Udell, 2009). They gradually eased the lending standards so as to accommodate more loans to new potential buyers who were marginally qualified. These loans, made to borrowers with poorer credit history, are classified as Alt-A and subprime mortgages. A 'cycle of ever-easier credit' was created (Lindsey, 2007).

Easier credit gave rise to increasing housing demand and this resulted in an upward price spiral. There was always demand to match the supply of homes by home owners who were able to profit from capital gains so long as the housing prices were still appreciating. Driven by the low default rates, lenders' optimism about the real estate market and their willingness to extend credit eased the credit standards further. Since the down payment for home-buying and capital requirements for loans were low, more speculative investors came into the market and bought homes solely for speculative purposes. By 2006, the median down payment requirements for first time home buyers was only 2% compared to the normal 20% a decade ago. In fact, about 40% of the first time home buyers had not even paid down-payments and borrowed mortgages that were worth more than the cost of their homes (Lindsey, 2007). The ability and commitment to repay the loans of the subprime mortgage borrowers were in fact low. Over time, the credit standards had changed from very restrictive to very accommodative while housing prices spiraled upwards.

2.2.2 The types and designs of mortgages in the US

Before I continue my discussion on the rapid growth in the US residential and structured finance markets (e.g. mortgage-backed securities markets), I will briefly review the types of mortgages available in the US and their respective features. There are in general four types of mortgages: prime mortgages, jumbo mortgages, Alternative-A (Alt-A) mortgages, and subprime mortgages.

First, prime mortgage borrowers are usually of good credit quality and pay less up-front fees, insurance costs and lower interest rates. Prime mortgages can be sold to government-sponsored enterprises (e.g. Fannie Mae and Freddie Mac) for securitising. Second, jumbo mortgages are loans with amounts that exceed the limits set by Fannie Mae and Freddie Mac and they have higher average interest rates. Third, Alt-A papers are loans that do not conform to the limits set by Fannie Mae and Freddie Mac, as a result of lower credit scores and higher loan-to-income and loan-to-value ratios. They are riskier than the prime mortgages but less risky than the subprime mortgages. The lowest credit quality mortgage loans are the subprime mortgages in which the borrowers usually have a previous record of delinquency, foreclosure, or bankruptcy, a credit score of 580 or below according to the Fair, Isaac and Company (FICO) scale, or a debt-to-income ratio of 50% or greater. Another approach of defining subprime mortgages is based on the subprime lenders' practices (i.e. fewer number of loan originations, higher proportion of loan refinanced and a lower percentage of their portfolios sold to the government-sponsored enterprises) (Sengupta and Emmons, 2007).

The main differences, as pointed out by Mizen (2008), between prime and subprime mortgages lie in the higher up-front fees, insurance costs, average interest rates borne by subprime borrowers as penalties for their lower credit quality. In addition, subprime mortgages also have a higher probability of prepayment and foreclosure than those of the higher quality prime loans. Since there are in general two approaches to defining subprime mortgages (Sengupta and Emmons, 2007), it is worth pointing out that not all subprime mortgage borrowers are of poor past credit history or quality.

On the other hand, various types of mortgage contracts are designed to accommodate the needs and financial situations of different borrowers. While a standard mortgage contract usually comes with a fixed-rate and a long maturity, the option adjustable-rate (OAR) mortgages borrowers are typically given four monthly payment options at the initiation of the loan and are allowed to defer some of the interest payments to later periods. The OAR accommodates borrowers with growing or fluctuating income and allows them to structure their payments with higher flexibility.

Another type of mortgage contract refers to the hybrid adjustable-rate mortgages (ARMs). In a hybrid ARM, interest rates are fixed for a pre-specified period and then reset to floating rates thereafter. Though hybrid ARMs are designed for borrowers who expect income rises in a few years time, Weaver (2008) points out that the popularity of hybrid ARMs was in part responsible for the massive waves of subprime mortgage defaults in 2007. The author points out that most of the recent origination of subprime mortgages are of a hybrid adjustable-rate design (also known as a 2/28 or 3/27).[6] The author contends that the large amount of ARMs issued resulted in massive waves of payment shocks when the ARMs were reset at the onset of the subprime crisis.

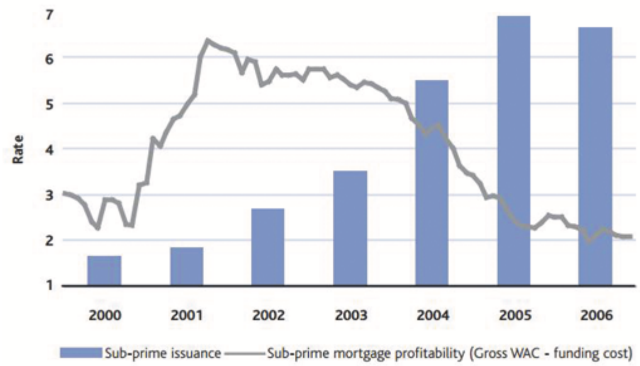
2.2.3 The rapid growth of the subprime mortgage market

Fuelled by the housing boom and the accommodative credit policies, the residential mortgage markets grew excessively. The origination of subprime mortgage debt has helped fund more than five million home purchases, in which over one million purchases were first-time homeowners. It has also stimulated growth in home construction (Jaffee, 2008). Mizen (2008) points out that subprime loans were heavily concentrated in urban areas of certain US cities where homeownership had not previously been common and also in areas that were economically depressed. A number of borrowers who faced financial difficulties switched from prime conforming loans to subprime loans that are easier to obtain but with higher average costs.

One major reason for the substantial increase in subprime mortgage issuance is that the subprime mortgages were relatively profitable for issuers. As shown in Figure 2-1, the profitability of subprime mortgage lending was especially high in the first four years of the 2000s (Weaver, 2008). Jaffee (2008) notes that there were two periods of significant expansion of subprime credit. The first period started in the late 1990s and lasted to the dotcom crisis in 2001. The second period lasted between 2002 and 2006 (as shown in Figure 2-2). In particular, Jaffe (2008) notes that, during the second period of expansion between 2002 and 2006, annual loan volumes of subprime mortgages were over US$600 billion in 2005 to 2006, accounting for over 20% of the total annual mortgage issuances. During the period between 2001 and 2005, the number of subprime loans issued increased by about 450%, from 624,000 to 3,440,000, while the average subprime loan value increased by 72%, from US$151,000 in 2001 to $259,000 in 2006. The total issued subprime mortgage loan values were US$94 billion in 2001, which rose more than 700% to US$685 billion in 2006 (Demyanyk and Hermert, 2008, cited in Swan, 2009). For the outstanding subprime mortgages, as shown in Figure 2-3, subprime mortgages amounted to 12% of the total outstanding US residential mortgage market in 2007Q1. While the US subprime mortgage market increased substantially over the first half of the 2000s, the credit standards did not improve. Figure 2-4 shows the different mortgage loan products (with different features) offered to subprime mortgage borrowers and the

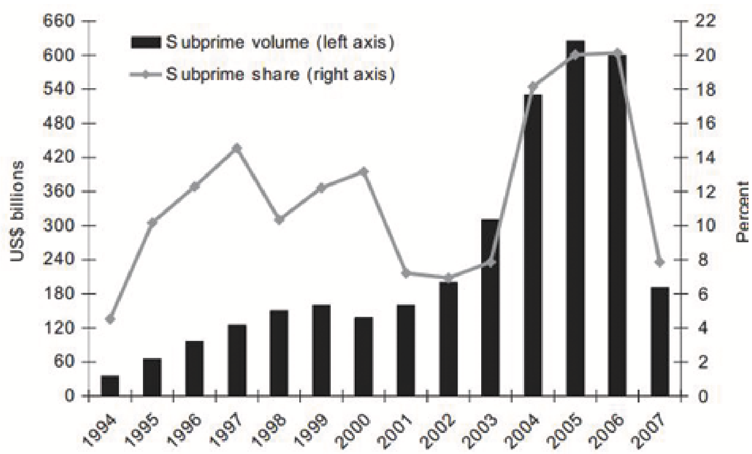
[6] A 2/28 is an ARM that holds the initial interest rate fixed for 2 years, and is then reset to the prevailing rate.

Figure 2-1: The rate of subprime mortgage issuances and profitability



This figure plots the rate of subprime issuances and the profitability of subprime loans issuance over the period 2000 to 2006 (source: Deutsche Bank, adopted from Weaver, 2008).

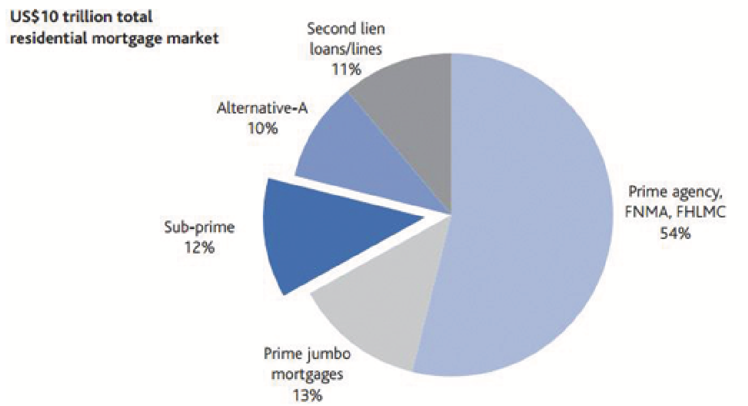
Figure 2-2: Dollar amount of subprime mortgage origination



This figure plots the dollar amount of subprime mortgage origination over the period of 1994-2007. The solid bars represent the volume in market value of subprime mortgage issuance while the solid line plots the percentage of subprime mortgage issuance of the total mortgage issuance at each year (source: Inside Mortgage Finance, adopted from Jaffe, 2008).

proportion of each product to the total subprime mortgage originated within that product type at a peak time of subprime mortgage lending. The issuance of subprime mortgages was centered on hybrid ARMs with two-year teaser rates and was characterised by relatively low credit scores. The borrowers were subjected to risks with regard to the uncertainty in the prevailing mortgage rates.

Figure 2-3: The proportion of subprime mortgages outstanding in 2007Q1



This pie chart shows the proportion of the subprime mortgages outstanding to the total mortgages outstanding in 2007Q1 (source: Census Bureau, eMBS, Loan Performance, Deutsche Bank, adopted from Weaver, 2008).

Figure 2-4: The product features of the subprime mortgages issued in the US

Mortgage product	% of US sub-prime originations, at peak
Interest only	37%
No money down	38%
No proof of income	43%
Low, "teaser" interest rate, "exploding" after two years	~80%
"Layered risk"; combines all of the above*	26%

** Plus a high debt-to-income ratio and low credit score (600-620), with the exception of LTV, which would have been 90-95 per cent rather than 100 per cent*

This figure shows the product features offered to the subprime borrowers during the peaks of subprime mortgage issuances. The proportion of subprime mortgages under each feature is provided (source: Deutsche Bank, adopted from Weaver, 2008).

The negative effects of the payment shocks would be tremendous given the large amount of outstanding variable rate subprime mortgages and the poor credit quality of the subprime borrowers. The subprime mortgage market continued to grow as housing prices were still increasing and there were still home buyers who were willing to purchase. While mortgage market restructuring and the easing of credit standards solved some of the older problems in the last credit cycle, new problems and shortcomings emerged as a result of the securitisation process. In the next few sections, I will explain the securitisation process and discuss how it relates to the recent crises.

2.2.4 The securitisation of mortgage loans and the CDOs

The securitisation of mortgage loans refers to the process of packaging cash flows (both interest and principal) from the borrowers of mortgage loans and then selling these cash flows to underwriters for the issuance of new securities. There are, in general, two types of securitisation: pass-through and tranched securitisation.

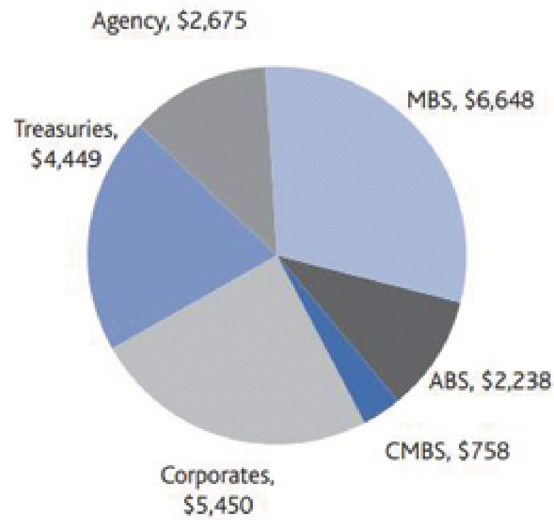
In a pass-through securitisation, the cash flows of the underlying mortgages are 'passed through' to the investors who hold the MBSs. The introduction of pass-through securities dates back 40 years to a time when the underlying mortgages and MBSs were all guaranteed by the US government.[7] It was not long until Fannie Mae and Freddie Mac started to run their own non-government guaranteed MBS programme. Even though these MBSs were not government guaranteed, they are commonly thought as default risk free because the two enterprises guarantee the interest and principal payments (Jaffee, 2008).

The second type refers to the tranched securitisation in which some investors hold more senior claims than others within a subordination structure. Like the mechanism of a waterfall, in the event of default, losses are absorbed by the lowest priority class of investors and the unabsorbed losses are then absorbed by the next lowest priority class, and so on. The structure allows investors of various tranches to take on different levels of risks (i.e. the most senior tranche has the highest credit quality while the lowest residual equity tranche are the riskiest). Apart from the structure, these tranched structured finance products use credit enhancing extensively to provide additional insurance.

Looking at the mortgage loan securitisation, in 2001 about 46% of the subprime mortgages and 18% of the Alt-A mortgages were securitised. Most of these MBSs were 'agency' issues that had higher credit quality and regulations. Over time, the proportion of 'non-agency' issues of MBSs grew significantly with the largest growth in the subprime and Alt-A loan sectors. By 2006, about 75% of the subprime loans and 91% of the Alt-A loans were securitised. As shown in Figure 2-5, the amount of outstanding residential mortgage-backed securities (RMBS) account for the largest

[7]The MBSs were issued by the Government National Mortgage Association (Ginnie Mae; GNMA), a government agency within the US Department of Housing and Urban Development. The underlying mortgages must be government guaranteed.

Figure 2-5: The proportion of fixed income instruments outstanding in 2007Q1



This pie chart shows the proportion of fixed income instruments outstanding in the mortgage markets in 2007Q1 (source: Securities Industry and Financial Markets Association (SIFMA), adopted from Weaver, 2008).

markets amongst the various types of US fixed income markets, reflecting the increasing importance of the structured finance market. On the other hand, recent developments in financial engineering have allowed investors and institutions to create new structured finance products to manage risks and portfolios in synthetic and sophisticated ways. One of the new financial securities refers to the CDO, which is a tranched and pooled structured finance product. The underlying collateral may include MBSs, RMBSs, Commercial mortgage-backed securities (CMBSs), CDOs, collateralised mortgage obligations (CMOs), credit default swaps (CDSs) and other ABSs (Mählmann, 2013). Special purpose investment vehicles (SIVs) are usually established while credit protection is sold on a range of underlying assets, including MBSs that usually have a yield which is 200-300 basis points higher than corporate bonds with similar ratings.

Driven by the attractive ratings and higher profitability, CDOs have become one of the most popular financial instruments for hedging and risk management purposes among fund managers and banking institutions and, hence, the CDO market experienced rapid growth at an average annual rate of 150% since 1998. The number of CDO tranches issued in 2006 (9,278) was almost double the number of tranches issued in 2005 (4,706) (see Benmelech and Dlugosz, 2009). By 2005, it was estimated that the overall CDO market was over \$1.5 trillion in market value (Celent Consultant, 2005). The total amount of CDO issuances peaked in the first half of 2007 with a volume of \$345 billion (SIFMA, 2010) while about 60% of the global CDOs issuance has concentrated in CDOs with ABSs as collateral (Mählmann, 2013).

2.2.5 Problems with the securitisation of mortgage loans

While the securitisation process allows lenders to acquire immediate liquidity through selling mortgages to underwriters, it also creates a number of problems and encourages risk-taking behaviour.

First, in the case of a single layer ABS securitisation, when an asset is securitised with its cash flows repackaged, they are usually taken off the balance sheets of the lenders (a feature of pass-through securities). Risks in the loan assets are effectively transferred from the original lenders to the underwriters (buyers) during the transaction. As the default risks are no longer borne by the lenders, they are keen to make more mortgage loans to borrowers than they could have based solely on credit profiles. The underwriters, who bought the loan assets, put them into trusts and issue MBSs to fund the purchases. In the process of MBS issuance, underwriters have again effectively transferred the credit risks to the MBS investors and made profits within a short time (Udell, 2009). Therefore, underwriters' incentives to monitor the borrowers' credit quality are essentially low. The process of securitisation creates a misalignment of risk and returns between borrowers and lenders that in effect encourages risk-taking behaviour.

Second, securitisation creates a separation between mortgage lenders and borrowers, and severs the problem of asymmetric information. The effective lender of the underlying mortgages of the MBS is the investor who bought the MBS, rather than the original mortgage lender. Investors are not able to accurately evaluate their risk exposure and make well-informed investment decisions without detailed information on the collateral (e.g. on the real estate assets) and the credit quality of the borrowers. The separation inevitably forces investors to over rely on statistical information provided by the MBS issuers, such as the loan-to-value ratios, qualitative descriptions of the homeowners' creditworthiness and, most prominently, on the credit ratings issued by the rating agencies. During tranquil periods of rising housing prices, this information alone is sufficient for evaluating credit quality. However, when the economy slowed and the housing bubble was about to burst, the statistical criteria were found to be largely inaccurate and resulted in substantial underestimation of risks (Weaver, 2008). The function of monitoring the credit quality of loan borrowers by banks or issuers became largely ineffective in the process of securitisation.

Third, the credit rating system may be subject to potential bias and conflicts of interest. First, the information which rating agencies relied on may not have been accurate or sufficient to objectively evaluate the risks. Second, the rating agencies face potential conflicts of interest as the rating fees are paid by the same underwriters or financial institutions that issued the structured securities. Agencies usually compete with each other for rating businesses. Tighter and more prudent rating standards on the MBSs would probably hurt the sales of MBSs and the profitability of the underwriters (Udell, 2009). Underwriters may be prone to select rating agencies that are less stringent and strict in assigning ratings so that higher valuation and liquidity can be achieved at the time of issuance and release. The result was a substantial underestimation of risk.

On the other hand, one important complication of securitisation in relation to the recent crisis refers to the extensive use of structured securities (e.g. ABSs, CDSs, MBOs, etc.) as the underlying collateral for the CDO tranches.[8] Under wrong actuarial assumptions, the rating agencies largely overlooked the high correlations between tranches and systematically underestimated the risk in CDOs (Jaffe, 2008; Weaver, 2008). Mezzanine bonds of low credit quality were allowed to be pooled into new AAA-rated CDO bonds, which were then sold to investors as low risk fixed income products. When house prices fell and the mortgage delinquency rates increased, the prices of CDOs withered as the tranches were simultaneously shocked. A number of international financial institutions, which were assured that the AAA rating provided sufficient protection, held large subprime CDO portfolios. Therefore, the troubles in the US subprime mortgage markets and the structured finance markets would not only affect the US financial markets but would also affected a number of international markets.

[8] Mählmann (2013) refers to those CDOs with structured finance products as underlying assets ABS-CDOs, which represent the largest proportion of global CDO issuances.

2.3 The outbreak of the subprime crisis

2.3.1 The bursting of the US housing bubble

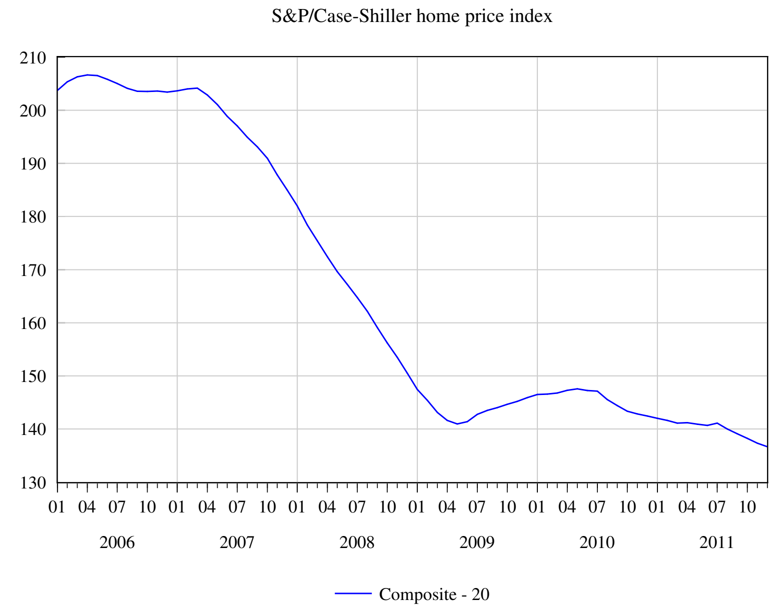
As mentioned in the previous sections, market restructuring, increasing housing demand, and the fast-expanding subprime mortgage market were all underlying causes of the development of a housing bubble in the US market.[9] The housing bubble would burst when there were no longer any investors or home buyers who were willing to buy homes. Meanwhile, the excess supply of houses would drive the prices down. As shown in Figure 2-6, the S&P/Case-Shiller Home Price Composite - 20 index, which tracks the average US housing prices, peaked in year 2006 and started to decline in mid-2007. When the house prices fell, borrowers were reluctant to sell their homes as selling their homes at lower prices result in negative equity and require paying additional collateral to lenders. Therefore, the number of housing transactions decreased gradually. In 2006, there were 9% fewer houses sold compared to that in 2005 while the price of the median home was just slightly lower than that in 2005 (Lindsey, 2007). On the other hand, mortgage lenders became more cautious in issuing new loans while appraisers, who assess the house values, also became more conservative because there were fewer comparable house sales and that the house sales were usually made at much lower prices. As the credit standards became more restrictive, the amount of mortgages and houses sales declined excessively. This resulted in a downward spiral of housing prices.

2.3.2 The mortgages' delinquencies and the failing structured finance market

Home buyers who financed their purchases with ARMs expected to sell their homes quickly to capture capital gains. However, when the prices and housing sales started to decline, some of them were reluctant to sell their houses and realise capital losses. After the expiration of the fixed-rate period, they inevitably had to pay the higher prevailing interest rates. As shown in Figure 2-7, the residential, commercial and total loans & leases delinquency rates (including both prime and subprime grades of loans) started to rise from 2006 onwards. As the threat of mortgage defaults heightened, the MBS prices declined sharply. The buy-side of the MBS market almost disappeared and the valuation of the subprime CDOs became extremely difficult due to the lack of transparency and the high uncertainty with regard to their collateral values (e.g. the value of the MBSs). Since

[9] Phillips and Yu (2011), using statistical techniques, document evidence of bubbles in US housing prices in February 2002.

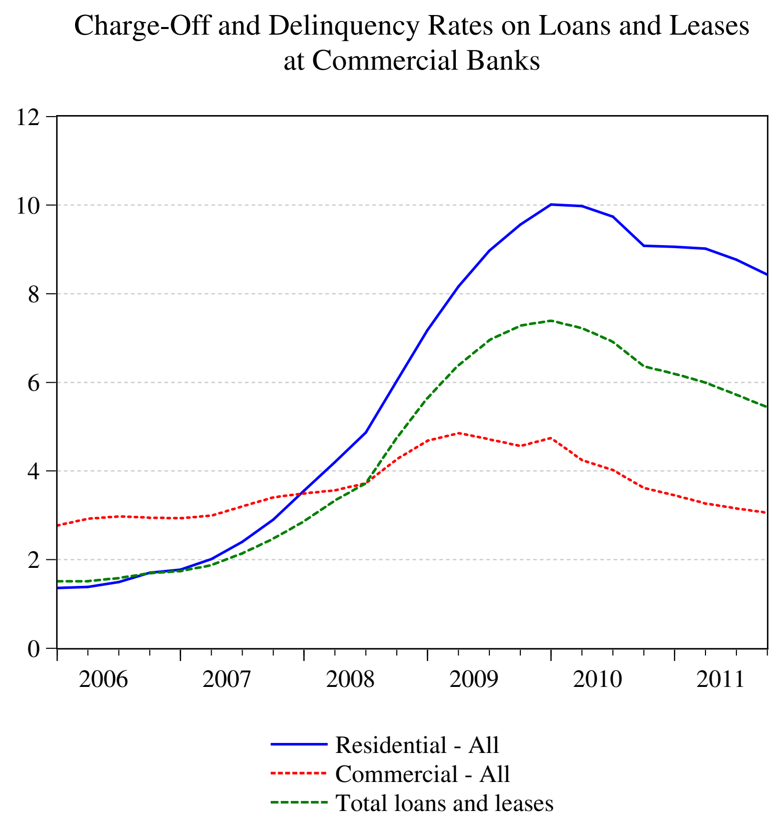
Figure 2-6: The S&P/Case-Shiller home price index



This figure plots the level of the S&P/Case-Shiller home price index over the sample between year 2006 to 2011 (source: Standard and Poors)

mid-2007, $220 billion of mark-to-market losses on ABS-CDOs backed by tranches of RMBSs and other ABSs were incurred amongst financial institutions around the world, which represented about 42% of all write-downs (all write-downs amounted to $520 billion) associated with the recent 2007 to 2009 financial crisis. Meanwhile, the volume of CDO issuance dropped dramatically to $5.7 billion in 2008Q4 (SIFMA, 2010). The number of rating downgrades of structured finance securities spiked in 2007 to 2008, in which about 95% of the downgrades were tied to RMBS, ABS, or CDO securities (Benmelech and Dlugosz, 2009). The ABX indices, which are benchmark indices for the US subprime RMBS market, started to decline sharply in early 2007 as shown in Fig. 4-1 of Chapter 4.

Figure 2-7: US loan delinquency rates



This figure plots the US loan delinquency rates of the residential, commercial and total loans & leases (including both prime and subprime grades of loans) (source: Federal Reserve; retrieved from: http://www.federalreserve.gov/releases/chargeoff/delallsa.htm).

2.3.3 The 'Credit Crunch' and the liquidity spiral

The subprime crisis, originally started from credit defaults in the subprime mortgage market, quickly spilled over to other US financial markets (Longstaff, 2010) and was characterised by severe market and funding illiquidity, commonly referred to as the 'credit crunch'.[10] Caruana and Kodres (2008, pp.69) point out that the average maturity of US short-term ABCPs shortened by six

[10]There is no consensus definition of the 'credit crunch' in regard to its nature, start and end dates. Academics and the media seem to commonly refer the period of 2007 to 2008 of the 'credit crunch' as credit fell short after the subprime structured finance market started to collapse (see e.g. Brunnermeier 2009; Reuters timeline 2008; Mizen, 2008).

days with outstanding ABCPs declines amounting to approximately $300 billion from August 2007 onwards.

In the literature, there is theoretical and empirical evidence that funding and market illiquidity have played important roles in the subprime and the subsequent global financial crises. In the following sections, we shall address a few important issues with regard to liquidity.

2.3.4 The SIVs and ABCPs

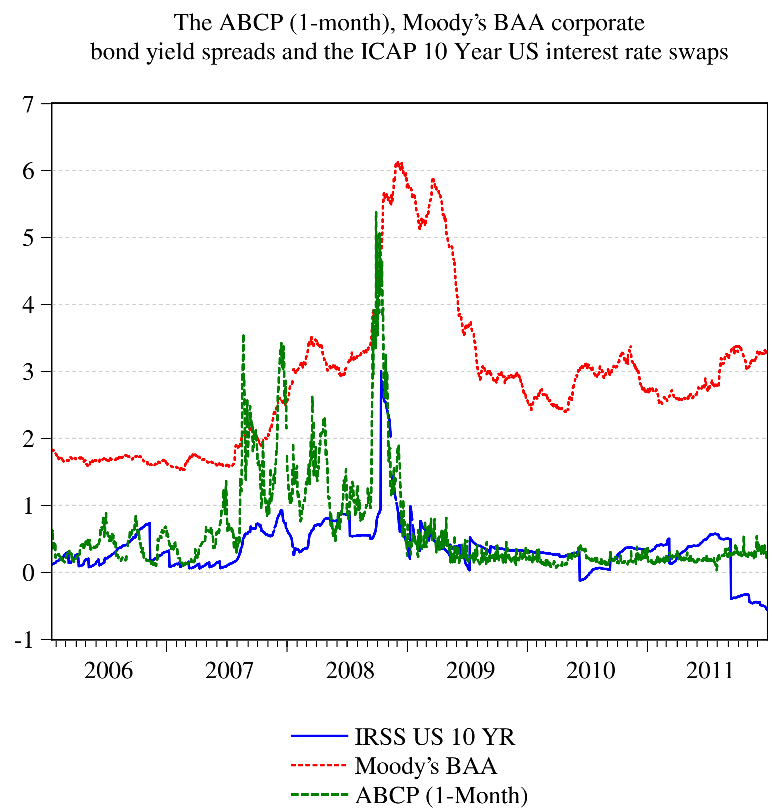
As pointed out by Brunnermeier (2009), banking institutions were subjected to higher funding illiquidity risks because of their increasing reliance on shorter maturity instruments, such as ABCPs. ABCPs are commercial papers that are collaterlised by assets, usually with a 30-day or 90-day maturity. One particularly important use of ABCPs by banking institutions in relation to the recent crisis was to fund the purchase of subprime structured finance securities in off-balance sheet SIVs and conduits.[11]

Over the years, ABS-CDOs have gained considerable popularity among institutional investors and banks for hedging and risk management purposes. Holding the CDO portfolios via off-balance sheet conduits, these institutions funded their purchases of CDOs with the issuance of short-term ABCPs, which require periodic roll-over (e.g. each month) (Brunnermeier, 2009). The maturity mismatch between the long-term structured securities and the short-term ABCPs enables the institutions to profit from the yield differences. A protection mechanism for the SIVs is established in that, if the ABCPs are insufficient to fund the CDOs, the owners of the SIVs are obliged to provide additional funding via credit line facilities.

During the crisis, the funding liquidity of financial institutions shrank as the market wide default risks increased and the banks' external access to external funding was restricted. Investors were unwilling to roll over their ABCPs resulting in a severe funding shortage in SIVs and conduits. As shown in Figure 2-8, the ABCP spreads (calculated as the yield differentials between one-month ABCPs and one-month Treasury bills) started to widen from mid-2007 onwards, and reached as

[11] In general, there are two types of SIVs. The first type refers to the self-standing SIVs that are essentially investment funds without connection to a commercial bank. The second type refers to SIVs that are wholly owned and operated by a commercial or investment bank ,of which the SIVs are run by bank employees and protected by credit line facilities provided by the same bank (Eichengreen, 2008). Self-standing SIVs are those vehicles that purchase longer-term assets financed by the issuance of ABCPs. The wholly owned SIVs are sometimes considered as a tool by financial engineers to disguise and repackage loan assets, escaping the scrutiny of the regulatory body. In our discussion, we are referring to both types of SIVs.

Figure 2-8: US yield spreads



This figure plots the yield spreads of the US Moody's BAA, asset-backed commercial papers (ABCP), and the 10-year US interest rate swaps (source: Datastream; authors' calculations).

high as 563 basis points in September 2008. As the structured securities' prices (values of the collateral) declined sharply, the funding shortage in these SIVs was excessive in that the credit line was not able to cover them. Financial institutions inevitably had to absorb these SIVs onto their balance sheets, resulting in huge losses and a significant amount of write-downs. As a result of the continuing losses in relation to their subprime mortgage businesses, a number of institutions filed Chapter 11 bankruptcy protection while some were bailed out by other institutions.

2.3.5 The relation between market and funding illiquidity

Brunnermeier and Pedersen (2009) propose a theoretical model that explains the relation between market illiquidity and traders' funding illiquidity. It also explains how a reinforcing liquidity spiral may arise in times of financial stress. In particular, during the crisis, the traders' ability to provide market liquidity was impaired because they faced losses in positions and larger margin requirements. When markets become illiquid, margin requirements may be driven higher as lenders become more conservative and prudent. In addition, the traders' initial asset position may also incur losses. The overall effects of the two forces further reduce the funding liquidity of the traders, resulting in potential deleveraging and a 'fire-sale' of assets in which the liquidity spiral starts over again.

Empirical studies have examined the validity of the hypotheses presented in Brunnermeier and Pedersen (2009) and have found consistent results that support the propositions of their model. Frank et al. (2008) document evidence of significant increases in comovements between market and funding illiquidity in the US financial system that are consistent with the liquidity spiral conjecture. Boyson et al. (2010) document evidence of contagion in hedge funds and find that they were exposed to some common risk factors associated with funding illiquidity. Gorton and Metrick (2012) document evidence that the LIBOR-OIS spreads were associated with the changes in credit spreads and the collateralised REPO rates. Their findings are consistent with Brunnermeier and Pedersen (2009) in that, when the uncertainty with regard to bank solvency increased, the margin requirements increased as a result of lower REPO collateral values. Longstaff (2010) finds evidence of contagion from the US structured market to a number of US asset markets during the subprime crisis. He further shows that contagion was associated with changes in various funding liquidity variables, including: the ratios of trading volumes of financial stocks to the overall market, the number of fails in REPO, and changes in ABCP yield spreads. Comerton-Forde et al. (2010) find a significant relation between the funding constraints faced by NYSE specialists and the time variation in market illiquidity, while Dick-Nielsen et al. (2012) find evidence of bond illiquidity during the subprime crisis.

2.4 The similarities and differences between the recent and previous crises

The previous sections have discussed how the crisis evolved and addressed issues with regard to the importance of market and funding illiquidity to contagion during the recent crisis. This section briefly reviews the literature and will summarise the similarities and differences of the recent crisis in comparison to previous crisis events.

Reinhart and Rogoff (2008) examine the early stage of the subprime crisis and 18 previous post-war banking crises in a number of industrialised countries and have identified a few similarities between the crisis episodes. In particular, they find significant increases in housing prices prior to the crises and dramatic declines during and after the crises. They observe similar inverted V-shape patterns in output growth prior to the crises. Claessens et al. (2010) also point out that the housing price bubble prior to the subprime crisis is similar to those in the so-called Big Five banking crises.[12] They also note that the default correlation on the outset of the subprime crisis was high provided that a large proportion of domestic loan assets were denominated in foreign currencies, similar to that during the East Asian crisis in 1997.

On the other hand, Claessens et al. (2010) point out that the subprime crisis was characterised by the 'explosion' of opaque structured finance securities and the exceptionally high leverage (in contrast to previous crisis studies). In addition, international markets have undergone substantial market reforms and have become more integrated with larger increases in cross-border investments than those in the previous crisis episodes. Reinhart and Rogoff (2008) find that the run-up of public debts in the US ahead of the subprime crisis is lower than the average levels of previous events. in addition, the authors note that the account deficits were on an increasing trend that was worse than any previous crises.

2.5 The crisis subperiods

This section will discuss and define the different phases of the recent 2007 to 2009 crisis and it will compare my crisis dates with those used in other studies. Our sample period covers the

[12] The Big Five banking crises refer to the banking crisis episodes in Finland (1991), Japan (1992), Norway (1987), Sweden (1991) and Spain (1977).

period of 19 January 2006 to 30 December 2011. Following the contagion literature, I will split the sample into four subperiods: pre-crisis, subprime, global and post-crisis subperiods. This allows us to detect significant contagion and facilitate comparison of empirical findings across periods of different levels of volatilities and market performance. Since there are no exact dates that best define the crisis outbreak[13], I will base my criteria of subperiod selection on historical events and market performances.[14]

For the pre-crisis subperiod, I will follow Longstaff (2010) and define the pre-crisis subperiod as the period between 20 January 2006 and 29 December 2006, during which the domestic US financial markets were relatively tranquil and free from substantial shocks and volatilities. Following Longstaff (2010), the subprime crisis subperiod is defined as the period between 2 January 2007 and 31 December 2007.[15] The subprime crisis subperiod is characterised by significant mark-to-market losses on the balance sheets of financial institutions worldwide in relation to their subprime mortgage businesses and structured credit instruments (e.g. HSBC, New Century Financials, Bear Stearns' bailing out of its structured credit hedge funds in June 2007). While some researchers define July 2007 as the start of the subprime crisis (credit crisis or liquidity crisis)[16], I define January 2007 as the beginning date of the subprime crisis subperiod due to the fact that this is precisely when the ABX indices started to decline sharply. In fact, in early 2007, the declines in ABX indices' prices already reflected the shocks in the structured finance market that had not yet been transmitted to other markets and fully reflected in other stress indicators (e.g. the TED spreads, the LIBOR-OIS spreads, the ABCP yield spreads or the Moody's Coporate bond yield spreads). Therefore, this definition of the subprime crisis enables me to focus on the spillovers of idiosyncratic shocks from the US structured finance market and allows my results to be readily comparable to those documented by Longstaff (2010).

The global crisis subperiod is defined as the period between 2 January 2008 and 31 March 2009, during which a number of financial institutions (i.e. Lehman Brothers) collapsed and were

[13]Not only are there no consensus start or end dates for the crisis episodes, some researchers do not distinguish between the subprime and the global crisis, and sometimes commonly refer them as 'the 2007 to 2009 financial crisis', 'global crisis', 'credit crisis' or 'liquidity crisis' (see, for example, Flannery et al., 2013; Bekaert et al., 2011).

[14]The historical evolution of the financial crises from the Federal Reserve Bank of St. Louis web site - http://timeline.stlouisfed.org/ is useful in this regard.

[15]Reinhart and Rogoff (2008) also define 2007 to 2008 as the subprime mortgage financial crisis.

[16]See, for example, Milunovich and Tan (2013); Edmonds et al. (2010); Flannery et al. (2013), for the crisis period defined as 2007Q3 to 2009Q3; Olson et al. (2012), for a structural break analysis on the US LIBOR-OIS spreads with the break in August 2007.

bailed out. While Longstaff (2010) define the entire year 2008 as the global crisis phase, we further extend the global crisis subperiod to include 2009Q1 based on the fact that the US and the G5 international equity markets crashed in late 2008 and tumbled in 2009Q1. Lastly, I will include a post-crisis window that covers the period between 2 September 2009 and 28 December 2011. The observations between April 2009 and August 2009 are intentionally omitted as the ABX BBB and BBB- indices were considerably thinly-traded. The daily return series during this subsample contained a number of consecutive zero returns, thus creating near singularity problems in regressions. Nonetheless, the post-crisis subperiod is not completely free of shocks and partly covers the ongoing European Sovereign Debt Crisis.

2.6 Conclusions

This chapter has reviewed the major issues with regard to the contexts, causes, consequences and evolution of the recent subprime and the subsequent global financial crises. In particular, it has discussed how the housing boom, the ever-easier credit standards, and the securitisation process explain the rapid growth in the US structured finance market and the substantial increases in the issuances of RMBSs, ABSs, and CDOs. It then explained how the bursting of the housing bubble triggered the waves of mortgage delinquencies and the subsequent failure of the structured finance market. Important issues with regard to funding and market illiquidity have been addressed along with supportive empirical evidence. It has also discussed and defined the crisis subperiods, based on historical events and market performances, for use in the empirical investigation in subsequent chapters.

This chapter provides comprehensive background information on the role played by the US structured finance market in the recent crisis. The next chapter will review the contagion literature with a focus on the definitions, theoretical basis, empirical methodologies and empirical findings.

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Chapter 3

Literature Review on Financial Contagion

3.1 Introduction

Despite the fast-expanding empirical literature on financial contagion, there is still widespread disagreement over the working definitions of contagion among researchers (Forbes and Rigobon, 2002). Since the widespread disagreement in definition inevitably makes comparison across findings relatively difficult, it is worthwhile investigating how the different empirical methodologies are motivated from specific definitions and how the findings should be interpreted.

In the literature, there are various excellent surveys on the theoretical and empirical aspects of contagion research (see, for example, Dornbusch et al., 2000; Kaminsky et al., 2003; Pericoli and Sbracia, 2003; Dungey et al., 2005). Motivated by the recent crisis events, a large number of empirical studies have been published in an attempt to detect the occurrence of contagion and explain its transmission mechanism. In this chapter, I shall review the theoretical and empirical contagion literature and address some of the major issues and recent developments in contagion research, with a particular focus on the transmission mechanism, the empirical methodologies, and the empirical evidence.

This chapter is structured as follows. Section 2 reviews the working definitions of financial contagion. Section 3 reviews a few major transmission mechanisms of contagion. Section 4 surveys the empirical literature and reviews a few widely-acknowledged empirical methodologies. Section

5 summarises the empirical evidence on contagion and Section 6 concludes.

3.2 The working definitions of financial contagion

Financial contagion can be broadly understood as the spread of adverse market disturbances from a shocked market to another (Dornbusch et al., 2000). Pericoli and Sbracia (2003) summarise and propose a useful classification of contagion definitions that is commonly referenced in the literature, as follows:

1. Contagion is a significant increase in the probability of a crisis in one country, conditional on a crisis occurring in another country (Dornbusch et al., 2000).

2. Contagion arises when volatilities of asset prices transmit from the country of crisis to another country (Edwards, 1998).

3. Contagion occurs when cross-country comovement of asset prices increases and the higher comovement cannot be explained by fundamentals.

4. Contagion is a significant increase in comovements of prices and quantities across markets, conditional on a crisis in one market (Dornbusch et al., 2000).

5. Contagion occurs when the transmission channel intensifies or changes after a shock in one market or country (Forbes and Rigobon, 2002).

Definition 1 centers on the idea of a significant increase in the probability of a crisis conditional on a crisis event. Definitions 2, 3 and 4 are somewhat similar in the sense that they more or less encompass the notion of market comovements, such as volatilities, asset returns, trade or financial flows. Definition 5 focuses on the sudden changes in the shock transmission mechanism during a crisis.

Note that the working definitions of contagion have changed over time. Earlier studies on contagion did not distinguish between contagion and interdependence (Pericoli and Sbracia, 2003). Forbes and Rigobon (2002) introduce a more stringent definition of contagion by distinguishing strictly between contagion and interdependence. According to the authors, interdependence is the degree of normal comovement between two or more markets during a tranquil period and should be taken into accounted; that is, only when there are significant increases in return comovements during a crisis does contagion exist. It is, therefore, necessary to split the samples into ‘tranquil’ and ‘crisis’ subperiods and examine the changes in correlation coefficients across the subperiods. Kaminsky et al. (2003) define contagion as the immediate short-term transmission of shocks across financial markets, which occur in a ‘fast and furious’ way. The authors define the gradual effects of the negative consequences brought on the crises as spillovers instead of contagion. Pericoli and Sbracia (2003) point out that contagion may not necessarily be ‘fast and furious’ and immediate, which is consistent with Longstaff’s (2010) findings of contagion travelling from the US structured finance market to other US financial markets within trading weeks.

In this thesis, my working definition of contagion is consistent with Forbes and Rigobon (2002) and distinguishes between contagion and interdependence. Following Longstaff (2010), I do not rule out the possibility that contagion may not be ‘fast and furious’.

3.3 The mechanisms and channels of transmission of contagion

With regard to financial contagion, three major research questions are commonly addressed. First, researchers are keen to identify and understand the possible channels and mechanisms in which shocks transmit during a crisis. Second, as an extension to the first research question, the second research question examines whether the identified channels and mechanisms may change during a crisis; that is, whether the transmission channels may discontinue, strengthen or become active only during crisis. Third, researchers seek to provide implications to various market users and policymakers in establishing effective measures to prevent and contain the negative consequences of the crisis events. In addition, empirical studies are important because they also provide important implications to the investment community with regard to the effectiveness of international portfolio diversification. Any significant increases in market comovements during the crisis temper the benefits of international diversification and leave investors exposed to substantial risks.

In the following sections, I will review and summarise various widely-acknowledged causes and transmission mechanisms of contagion in an intuitive manner. I follow the structure and classification of the survey by Dornbusch et al. (2000) and summarise the fundamental and investor behaviour related causes.

3.3.1 Fundamental causes

The fundamental causes of contagion commonly refer to the spillovers of shocks through structural changes in economic circumstances, trade linkages, financial linkages and competitive devaluations. The fundamental causes are closely related to market integration in which a structural change in a country induces shocks commonly experienced by many other countries. This may include structural shifts in the economy or the strengthening of some major currencies. Common shocks may trigger comovement in asset prices across international markets (Dornbusch et al., 2000). Shocks may transmit via the trade linkages that result in competitive devaluations. During a crisis, the shocked country may experience sharp depreciations in its currency, declines in asset prices and large capital outflows, which in turn make its products relatively cheaper compared to its competitors internationally. The trading partners of this country, facing the cheaper products from the shocked country, may voluntarily devalue their currencies in order to maintain the competitiveness of their own exports resulting in higher comovements in asset prices via trade linkages.

The second fundamental cause refers to the shock transmission via financial linkages in which direct financial effects spread across markets during a crisis. Some of the financial effects include the reduction in trade credits, foreign direct investments and capital flows (Dornburch et al., 2000). When a country is shocked, the other trading partners are affected due to their limited ability to invest abroad and extend credit. In addition, this may also result in declines in the availability of capital, higher costs of borrowing and may eventually lead to increased comovements in asset prices.

3.3.2 Investors-related causes

Apart from the fundamental causes, investors' related causes focus primarily on the role of investors in shock transmission, which includes the effects of herding, liquidity shocks, information asymmetries (Kiyotaki and Moore, 2002), multiple equilibria and perception about changes in the rules of financial transactions (Kaminsky et al., 2003).

The first investor related cause relates closely to the information transmission channel, in which the arrival of economic news directly affects the collateral values or cash flows in other markets (Kaminsky et al., 2003). This channel is consistent with the Efficient Market Hypothesis (EMH), in which any new market information will be absorbed and reflected in the asset prices immediately, and the contention that contagion should be 'fast and furious' and immediate. In other words, contagion is a direct consequence of the transmission of market information or economic news from the shocked market to other markets.

The second investor related cause of contagion relates closely to funding liquidity. In the model proposed by Shleifer and Vishny (1997), when a shock lowers the asset returns in one country, risk-averse arbitrageurs will liquidate their positions in other countries to meet the capital outflows and avoid further losses, which is referred to as a 'fire sale'. Calvo (1998) suggests that investors may liquidate their assets to meet the increasing margin requirements during crisis and may be prone to sell foreign assets in which the prices have not yet declined drastically in their portfolios. Allen and Gale (2000) propose a model that focuses on the role of commercial banks in shock transmission. The authors argue that financial shocks cause banks to liquidate cross-holdings across regions leading to shortfalls of funding liquidity in other regions. Kaminsky and Reinhart (2000) also share similar views with Allen and Gale (2000) and point out that foreign banks may tighten up credit lines and call back loans in order to rebalance their overall risk exposure during a crisis. In addition, Longstaff (2010) examines trading intensity in US financial stocks, the number of fails in the REPO market and the size of the ABCP market, and finds evidence that the shocks from the US structured finance market translated into subsequent higher funding illiquidity.

The third investor related cause refers to the way in which an individual investor follows the behaviour of a precedent individual without regard to his own information, which is commonly referred to as herding. Bikchandamn et al. (1998) propose a model of observational learning and a theory of informational cascade that seeks to uncover the relation between signals from actions by precedents, private information and private signals. An informational cascade occurs when an individual disregards his private information but decides to follow the signals given by the actions of his precedents. Note also that a person who follows others has a positive externality of inducing others to follow the herd (Banerjee, 1992, cited in Kaminsky et al., 2003). During a crisis, when asset prices have collapsed and liquidity has evaporated, institutional investors might liquidate and sell their asset positions to meet their capital outflows. Individual investors may follow without regard to their own knowledge about the markets, giving rise to further downside comovements of asset prices. Calvo and Mendoza (2000) propose a model in which there are large fixed costs associated with gathering and processing country-specific information. The existence of the fixed costs allows economies of scale to be enjoyed by informed investors. When uninformed investors observe the short positions of these informed investors, they are unable to determine whether the short positions are caused by margin calls or other negative market information on the fundamentals. The uninformed investors may follow the informed investors and enter into short positions, resulting in herding effects and asset comovements.

The investors related cause with regard to information asymmetry focuses on the investors' expectations and on the fact that investors have imperfect market information. In general, investors are informed about the markets based on some composite financial indicators and make their investment decisions accordingly. However, these indicators may not reflect accurately the situation with regard to the severity of crisis events in an individual country. Investors formulate their expectations rationally and infer that crises will hit their own countries, thus leading to possible herding effects and comovement in asset prices.

Other investors' related causes include multiple equilibria and changes in the market rules. For multiple equilibria, a crisis in one country may force other countries into bad equilibria. In other words, changes in investors' expectation are self-fulfilling and move other countries into new equilibria. For changes in the rules, this refers to the changes in the assessment of the rules and ways in which financial transactions take place across countries and markets. One example mentioned in Dornbusch et al. (2000) refers to the increasing doubt towards the International Monetary Fund (IMF) in its ability to bail out distressed countries as the lender of last resort.

3.3.3 The risk premia transmission channel

The risk premia transmission channel refers to the comovements of asset prices that occur as a result of changes in risk premia after a crisis event has taken place. An idiosyncratic shock to one market results in subsequent changes in investors' risk aversion and increases in risk premia required by investors in other markets.

Recent studies document a significant role on market illiquidity risks in asset pricing (see, for example, Amihud, 2002; and Acharya and Pedersen, 2005). Significant time variations in market illiquidity risk premia and evidence of 'flight-to-liquidity' have been documented. Longstaff (2004) finds significant liquidity premia in the yield spreads between the more liquid US Treasury bonds over the Refcorp bonds suggesting some market liquidity components in Treasury bonds. Liu et al.

(2006) also find significant time-varying liquidity premia in the US Treasury bonds over the period between 1988 and 2002. These empirical findings suggest that investors have certain liquidity preferences and that 'flight-to-safety' phenomenon may be driven by liquidity, apart from credit risk concerns. In other words, the increase in market illiquidity risks during a crisis might have considerable impacts on the investors' risk aversion and result in subsequent systematic 'flights' to liquid assets. On the other hand, funding and market illiquidity may relate to each other closely. Brunnermeier and Pedersen (2009) propose a model that describes the relation between funding and market illiquidity in that traders' funding illiquidity result in higher transaction costs and, in turn, higher market illiquidity. The declines in asset prices as a result of market illiquidity further temper the traders' funding liquidity, result in a reinforcing liquidity spiral, and translate into higher cross-market price comovements and spillovers of volatility.

Another widely-acknowledged risk premia refers to the credit risk premia that compensates for default and counterparty risks. Vassalou and Xing (2004) find that equities' credit risk premia are systematic and significantly explain expected stock returns. Eichengreen et al. (2009) examine the common factors that underlie the CDS spreads of major banks and find increasing importance in these factors during the subprime crisis. In particular, these factors can be explained by the heightening credit risks in the US banking industry. These findings support the contention of significant time variations in credit risk premia in equity markets, especially in the financial sector. The increase in credit risk premia may result in portfolio rebalancing and reinforce risk-averse investors to 'flight' to less risky assets.

3.4 A survey of empirical methodologies of financial contagion studies

In the literature, there are a number of empirical methodologies used in detecting the presence of contagion. Given the disagreement on the working definitions of contagion, the interpretation of empirical results is dependent on the specific working definitions adopted to facilitate systematic comparison across findings. In this section, I review the literature with a focus on empirical methodologies and highlight their implications to contagion research.

3.4.1 Probit and logit models

Eichengreen et al. (1996) published one of the earliest papers to examine contagion and shock transmission. In particular, they studied cross-country contagion during various currency crisis episodes. The authors formulate their working definition of contagion by relating contagion to the significant increases in probability of speculative attacks in the domestic currency of one country, conditional on a currency crisis in another country (see Definition 1). The contagion definition leads naturally to an empirical framework that examines the relation between the occurrence of a binary outcome (dependent variable) and the determinants of that outcome (independent variables); that is, a probit or logit regression framework. In a probit model, the conditional probability of observing a desired outcome of the dependent variable (π_i) is written as:

$$\pi_i = \Phi(X'\gamma), \tag{3.1}$$

where $\Phi(\cdot)$ is the cumulative distribution function (CDF) of the standard normal distribution ensuring that π_i stays between 0 and 1, X' is a vector of independent variables while γ is a vector of coefficients.

Using a panel of quarterly data of macroeconomic and currency indices covering 20 industrial countries over the period between 1959 and 1993, the authors examine whether the currency crisis in country j translates into a higher probability of observing a currency crisis in other countries. Practically, to define the occurrence of a currency crisis, the authors construct an index ($EMP_{i,t}$) that proxies for the pressure of speculative attacks by computing the weighted averages of the exchange rate changes, reserve changes and interest rate changes as follows:

$$EMP_{i,t} = \alpha\Delta e_{i,t} + \beta\Delta(i_{i,t} - i_{G,t}) + \lambda\Delta(r_{i,t} - r_{G,t}), \tag{3.2}$$

where $e_{i,t}$ is the exchange rate, $i_{i,t}$ is the short interest rate (as a benchmark), and $r_{i,t}$ is the ratio of international reserves of country i. The subscript G denotes that it is a German variable. α, β and λ are weights while Δ is a symbol for change. The weights are computed by equating the volatilities of the three components in the EMP index to prevent any components from dominating the index variations.

Currency crisis is defined as the realisation of extreme values in the EMP index. A crisis dummy variable ($Crisis_{i,t}$) is introduced, which takes on the value 1 when a currency crisis is detected and 0 otherwise. The threshold value on the EMP index for a currency crisis is defined as:

$$\begin{aligned} Crisis_{i,t} &= 1 \quad \text{if } EMP_{i,t} > \mu_{EMP} + 1.5\ \sigma_{EMP}, \\ &= 0 \quad \text{otherwise,} \end{aligned} \tag{3.3}$$

where μ_{EMP} and σ_{EMP} are the sample mean and sample standard deviation of the EMP index.

The probit regression model is then written as follows:

$$Crisis_{i,t} = \omega \mathrm{D}(Crisis_{j,t}) + \lambda \mathrm{I(L)}_{i,t} + \varepsilon_{i,t}, \tag{3.4}$$

where $\mathrm{I(L)}_{i,t}$ is an information set of 10 macroeconomic control variables. The null hypothesis is no currency contagion, as given by $\omega = 0$.

Using the same probit model framework, Caramazza et al. (2000) study the significance of external and internal imbalances, financial weaknesses (as measured by reserve adequacy), trade and financial linkages, institutional factors (exchange rate regimes and capital controls), and the presence of nonlinear effects in explaining the currency crisis contagion, particularly during the three major crisis episodes in the 1990s.

As pointed out by Dungey et al. (2005), empirical studies based on conditional probabilities are attractive in that they allow researchers to generate probability estimates of contagion from one country to another. The change in probability of observing a currency crisis can be calculated by: $\Phi(Z_1) - \Phi(Z_0)$ where $Z_1 = \omega + \lambda \mathrm{I(L)}_{i,t}$ and $Z_0 = \lambda \mathrm{I(L)}_{i,t}$. However, Dungey et al. (2005) also notes that the use of dummy variables in general leads to losses of sample information, inefficient parameter estimates and thus a loss of power in the test.

3.4.2 GARCH models

An extensively researched area of contagion refers to the examination of spillovers of volatilities across markets during a crisis (see Definition 2). Motivated by the fact that return volatilities tend to cluster and spike during market distress, generalised autoregressive conditional heteroskedastic (GARCH) type models are particularly useful in modelling the dynamics of conditional volatilities and are often used to study the possible transmission of volatilities across markets. In this section, I review a few seminar papers on the spillovers of volatilities and provide details on the specifications of the GARCH type models used.

A seminal paper by Engle et al. (1990) investigates whether the conditional volatilities in intraday exchange rates exhibited 'heat wave' or 'meteor shower' behaviour.[17] Using per hour volatilities of four major economic segments (New York, Tokyo, Pacific and Europe), the authors test whether the conditional volatilities in one market predict those in other market segments. Empirically, they employ a GARCH(1,1) model and formulate the conditional volatility functions as a vector autoregressive model to test for the cross-market dynamics. The main model specification is as follows:

$$\begin{aligned} &\varepsilon_{i,t}|\psi_{i,t} \sim N(0, h_{i,t}) \text{ for } i = 1, 2, ..., n. \\ &h_{i,t} = \omega_i + \beta_i h_{i,t-1} + \sum_{j=1}^{i-1} \alpha_{ij}\varepsilon_{j,t}^2 + \sum_{j=i}^{n} \alpha_{ij}\varepsilon_{j,t-1}^2. \end{aligned} \tag{3.5}$$

In the GARCH model, the conditional volatilities of market i are dependent on its own lag (the second term), the contemporaneous conditional volatilities of the closed market segment (the third term) and the lagged conditional volatilities of the remaining markets. The heat wave null hypothesis is that the α_{ij} are jointly equal to zero; that is, there are no volatility spillovers. The authors then compute the impulse responses of the conditional volatilities by rewriting the equation as a vector of moving averages with infinite order. The empirical findings reject the heat wave hypothesis and show that Japanese news had the largest magnitude of volatility spillovers.

Engle (2002) proposes a new class of multivariate GARCH estimators, called the Dynamic Conditional Correlation GARCH (DCC GARCH) model, as a generalisation to the Bollerslev (1990) constant conditional correlation (CCC) estimator. The estimation of the DCC MGARCH model involves first estimating univariate GARCH models on individual time series to obtain consistent estimates of time-varying conditional volatilities, and then using those estimates to estimate the

[17]The authors utilise meteorological analogies and relate the 'heat wave' hypothesis to volatilities that have only country-specific autocorrelation while 'meteor shower' for volatilities that have cross-market intra-daily spillovers of volatilities.

correlation parameters. The main specification of the DCC GARCH model is as follows:

$$\begin{aligned}
r_t|\Omega_{t-1} \sim\ & N(0, D_t H_t D_t), \\
D_t^2 =\ & diag\{\omega_i\} + diag\{\kappa_i\} \bullet r_{t-1}r'_{t-1} + diag\{\lambda_i\} \bullet D^2_{t-1}, \\
\varepsilon_t =\ & D_t^{-1} r_t, \\
Q_t =\ & S \bullet (\iota\iota' - A - B) + A \bullet \varepsilon_{t-1}\varepsilon'_{t-1} + B \bullet Q_{t-1}, \\
R_t =\ & diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}, \\
S_t =\ & E[\varepsilon_t \varepsilon'_t],
\end{aligned} \tag{3.6}$$

where r_t is a $n \times 1$ vector of pre-whitened returns, S_t is the unconditional correlation matrix of the residuals ε_t, $\bullet$ is the Hadamard product, ι is a vector of ones. D_t is a diagonal matrix comprises of the standard deviations from individually estimated univariate GARCH models with the i^{th} element denoted as $\sqrt{h_{i,t}}$ while Q_t is a positive semidefinite covariance matrix. The first equation states that the pre-whitened returns have a normal distribution while the second equation shows that the asset returns follow univariate GARCH processes.

The log-likelihood function for the DCC estimators is given by:

$$\begin{aligned}
r_t|\Omega_{t-1} \sim & \ N(0, H_t), \\
L = & -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|H_t| + r'_t H_t^{-1} r_t), \\
= & -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t R_t D_t| + r'_t D_t^{-1} R_t^{-1} D_t^{-1} r_t), \\
= & -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + \log|R_t| + \varepsilon'_t R_t^{-1} \varepsilon_t), \\
= & -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + r'_t D_t^{-2} r_t - \varepsilon'_t\varepsilon_t + \log|R_t| + \varepsilon'_t R_t^{-1}\varepsilon_t).
\end{aligned} \tag{3.7}$$

The author proposes a few estimation methods that give consistent but inefficient estimates of the model parameters, even though the covariance matrix is very large. The log-likelihood can be decomposed into two parts: a volatility part and a correlation part.

$$L(\theta, \phi) = L_v(\theta) + L_c(\theta, \phi), \tag{3.8}$$

where the subscript v denotes the volatility component and c denotes the correlation component.

Practically, the volatility part is the sum of individual GARCH likelihoods:

$$L_v(\theta) = -\frac{1}{2}\sum_t \sum_{i=1}^{n} (\log(2\pi) + \log(h_{i,t} + \frac{r_{i,t}^2}{h_{i,t}}), \tag{3.9}$$

which are maximised when each GARCH likelihood is maximised separately. Since the squared residuals are not dependent on the parameters, the correlation part can be written as follows:

$$L_c(\theta, \phi) = -\frac{1}{2}\sum_t (\log|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t). \tag{3.10}$$

Practically, the DCC-GARCH estimator delivers the parameters that maximise the likelihoods:

$$\hat{\theta} = \arg\max\{L_v(\theta)\}, \tag{3.11}$$

with the estimated parameters in D used to estimate the parameters (ϕ) in R_t:

$$\max_{\phi}\{L_c(\hat{\theta}, \phi)\}. \tag{3.12}$$

The author shows that when the first step estimates are consistent, the second step will also give consistent estimates, as long as the function is continuous in the neighborhood of the true parameters.

The DCC-GARCH model continuously adjusts the correlation for the time-varying volatility and thus the contagion tests are not subject to the heteroskedasticity bias, as pointed out by Forbes and Rigobon (2002).

3.4.3 Correlation coefficient analysis

Correlation coefficient analysis is one of the most popular empirical approaches to detecting contagion in the literature. The study of market comovements is motivated from the observation that, when a crisis episode occurs, a number of markets are adversely affected in a consistent and correlated manner, and are unexplained by the underlying fundamentals. The correlation coefficient analysis is convenient and practical because it provides direct implications to international portfolio diversification and risk management. For instance, in times of increased market comovements, diversification benefits brought about by holding international assets become less effective and portfolio risks would be underestimated. The empirical methodology parallels Definition 3 in which contagion is defined as significant increases in market comovements conditional on a crisis event.

Forbes and Rigobon (2002) establish a stringent contagion definition that only a significant increase in the correlation coefficient (after accounting for the normal degree of interdependence) is evidence of contagion. The authors point out that the conditional correlation coefficient increases when the volatilities of the shocked market have increased during a crisis, even when the unconditional correlation coefficient remains constant. To this end, they propose a correction for heteroskedasticity and show that contagion documented using conditional volatilities without the adjustment is spurious. The heteroskedasticity correction is written as follows:

$$\rho_{adj} = \frac{\rho^*}{\sqrt{1 + \delta[1 - (\rho^*)^2]}}, \tag{3.13}$$

where

$$\delta = \frac{\sigma_{ii}^h}{\sigma_{ii}^l} - 1. \tag{3.14}$$

Here, ρ_{adj} is the heteroskedasticity-adjusted unconditional correlation coefficient while ρ^* is the conditional correlation coefficient. δ is the relative increase in variances during a crisis in which σ_{ii}^h and σ_{ii}^l are the variances of returns of market i during the high and low volatilities periods, respectively. δ represents a non-linear transformation to the conditional correlation.

The test for significant increases in correlation coefficients is thus formulated as in the following null hypothesis:

$$H_0 : \rho_{adj} = \rho^*, \tag{3.15}$$

while the alternative hypothesis is written as follows:

$$H_1 : \rho_{adj} > \rho^*. \tag{3.16}$$

The t-statistics for testing the null hypothesis can be written as (Dungey et al., 2005):

$$t\text{-}stat = \frac{\hat{\rho_{adj}} - \hat{\rho^{*}}}{\sqrt{\frac{1}{T_h} + \frac{1}{T_l}}}, \tag{3.17}$$

where T_h and T_l refer to the number of observations during the high and low volatility subperiods, respectively. The standard errors are derived from the asymptotic distribution of the estimated correlation coefcients.

By contrast, Dungey et al. (2005) show that this bivariate correlation coefficient test can be formulated within a regression framework in which the standard errors are the ordinary least square standard errors whilst the approach of Forbes and Rigobon (2002) uses asymptotically adjusted standard errors.

Corsetti et al. (2005) argue that the heteroskedasticity correction in Forbes and Rigobon (2002) is based on unrealistic assumptions with regard to the idiosyncratic variance and may bias the result towards finding no contagion at all. Pesaran and Pick (2007) point out that correlation tests may suffer from an upward bias because of potential endogeneity in the variables. The authors also point out that the splitting of 'tranquil' and 'crisis' periods is somewhat arbitrary and difficult to justify. Dungey et al. (2005) note that tests based on correlation coefficients are conservative and in general find no evidence of contagion.

3.4.4 Vector autoregressive models

A vector autoregressive (VAR) model treats all variables in the system endogenously, and each variable is expressed as a function of its own lags and the lags of the remaining variables. A reduced-form (RF) VAR(p) can be written as:

$$\mathbf{y_t} = \alpha_\mathbf{0} + \mathbf{A_1 y_{t-1}} + \mathbf{A_2 y_{t-2}} + \cdots + \mathbf{A_p y_{t-p}} + \mathbf{u_t}, \tag{3.18}$$

where

$$\mathbf{y_t} = \begin{pmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{n,t} \end{pmatrix}, \alpha_\mathbf{0} = \begin{pmatrix} \alpha_{1,t} \\ \alpha_{2,t} \\ \vdots \\ \alpha_{n,t} \end{pmatrix}, \mathbf{A_i} = \begin{pmatrix} a^{(i)}_{1,1} & a^{(i)}_{1,2} & \cdots & a^{(i)}_{1,n} \\ a^{(i)}_{2,1} & a^{(i)}_{2,2} & \cdots & a^{(i)}_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a^{(i)}_{n,1} & a^{(i)}_{n,2} & \cdots & a^{(i)}_{n,n} \end{pmatrix} \mathbf{u_t} = \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{n,t} \end{pmatrix}$$

The RF VAR can be extended to include a set of exogenous regressors $\mathbf{x_t}$ where $\mathbf{x_t} = [x_{1,t}, ..., x_{q,t}]'$ in a VAR(p) with q exogenous variables.

There are, in general, three different approaches to using the VAR model to test for contagion. The first method refers to using the VAR model to filter (or pre-whiten) asset returns with some exogenous macroeconomic variables and then using the residuals of the endogenous variables for further analysis. Forbes and Rigobon (2002) apply a bi-variate VAR model with interest rates as exogenous variables and study the heteroskedasticity-adjusted correlation across the pair of residual series to test for the existence of contagion. Favero and Giavazzi (2002) study the spillovers of devaluation expectations among member countries of the European Exchange Rate Mechanism (ERM) within the European Monetary System (EMS). Using weekly Euro rate spreads, the authors examine the distribution of the VAR residuals of the rate spreads and define non-linearity and heteroskedasticity in the VAR residuals as shocks. The authors identify the unusually large residual observations by dummy variables for each shock and use structural models (simultaneous equations) to test for the existence of cross-market contagion.

Second, the VAR model allows researchers to evaluate the dynamics of the variables of interest by computing impulse response functions. To show how it works, I rewrite the VAR equation as a vector moving averages (VMA) of infinite order:

$$\begin{aligned}
\mathbf{y_t} &= \mu + \mathbf{\Phi}(L)\mathbf{u_t} = \mu + \sum_{j=1}^{\infty} \mathbf{\Phi_{\boldsymbol{j}}} \mathbf{u_{t-j}}, \\
\mathbf{I_n} &= (\mathbf{I_n} - \mathbf{A}(L))\mathbf{\Phi}(L).
\end{aligned} \tag{3.19}$$

The $\mathbf{\Phi_{\boldsymbol{j}}}$ represents a n by n matrix of moving average coefficients of the RF VAR innovations at time $t-j$. $\Phi^{(j)}_{i,k}$ measures the response of variable i to a previous unit shock in innovation k, occurring in time $t-j$. The impulse responses can be shown graphically by plotting the $\Phi^{(j)}_{i,k}$ against j. Baig and Goldfajn (1999) study contagion among five Asian countries during the Asian financial crisis in 1997. Using a VAR model framework, impulse response results show that the Thai Baht had a significant immediate impact on the Malaysian, Indonesian, and the Philippines currency rates, which lasted for about four days.

One of the drawbacks with regard to the RF VAR model, despite its relative ease in identification and implementation, is that the impulse response analysis does not provide relevant economic meaning because the unit shock (RF VAR innovations) to the RF VAR system is a linear combination of the VAR endogenous variables' structural shocks, which are not identified.[18] Therefore, to derive an economic interpretation of the impulse responses, one has to derive the structural innovations by imposing sufficient restrictions to the system of equations to identify the structural VAR model.

The third type of contagion test refers to the examination of block predictive power of the independent variables over the contemporaneous dependent variables on the VAR functions via the Granger-causality test. Longstaff (2010) estimates VAR(4) models using weekly domestic US market variables as endogenous variables and the ABX indices' returns as strictly exogenous regressors. The F-tests of joint significance on the ABX factor loadings show that the lagged ABX index returns Granger-caused the contemporaneous US market returns only in 2007 (i.e. during the subprime crisis). The increases in predictive power of the lagged variables conditional on a crisis event are consistent with increases in cross-market linkages and thus the existence of contagion.

3.4.5 Factor models

Dungey et al. (2005) review the empirical methodologies of contagion and propose a unified latent factor model framework that encompasses a few widely-acknowledged empirical models of contagion (see, for example, Corsetti et al., 2001; Dungey and Martin, 2001; Dungey et al., 2002a, b; Forbes and Rigobon, 2002; Bekaert et al., 2005). Factor models are used extensively in the literature and bring the benefit of the possibility of volatility decomposition while accounting for interdependence between markets. According to Dungey et al. (2005), a general setting of a latent factor model, assuming a hypothetical world with only two asset markets in which contagion transmits from market 1 to 2, can be shown as follows:

[18] A structural VAR representation captures the dynamics and has impulse response functions expressed in terms of the structural innovations that provides relevant economic interpretation. A few common approaches for identification restrictions include the application of a Cholesky decomposition to the RF VAR innovation's covariance matrix (the so-called Sims-Bernanke Decomposition, cited in Enders, 2003, p. 75) (or equivalently, the recursive causal ordering identification), the short-run zero restrictions on the structural matrix **A** in the AB SVAR models, the long-run restrictions on the cumulative impulse response function matrix (The Blanchard-Quah Decomposition, cited in Enders, 2003, pp. 82), etc. (For more details, please refer to Sims (1980); Stock and Watson (2001); and NBER Summer Institute (2008).

$$
\begin{aligned}
y_{1,t}^{(Pre)} &= \alpha_1 w_t + \beta_1 u_{1,t}, \\
y_{2,t}^{(Pre)} &= \alpha_2 w_t + \beta_2 u_{2,t},
\end{aligned} \tag{3.20}
$$

$$
\begin{aligned}
y_{1,t}^{(Crisis)} &= \alpha_1 w_t + \beta_1 u_{1,t}, \\
y_{2,t}^{(Crisis)} &= \alpha_2 w_t + \beta_2 u_{2,t} + \lambda u_{1,t},
\end{aligned} \tag{3.21}
$$

where the $y_{i,t}^{(Pre)}$ and $y_{i,t}^{(Crisis)}$ represent the demeaned asset returns of asset market i at time t during the pre-crisis and the crisis subperiods, respectively. w_t refers to a latent (or observed) world factor that affects the asset markets commonly while $u_{i,t}$ refers to an idiosyncratic factor local to market i. The $y_{2,t}^{(Crisis)}$ expression now allows for the contagious effects from asset market 1 by incorporating the idiosyncratic factor $u_{1,t}$ into the equation and, hence, a test of contagion can be carried out by comparing the parameters across the pre-crisis and crisis models.

From Equation 3.21, the covariance between the returns of market 1 and 2 during the crisis period can be written as:

$$
cov[y_{1,t}^{(Crisis)}, y_{2,t}^{(Crisis)}] = \alpha_1 \alpha_2 + \lambda \beta_1. \tag{3.22}
$$

A change in covariance between the pre-crisis and crisis period can be written as:

$$
cov[y_{1,t}^{(Crisis)}, y_{2,t}^{(Crisis)}] - E[y_{1,t}^{(Pre)}, y_{2,t}^{(Pre)}] = \lambda \beta_1. \tag{3.23}
$$

A test of contagion can be hence framed as a test of the restriction of $\lambda = 0$ in the crisis model (see Dungey et al., 2002a, b; Dungey and Martin, 2004). In addition, the two asset market model framework can be extended to include i markets in a multivariate setting and for simultaneous cross-market spillover effects, as follows:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{i,t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_i \end{pmatrix} w_t + \begin{pmatrix} \beta_1 & & & 0 \\ & \beta_2 & & \\ & & \ddots & \\ 0 & & & \beta_i \end{pmatrix} \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{i,t} \end{pmatrix} + \begin{pmatrix} 0 & \lambda_{1,2} & \cdots & \lambda_{1,i} \\ \lambda_{2,1} & 0 & \cdots & \lambda_{2,i} \\ \vdots & & \ddots & \\ \lambda_{i,1} & \lambda_{i,2} & \cdots & 0 \end{pmatrix} \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{i,t} \end{pmatrix} \tag{3.24}$$

The design of the matrix containing the λ depends on the theoretical assumption with regard to the direction of contagion. In addition, regional factors can be incorporated into the model, as in Dungey et al. (2006) and as suggested by Kaminsky and Reinhart (2000).

Within a factor-model framework, Bekaert et al. (2005) formulate a two-factor model (US equity market factor and the regional market factor) to evaluate the world and regional market integration and to test for cross-market contagion using a sample of 22 countries (three geographical regions) over the period between 1980 and 1998. The authors assume a GARCH error structure with asymmetric effects in the conditional variances of the asset return. The model is written as follows:

$$\mathbf{R_{i,t}} = \delta_i' \mathbf{Z_{i,t-1}} + \beta_{i,t-1}^{US} \mu_{US,t-1} + \beta_{i,t-1}^{reg} \mu_{reg,t-1} + \beta_{i,t-1}^{US} e_{US,t} + \beta_{i,t-1}^{reg} e_{reg,t} + e_{i,t}, \tag{3.25}$$

$$e_{i,t} | I_{t-1} \sim \ \mathbf{N}(o, \sigma_{i,t}^2), \tag{3.26}$$

$$\sigma_{i,t}^2 = a_i + b_i \sigma_{i,t-1}^2 + c_i e_{i,t-1}^2 + d_i \eta_{i,t-1}^2, \tag{3.27}$$

where $\mathbf{R_{i,t}}$ is a vector of excess returns of the national stock market indices, $\mu_{US,t-1}$ and $\mu_{reg,t-1}$ are the expected conditional excess returns of the US and regional markets, respectively, conditional on the information available at time $t-1$. $e_{i,t}$ is the idiosyncratic shock of market i, $\eta_{i,t-1}$ is the negative shock of returns of country i with its maximum value bound by zero. $\mathbf{Z_{i,t-1}}$ contains a constant and the lagged local dividend yields by one month. The authors further assume a time-varying coefficient structure by expressing the risk parameters ($\beta_{i,t-1}^{US}$ and $\beta_{i,t-1}^{reg}$) as functions of export ratios and size of trade to GDP.

$$\beta_{i,t-1}^{US} = p_{1,i}' \mathbf{X_{i,t-1}^{US}} + q_i' \mathbf{X_{i,t-1}^{w}} \cdot w_{US,t-1}, \tag{3.28}$$

$$\beta_{i,t-1}^{reg} = p_{2,i}' \mathbf{X_{i,t-1}^{reg}} + q_i' \mathbf{X_{i,t-1}^{w}} \cdot (1 - w_{US,t-1}), \tag{3.29}$$

where the instruments $\mathbf{X_{i,t-1}^{US}}$, $\mathbf{X_{i,t-1}^{reg}}$ and $\mathbf{X_{i,t-1}^{w}}$ refer to the information variables that capture the covariance risk of market i with the US, region and the world, respectively. For the US information variables, the authors use a constant and the sum of exports to and imports from the US divided by the sum of total exports and total imports; while for the world covariance risks, a constant and the country's total size of trade as a percentage of GDP. Trade variables are lagged by six months.

The expected excess return of market i is a linear function of some local information variables ($\mathbf{Z_{i,t-1}}$), the expected returns of the US and its respective regional markets.

$$\begin{aligned} E[\mathbf{R_{i,t-1}}|\mathbf{I_{i,t-1}}] &= \delta_i'\mathbf{Z_{i,t-1}} + \beta_{i,t-1}^{US}\mu_{US,t-1} + \beta_{i,t-1}^{reg}\mu_{reg,t-1}, \\ &= \delta_i'\mathbf{Z_{i,t-1}} + [\beta_{i,t-1}^{US} + \beta_{i,t-1}^{reg}\beta_{reg,t-1}^{US}](\delta_{US}'\mathbf{Z_{US,t-1}}) + \beta_{i,t-1}^{reg}(\delta_{reg}')\mathbf{Z_{reg,t-1}}, \end{aligned} \tag{3.30}$$

while the unexpected return of market i (the return residual of market i) is driven by:

$$\varepsilon_{i,t} = \beta_{i,t-1}^{US}e_{US,t} + \beta_{i,t-1}^{reg}e_{reg,t} + e_{i,t}. \tag{3.31}$$

In addition, the variance and covariances are expressed as follows:

$$h_{i,t} = E[\varepsilon_{i,t}^2|\mathbf{I_{t-1}}] = (\beta_{i,t-1}^{US})^2\sigma_{US,t}^2 + (\beta_{i,t-1})^2\sigma_{reg,t}^2 + \sigma_{i,t}^2, \tag{3.32}$$

$$h_{i,us,t} = E[\varepsilon_{i,t}\varepsilon_{US,t}|\mathbf{I_{t-1}}] = \beta_{i,t-1}^{US}\sigma_{US,t}^2, \tag{3.33}$$

$$h_{i,reg,t} = E[\varepsilon_{i,t}\varepsilon_{reg,t}|\mathbf{I_{t-1}}] = \beta_{i,t-1}^{US}\beta_{reg,t-1}^{US}\sigma_{US,t}^2 + \beta_{i,t-1}^{reg}\sigma_{reg,t}^2, \tag{3.34}$$

$$h_{i,j,t} = E[\varepsilon_{i,t}\varepsilon_{j,t}|\mathbf{I_{t-1}}] = \beta_{i,t-1}^{US}\beta_{j,t-1}^{US}\sigma_{US,t}^2 + \beta_{i,t-1}^{reg}\beta_{j,t-1}^{reg}\sigma_{reg,t}^2. \tag{3.35}$$

The authors propose a few testable hypotheses. The first hypothesis tests whether the local instruments have significant explanatory power with the results as an indication of market integration (global or regional). Second, the model emcompasses the one factor CAPM (US market as the market portfolio) as well as a world market integration model (world market portfolio in the traditional CAPM), allowing the test on market integration with the US or with the world capital market. Third, the authors examine the level of contagion by testing if the residual of market i is explained by the regional residuals, US market residuals and the country group residuals using five crisis dummy variables.

$$
\begin{aligned}
\widehat{e_{i,t}} &= w_i + v_{i,t}\widehat{e_{g,t}} + u_{i,t}, \\
v_{i,t} &= v_0 + v_1\mathbf{D_{i,t}}, \qquad (3.36)
\end{aligned}
$$

where $\widehat{e_{i,t}}$ and $\widehat{e_{g,t}}$ are the estimated idiosyncratic shocks of market i and region g. Region g can take on three cases: region, US market, and the country group that country i does not belong to.

A recent paper by Bekaert et al. (2011) examines contagious effects within a three-factor model framework (the US, regional and world factors) using country-industry equity portfolios from 55 countries during the 2007 to 2009 financial crisis. Their model can be written as:

$$R_{i,t} = E[R_{i,t}] + \beta'_{i,t}F_t + \eta_{i,t}CR_t + e_{i,t}, \qquad (3.37)$$

$$\beta_{i,t} = \beta_{i,0} + \beta'_1 Z_{i,t-k} + \gamma_{i,t}CR_t, \qquad (3.38)$$

$$\gamma_{i,t} = \gamma_{i,0} + \gamma'_1 Z_{i,t-k}, \qquad (3.39)$$

$$\eta_{i,t} = \eta_{i,0} + \eta'_1 Z_{i,t-k}, \qquad (3.40)$$

where $R_{i,t}$ refers to the excess returns of portfolio i during week t, $E[R_{i,t}]$ is the expected excess returns as a linear function of past excess returns and local dividend yields, F_t is the vector of the US, regional and world factors. CR_t is a crisis dummy variable while $Z_{i,t}$ is a vector of lagged instruments of fundamental variables. Using weekly returns and a sample period of 1995 to 2009, the authors estimate the scaled model by means of pooled OLS regressions.

3.4.6 Principal component analysis

Principal component analysis (PCA) is a mathematical procedure that orthogonally transforms a set of possibly correlated variables into a set of linearly uncorrelated variables, which are called principal components. The PCA is based on eigen decomposition of the covariance-variance matrix or the correlation matrix, in which the principal components are computed using the eigenvectors as weights to the linear combinations associated with the largest eigenvalues (the variances explained by the principal components). Another way to understand the procedure is that PCA rotates the axis and transforms the data to a new coordinate system with the largest variance of the data projection lying on the first coordinate (the first principal component), and the second largest variance on the second coordinate, and so on. Conceptually, the PCA allows researchers to extract common latent factors from a high-dimensional data set and to focus on the variables that explain the most variations in the underlying data (dimension reduction).

Calvo and Reinhart (1995) study the weekly return comovements between the Asian and Latin American emerging market stock markets during the Mexican crisis. The authors argue that the first principal component relates closely to the common external fundamentals and document apparent increases in the explanatory power of the first component during February 1994 to December 1994. They also document substantial increases in explanatory power in the second principal component, which they refer to as some 'Mexico' crisis effects, most notably in Latin America. Kaminsky and Reinhart (2001) study the daily returns of four types of asset markets in 35 developed and developing economies during 1997 to 1999 and find that South Korea, Malaysia, Turkey and Greece have the lowest market comovements with other economies in their respective regions. For the G7 economies, the authors document strong evidence of comovements between the UK, France, Germany and Italy, and between the US and Canada, while the comovements between Japan with the rest of the G7 countries were the lowest. Eichengreen et al. (2009) use PCA to examine the common factors that drove the CDS spreads of major banks and find increasing importance in these factors during the subprime crisis. These factors are found to be associated with heightening credit risks within the US banking industry.

In the next section I will summarise the major empirical findings of the methodologies that have been reviewed above.

3.5 Summary of empirical evidence

3.5.1 Probit and logit models and leading indicators studies

Eichengreen et al. (1996) test for contagion conditional on currency crises using a sample comprising of quarterly data from 20 industrial countries during the period between 1959 and 1993. Within a probit regression framework, their empirical results reject the hypothesis of no contagion, so that the occurrence of a currency crisis in one country increases the probability of a speculative attack in the domestic currency of other countries by approximately eight per cent. In the second part of their analysis, they replace the crisis dummy variable with some weighted variables according to two weighting schemes. The two weighting schemes relate to the extent and intensities of trade linkages and the similarities of macroeconomic variables between the shocked and unaffected countries. Their results lend support to currency contagion being transmitted via trade linkages rather than macroeconomic similarities.

Caramazza et al. (2000) use panel probit models with monthly data for 61 industrial and developing countries over the period between 1990 and 1998 to examine the roles of external and internal (macroeconomic) imbalances, financial weaknesses (reserve adequacy), trade and financial linkages (channels for contagion), and institutional factors (exchange rate regimes and capital controls) in explaining the spillover effects during the Mexican devaluation in 1994, the East Asian Crisis in 1997, and the Russian defaults on bonds in 1998. The empirical results show that indicators of financial linkages and weaknesses are significant in explaining the crisis effects while weak output growth has a larger role than external imbalances in reducing the probability of the occurrence of a crisis. In addition, spillovers via trade linkages have a larger role for countries with weak current account balances while the exchange rate and capital control regimes are found to be irrelevant in explaining the occurrence of a crisis.

Kaminsky (1999) uses monthly data of 102 financial crises from 20 developing countries during the period between 1970 and 1997 to investigate the causes of crises and examine the validity of some indicators in forecasting financial crises. The results show that crises develop alongside multiple economic problems. The author aggregated individual indicators of currency and banking crises into four composite indicators and tested their abilities to predict crises (out-of-sample), and found that the probability of a currency crisis had increased for Thailand, the Philippines and Malaysia over the period between 1996 and 1997. The overall findings suggest that composite leading indicators bear some degree of predictability over the occurrence of crisis events. Hardy and Pazarbasioglu (1998) use a sample of 50 developing countries from 1976 to 1997 to examine the predictability of a set of macroeconomic indicators over the occurrence of crises. The results show that real GDP growth, domestic inflation, credit expansion, capital inflows, real interest rates and real effective exchange rates are significant predictors.

3.5.2 GARCH type models

Hamao et al. (1990) test for spillovers of volatilities during the New York Stock Exchange crashes in 1987 and find empirical evidence of volatility spillovers from New York to the Tokyo, from New York to London and from London to Tokyo during the crisis. Engle et al. (1990) investigate the causes for the clustering of exchange rates and the comovements in conditional volatilities. Using intra-daily log first-differences of the yen/dollar exchange rates quoted in Tokyo, London and New York during 1985 to 1986, the authors examine the validity of their 'heat waves' and 'meteor shower' hypotheses. The empirical results reject significantly the 'heat wave' hypothesis and show that Japanese news had the largest impact on volatility spillovers of the yen/dollar exchange rate. In addition, a short-run cross-market dynamic effect is documented in the volatility. Edwards (1998), using a GARCH model and three emerging market short term nominal interest rates with high frequency, document significant uni-directional volatility spillovers from Mexico to Argentina after the Mexican crisis in 1995. Ng (2000) studies the volatility spillovers from the US (world factor) and Japan (regional factor) to six Pacific-Basin countries using a GARCH type model and finds stronger regional spillovers than those from the world factor. In (2007) examines the volatility spillovers among the US, UK and Japanese swap markets using a VAR-EGARCH model. The author finds that the slopes of the term structure in all three countries explain the swap spreads and that the US swap market had an important uni-directional impact on the UK and Japanese swap markets.

For DCC-GARCH models, Chiang et al. (2007) estimate DCC-GARCH models using daily returns from nine Asian stock market indices over the period between 1990 and 2003, and find evidence of contagion. The authors show that the East Asian Crisis can be classified into two phases: the first phase was characterised by increases in dynamic conditional correlations while the higher correlation continued into the second phase, which was consistent with herding. Cho and Parhizgari (2008) estimate the dynamic conditional correlations across eight stock markets using Thailand and Hong Kong as sources of shocks during the East Asian Crisis of 1997. The authors interpret the findings of structural breaks in the dynamic conditional correlations as evidence of contagion and statistically test the means and medians of the correlations across the crisis subperiods. They find evidence of contagion from Thailand and Hong Kong, contrary to Forbes and Rigobon (2002). Using DCC-GARCH models, Marçal et al. (2011) also find evidence that contagion has transmitted from the Asian markets to the Latin American economies over the period 1994 to 2003.

For more recent empirical evidence, Frank et al. (2008), using ABCP and LIBOR-OIS as proxies for funding illiquidity, and 2-year on-the-run spreads as proxies for market illiqudity, apply and modify the DCC-GARCH model to account for structural breaks. They document substantial increases in comovements between market and funding illiquidity in the second half of 2007, which is consistent with the hypothesis of a reinforcing liquidity spiral. Naoui et al. (2010) study the comovements between the daily returns of composite equity indices of six developed and ten emerging stock markets and find substantially higher dynamic conditional correlations over the period August 2007 to February 2010, which is consistent with contagion. Guesmi et al. (2013) estimate the DCC-GARCH models to examine the changes in dynamic conditional correlations between the US and 17 OECD stock markets and find significantly higher mean levels of conditional correlation during the recent 2007 to 2009 financial crisis, which is consistent with contagion.

3.5.3 Correlation coefficient analysis

Forbes and Rigobon (2002) propose a heteroskedasticity correction to the correlation coefficient analysis and find only one case of contagion during the East Asian Crisis of 1997, there were no cases of contagion for the Mexican crisis in 1994 and none for the New York Stock Exchange crash in 1987. Corsetti et al. (2001) point out that the heteroskedasticity correction is based on an unrealistic assumption and propose a factor-model to examine the cross-market correlation. Using daily returns on 17 stock markets over the period between 1996 and 2000, the authors test for contagion during the East Asian Crisis in 1997 and find evidence of contagion in the stock markets in Singapore, the Philippines, Italy, the UK and France. Boyer et al. (1999), using daily returns on the German mark/dollar and yen dollar exchanges rates and a sample period of 1991 to 1998, document no contagion based on adjusted correlation coefficients, which is consistent with Forbers and Rigobon (2002). Loretan and English (2000) detect only one case of contagion after the Mexican Crisis in 1994 using the German and UK stock market daily returns, yen/dollar and mark/dollar exchange rates and 10-year government bond yields.

3.5.4 Vector autoregressive models (VAR)

Using VAR models, Baig and Goldfajn (1999) test for the existence of contagion during the East Asian Crisis in 1997. The authors analyse the stock market returns, interest rates, sovereign spreads and exchange rates of five Asian countries, which include Thailand, Malaysia, Indonesia, Korea and the Philippines, and document significantly higher correlations in exchange rates and sovereign spreads during the crisis consistent with contagion.

Favero and Giavazzi (2002) use three-month German rates and three-month European interest rates during the period of 1988 to 1992 to test for the presence of non-linearities in the way devaluation expectations spread across countries during the ERM crisis. The countries are members of the ERM of the EMS. The authors find that the widening of interest rate spreads (spreads on German short term interest rates) in one country was associated with the narrowing of a spread in another country, which is consistent with a 'flight-to-safety' phenomenon. Using the same dataset as Favero and Giavazzi (2002), Pesaran and Pick (2007) find that contagion indices (corresponding to sharp falls in spreads), which were originally significant under OLS, become insignificant when endogeneity has been taken into account while the indices corresponding to sharp rises in the spreads remain significant after taking into account the endogeneity issue. The empirical findings are consistent with Favero and Giavazzi (2002) in that contagion existed across the European bond markets during the ERM crisis.

Longstaff (2010), assuming that the US structured finance market was the origin of the US subprime crisis, tests for the existence of contagion and the validity of the liquidity transmission channel during the subprime crisis in 2007. His findings, based on VAR models, show that past returns of the ABX indices significantly predicted the future returns in other US financial markets. He points out that the contagion transmission was inconsistent with the information transmission hypothesis but consistent with the funding liquidity transmission mechanism.

3.5.5 Factor models

Using a latent factor model, Dungey and Martin (2001) study contagion and spillover effects across the currencies and stock markets of six countries during the 1997 to 1998 East Asian Crisis. The authors document significant contagion from the currency markets to the equity markets but not the opposite, except in Indonesia. Dungey et al. (2002a), using a dynamic latent factor model and indirect inference techniques, test for contagion in 12 international bond markets during the Russian bond default crisis in August 1998 and the LTCM crisis in September 1998. The authors decompose the daily bond spreads into a world factor, country factor, regional factor and a contagion component and find evidence of significant contagion. In particular, during the Russian bond default crisis, the authors find evidence of significant shock transmission from Russia to Brazil, Bulgaria, the Netherlands, and the US while for the US LTCM crisis, shocks transmitted from the US to Argentina, Russia, Poland, Thailand, Brazil and the Netherlands.

Bekaert et al. (2005) investigate empirically the degree of market integration and contagion over the sample period 1980 to 1998 using 22 countries from three geographical regions within a two-factor asset pricing model with time-varying coefficients. Defining contagion as the increase in residual correlations over what is expected, the authors find little evidence of contagion during the Mexican crisis but strong evidence of contagion among Asian countries during the East Asian crisis. Bekaert et al. (2011) test for the existence of contagion using a three-factor model on country-industry portfolios from 55 countries during the recent 2007 to 2009 financial crisis. The authors document weak evidence of contagion from the US to other countries' equity portfolios but strong evidence of contagion from domestic equity markets to domestic equity portfolios. In addition, the findings suggest that countries with weak fundamentals, poor sovereign ratings, and high fiscal and current account deficits suffered more contagious effects, from both the US and domestic equity markets.

3.6 Conclusions

In this chapter, I have provided a comprehensive and detailed review of the major issues in the financial contagion literature, including an explanation of the disagreement of contagion working definitions, a review on the major theoretical aspects and causes of financial contagion, a survey of the empirical methodologies and a summary of major empirical findings. The objective of this chapter is to foster a broad and in-depth understanding of the empirical literature with the help of a useful categorisation of working definitions and empirical methods.

My empirical investigation in subsequent chapters is closely related to the methods of correlation analysis, VAR models and factor models, which are widely-acknowledged and accepted in the literature. Despite a large volume of contagion papers on the recent 2007 to 2009 financial crisis, to my knowledge, this thesis is the first study that comprehensively tests for contagion travelling from the US structured finance market to the international markets. This is surprising given the increasing importance and market size of the structured finance market to contagion and financial stability. I fill this gap by first testing for the existence of contagion and then evaluating the validity of a few widely-acknowledged contagion transmission channels while taking every necessary step to ensure the robustness of my findings. In addition, I innovate and test whether there are any crisis-related factors in relation to the structured finance market that have affected the US equity market during the subprime and global financial crises.

In the next chapter, I present my first empirical investigation of contagion travelling from the US structured finance market to the broad equity, financial equity and government bond markets in the G5 countries.

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Chapter 4

An Empirical Investigation of Contagion During the Recent 2007 to 2009 Financial Crisis: Evidence from the G5 Countries

4.1 Introduction

Longstaff's (2010) paper is one of the earliest studies to examine contagion during the recent 2007 to 2009 financial crisis. The author documents evidence of significant increases in cross-market linkages between the less liquid US subprime structured finance market and a number of domestic US asset markets, which is consistent with the existence of contagion. Longstaff's (2010) investigation focuses exclusively on domestic US markets and does not consider international cross-market spillovers. I will fill this gap and examine contagion travelling from the US structured finance market to a number of international developed markets.

There are a number of reasons why contagion may have been present across international markets during the subprime crisis. First, financial institutions that suffered huge write-downs are in general large in size and are characterised by extensive cross-market functionality. The huge losses brought by the write-downs of subprime structured finance portfolios in these institutions raised widespread concern about insolvency and possible increases in risk aversion across economies. Investors, anticipating the spillovers of shocks, may divert their investments away from distressed sectors to safer markets, leading to increases in market comovements during the crisis. Second, the realisation of extreme market illiquidity in the US structured finance market may force lenders to tighten their credit, resulting in a severe funding illiquidity in a number of markets. Market makers and institutional investors, who faced higher funding costs, were unable to provide sufficient market liquidity resulting in surging market illiquidity and declines in asset prices (Brunnermeier and Pedersen, 2009). Third, hedge funds and institutional investors with levered positions were forced to liquidate assets in unaffected markets to meet margin calls, redemptions and contingent liabilities as the collateral values of their structured finance portfolios declined.[19] All these arguments imply spillovers of shocks from the US to the international markets during the recent crisis and motivate my empirical investigation.

This chapter is an empirical investigation of contagion from the US structured finance market to a number of international equity and government bond markets of the G5 countries during the subprime and the subsequent global financial crises. The US structured finance market in this chapter refers specifically to the US subprime RMBS market, which was one of the earliest markets to collapse during the crisis (Longstaff, 2010) and was tracked by a family of subprime RMBS benchmark indices - the ABX indices. The G5 countries are developed economies that include the US, UK, France, Germany and Japan and represent over half the world's total Gross Domestic Product (GDP). Following Longstaff (2010), in the first part of this analysis I will formulate my contagion tests within a VAR model framework and I will seek to detect any significant predictive power (Granger-causality) in the ABX indices over the international market returns. The main benefit of using a VAR model is that it enables me to account for possible endogeneity between the various market variables and focus on inquiring whether the past performance of the ABX indices explains the contemporaneous returns of the international markets. Furthermore, I will test the validity of a few widely-acknowledged contagion transmission channels relating to funding illiquidity, credit risk and trading patterns of financial stocks. In the second part of this analysis, to ensure the robustness of my findings, I will exploit an alternative method of testing for contagion following

[19] Allen and Gale (2000) propose a model in which banking institutions may liquidate cross-holdings of deposits across regions during a crisis to meet funding liquidity requirements, while Kodres and Pritsker (2002) propose a model within a hedging framework in which shocks propagate through portfolio rebalancing for the purposes of macroeconomic risk adjustments.

Forbes and Rigobon (2002) and analyse the correlation coefficients between the international market and the ABX indices to detect any significant increases in unconditional correlations during the crises.

The remainder of this chapter is organised as follows. Section 2 explains my hypotheses. Section 3 introduces the ABX indices, which are the benchmark indices for the structured finance market. Section 4 explains my methodological framework and provides details on my data and variable construction. Section 5 presents and discusses my empirical findings. Section 6 tests the validity of the contagion transmission channels. Section 7 reports the results of the contagion tests based on daily frequency data. Section 8 reports additional test results that account for simultaneous spillovers from various major US markets to the international markets. Section 9 presents the findings of the correlation coefficient analysis of Forbes and Rigobon (2002) and Section 10 concludes this chapter.

4.2 Hypotheses

The first part of this analysis aims to identify any significant increases in cross-market linkages by examining the dependencies between the US structured finance market and a number of international equity and government bond markets before, during, and after the crisis. The first hypothesis can be written as:

H1: *There are significant increases in the predictive power of the lagged US structured finance market index returns (as measured by the ABX indices) for the G5 equity and government bond market index returns during the subprime and the global financial crises.*

Prior to the subprime crisis, the explanatory power of the ABX indices over the international market returns reflects the level of interdependence between the structured finance market and the international markets during the tranquil pre-crisis subperiod and is expected to be negligible prior to the crisis. During the crisis subperiods, as shocks propagate from the structured finance market to the international markets, I expect to identify substantive increases in the predictive abilities of the lagged ABX index returns over the international market returns. In addition, a post-crisis window is included in the analysis to test whether the predictive abilities of the ABX indices persisted after the recent crisis.

On the theoretical side, there are a number of studies that explain how contagion transmits from one market to another. These studies are of fundamental importance to understanding the dynamics of shock spillovers. A brief review on the liquidity and risk premia transmission channels is offered in the following sections.

4.2.1 The liquidity transmission channel

The liquidity transmission channel refers to the mechanism by which an idiosyncratic shock to a market translates into a subsequent fall in liquidity in other markets. In the literature, liquidity is defined as funding liquidity (which is the ability to fund any solvent agent to fulfill their immediate demand for money) and as market liquidity (which refers to the ease by which an asset position can be sold in financial markets). Recent studies consider market illiquidity as a systematic risk factor within an asset pricing context (see, for example, Amihud, 2002; Acharya and Pedersen, 2005) and find significant relations between market illiquidity risk and the cross-section of expected returns. Previous studies have shown that market illiquidity risk is priced. Consequently, I will review the market liquidity transmission channel together with the risk premia channel in the next section.

Contagion transmission via funding liquidity refers to a situation where institutional investors or mutual funds liquidate their holdings to fund their future redemptions and contingent liabilities during a period of market distress. Levered hedge funds may be obliged to liquidate assets in unaffected markets to meet margin calls, which leads to higher market comovements during the crisis (Calvo and Mendoza, 2000; Kodres and Pritsker, 2002; Ben-David et al., 2012). Allen and Gale (2000) present a model that focuses on the role of the banking system in financial contagion. The authors argue that financial shocks cause banks to liquidate cross-holding deposits across regions, leading to severe cross-market funding illiquidity and asset comovements. Similarly, Kaminsky and Reinhart (2000) point out that banks in tranquil markets may tighten credit lines for prudence motives and rebalance their overall risk exposure in anticipation of shocks. The main implication of these studies is that funding illiquidity may induce substantive liquidations and downside price pressure on financial assets during the crisis. Following Longstaff (2010), I will evaluate the validity of the funding liquidity channel and test whether the ABX index returns predict the level of trading intensity in the financial stocks of the G5 countries. A higher level of trading activities in financial stocks during the crisis, as predicted by the ABX index returns, is consistent with possible portfolio rebalancing by institutional investors due to financial constraints and funding liquidity purposes. My second hypothesis is formulated as follows:

H2: *There were significant increases in the predictive power of US structured finance market returns for the level of trading intensity in G5 financial stocks relative to the market (as measured by the trading ratios: the aggregate trading volume in market value of a financial equity index to the aggregate trading volume in market value of an equity market composite index) during the subprime crisis.*

4.2.2 The risk premia transmission channel

The risk premia transmission channel refers to the comovement of asset prices that occurs as a result of changes in risk premia after a shock hits a market. For instance, an idiosyncratic shock to one market leads to subsequent increases in risk premia expected by investors in other markets.

Amihud (2002), and Acharya and Pedersen (2005) document the significant role of aggregate and idiosyncratic market illiquidity in asset pricing. Their findings show that market illiquidity risk is priced with considerable time variation and suggest a possible 'flight-to-liquidity' phenomenon. Longstaff (2004) finds significant liquidity premia in the yield spreads between the more liquid US Treasury bonds over the Refcorp bonds suggestive of some market liquidity component in the Treasury bond yields. Liu et al. (2006) document significant time-varying liquidity risk premia in US Treasury bonds between 1988 and 2002. These studies support the notion that investors have certain liquidity preferences and that the 'flight-to-safety' phenomenon may be driven by market liquidity apart from credit risk considerations. In the context of contagion, shocks might have been transmitted via changes in market illiquidity risk and translated into subsequent 'flights' into more liquid assets and systematic changes in trading patterns. In addition, funding and market illiquidity might be reinforcing. Brunnermeier and Pedersen (2009) present a model that establishes the relation between funding and market illiquidity. The authors argue that traders' funding illiquidity results in higher transaction costs and risks in financing trades that in turn result in higher market illiquidity and lower asset prices.

One other widely-acknowledged risk premia refers to the credit risk premia that compensates for default and counterparty risks. Vassalou and Xing (2004) empirically show that credit risk is systematically priced and explains the cross-section of expected returns. Eichengreen et al. (2009) study the common factors that have driven the CDS spreads of major banks and document the increasing importance in these factors during the subprime crisis. In particular, these common factors are associated with the heightening default risks of the US banking industry. The evidence of these studies reveals possible time variations in the price of credit risk in the US equity market and in the financial sector. The credit risk premia may have heightened significantly during the crisis, leading to substantial portfolio rebalancing and possible 'flight-to-safety' from the less risky assets to the safer and more liquid assets. This chapter evaluates the validity of the risk premia transmission channel by testing the following hypothesis:

H3: *The level of credit risk and market illiquidity risk were significantly predicted by the ABX index returns during the subprime crisis.*

I expect substantive increases in the predictive ability of the ABX index returns over the level of credit risk and market illiquidity risk (as measured by the interest rate swap spreads (IRSS)) during the crisis and shall interpret these increases as evidence of contagion via the risk premia channel.

4.2.3 The 'flight-to-safety' phenomenon

In the literature, several empirical studies have examined the 'flight-to-safety' phenomenon in which investors switch from equity to other asset classes during a crisis to reduce their risk exposure (see, for example, Goeij and Marquering, 2004; Baur and Lucey, 2009). Despite the fact that both directions of flights between stocks and government bonds have been identified empirically, the 'flight-to-safety' phenomenon is consistent with the risk premia channel in that an increase in the required risk premia or risk aversion in a stock market (for instance, as a result of market illiquidity or shifts in expectations) may induce investors to pursue safer fixed-income investments. In this study, I will test whether the comovements between the weekly returns of the domestic equity and government bond market indices might be predicted by the ABX index returns to reveal the extent of the impact of the structured finance market on the degree of 'flight-to-safety' in the G5 countries. Hence, my hypothesis is written as follows:

H4: *The conditional correlations (between the returns of domestic equity and government bond indices) were predicted by the ABX index returns during the subprime crisis.*

In the next section, I will introduce the benchmark indices for the structured finance market, the ABX indices, and report summary statistics.

4.3 The ABX indices

Following Longstaff (2010), the ABX indices are used to track the performance of the US structured finance market. The ABX indices are equally-weighted and static portfolios that reference 20 subprime RMBS transactions. Every six months, the ABX indices are reconstituted with new on-the-run index vintages, each referencing 20 new subprime RMBS deals that have been issued during the six months prior to index initiation. There are five sub-indices within the ABX family that correspond to the AAA, AA, A, BBB and BBB- credit ratings of the underlying RMBS deals. The ABX.HE.06-1 series is the first vintage followed by the ABX.HE.06-2 series, which was formed in July 2006, while the ABX.HE.07-1 and ABX.HE.07-2 indices were issued in January and July 2007, respectively. The subprime RMBS issuance declined dramatically during the crisis and no more ABX indices were issued. The ABX.HE.07-2 index remained the on-the-run ABX index up to the end of my sample period.[20]

Throughout this chapter, I will obtain the ABX indices from Reuters and consistently use the daily and weekly lagged returns (based on quotes on Wednesdays) of the ABX.HE.06-1 index vintage (the first vintage of the ABX index) as exogenous variables in my empirical model. Reuters is used because it is the longest vintage series available within the ABX family and covers the entire subprime and global crises. Fig. 4-1 plots the price levels of the five ABX subindices belonging to the ABX.HE.06-1 vintage from January 2006 to December 2011. All five indices were, in general, close to their par value of \$100 in 2006 and started to decline sharply in early 2007. In particular, the three lowest-rated indices fell dramatically from 2007Q2 onwards and tumbled during the first half of 2009. The three highest-rated ABX indices largely started to recover, most remarkably in the ABX AAA and AA indices, from the second half of 2009 onwards. Throughout the rest of the sample period, the ABX AAA index remained largely free of significant shocks while both the ABX

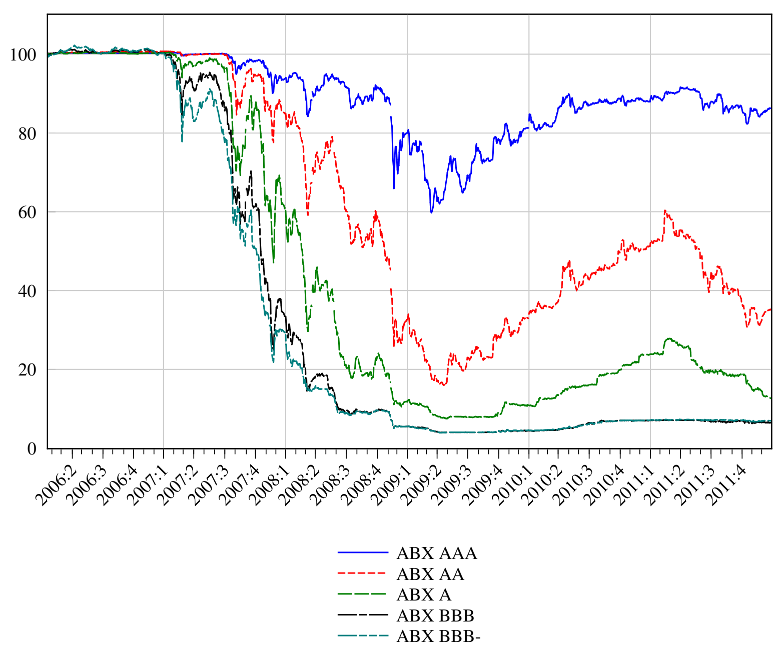
[20] The ABX PENAAA indices, which reference AAA-rated bonds that are second to last in principal distribution priority, were introduced in May 2008.

AA and A indices started to decline again at the start of year 2011. Fig. 4-2 plots the log first differences (continuous returns) of the ABX indices over my sample period. Again, I observe largely no shocks in the ABX indices during 2006 and substantively higher volatilities from 2007 onwards, which was during the subprime crisis subperiod. In addition, the ABX index returns exhibited considerable correlation and skewness during the crisis subperiods. The high volatilities persisted throughout 2007 and 2008, with occasional negative spikes in returns. The three highest-rated ABX indices started to recover from mid-2009, as shown by the clustered positive spikes of returns. The volatilities of the ABX indices remained largely lower in 2010 and started to rise again moderately from mid-2011 onwards.

Table 4.1 reports the descriptive statistics of the log first differences of the ABX indices. During the pre-crisis subperiod, the mean returns are all positive among the five ABX indices and have become negative during the subprime crisis, global crisis and post-crisis subperiods while the negative mean returns were the largest in the BBB and BBB- indices. The standard deviations of all ABX indices are remarkably higher during and after the crises. Throughout the entire sample period, the correlation between the weekly returns of the ABX AAA and AA indices is considerable while the cross-correlations between the A, BBB and BBB- indices are high.

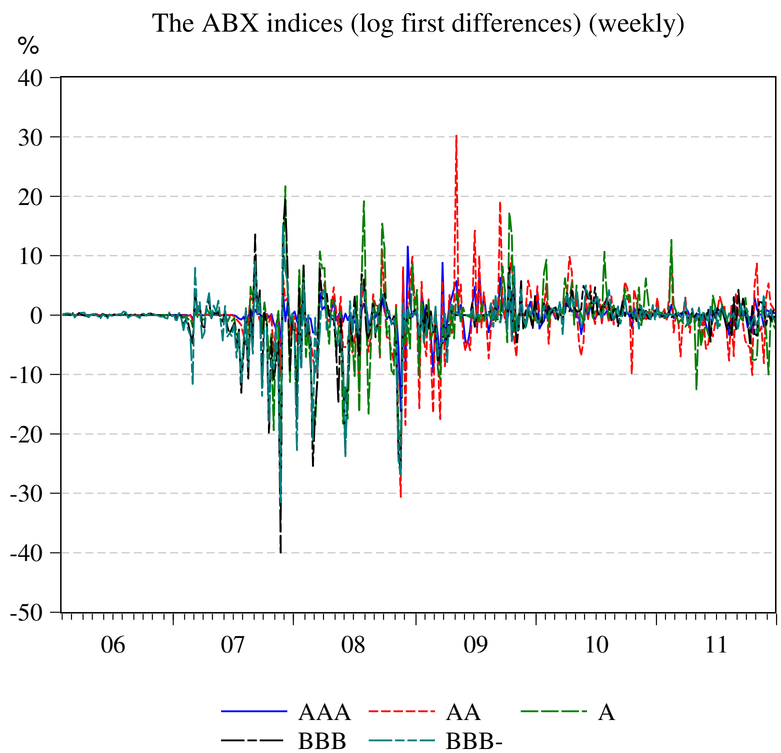
There are a few precautions with regard to the use of the returns of the ABX.HE.06-1 indices as exogenous variables in my analysis. First, each ABX vintage is in fact only a small subset of the universe of subprime RMBS and ABS products and, therefore, is inevitably limited in market coverage. In addition, for each referenced MBS deal, only part of the capital structure is referenced by the five tranches of the ABX indices (see Fender and Scheicher, 2009). In particular, the ABX AAA index does not reference the most senior tranche of the MBS deals, such that the ABX prices reflect higher durations than those remaining AAA-rated subprime RMBSs (Fender and Hördahl, 2008). Nonetheless, Fender and Hördahl (2008) note that the bias with regard to the insufficient market coverage may not be significant as the RMBS deals referenced by the ABX indices are likely to be similar with the remaining subprime RMBSs in collateral and loan-to-value ratios, suggesting that the ABX HE.06-1 vintage represents a reasonably satisfactory benchmark for the US structured finance market.

Figure 4-1: The ABX indices (level data) (weekly)



This figure plots the level of the five ABX indices, which reference subprime RMBS deals of AAA, AA, A, BBB and BBB- credit ratings, respectively, over the sample period of January 2006 to December 2011. The ABX indices plotted belong to the ABX HE.06-1 vintage.

Figure 4-2: The ABX indices (log first differences) (weekly)



This figure plots the log first differences (continuous returns) of the five ABX indices, which reference subprime RMBS deals of AAA, AA, A, BBB and BBB- credit ratings, respectively, over the sample period from January 2006 to December 2011. The ABX indices plotted belong to the ABX HE.06-1 vintages.

4.4 Methodologies

This chapter adopts a vector autoregressive (VAR) model framework with exogenous variables to test for contagion from the US structured finance market to the G5 international markets during the subprime and global crisis. VAR models have been widely used in the literature to study the cross-market spillovers of shocks during crisis (see, for example, Baig and Goldfajn, 1999; Nagayasu, 2001; Favero and Giavazzi, 2002; Forbes and Rigobon, 2002; Pesaran and Pick, 2007; Longstaff, 2010).[21]

Using weekly returns of the domestic equity and government bond indices that are modelled within a system of equations for each country, I am able to account for any potential endogeneity between the markets and test for any significant predictive power in the ABX index returns over the international market returns. Any increases in predictive power (Granger-causality) of the ABX index returns over the international market returns during the crisis are reasonably interpreted as evidence of contagion from the US structured finance market to the international markets. To capture the dynamic effects of shock propagation, a lag length of four (equivalent to a month) has been selected for the VAR models.[22] Since the structured finance market was primarily driven by the US housing and the subprime credit markets that were relatively exogenous to the US and the international stock and government bond markets, I follow Longstaff (2010) and assert that the ABX index returns are strictly exogenous in the VAR model.[23] The VAR(4) models can be written in the following reduced form with n endogenous variables:

$$\mathbf{y}_t = \boldsymbol{\alpha}_0 + \sum_{s=1}^{4} \boldsymbol{\beta}_s \mathbf{y}_{t-s} + \sum_{s=1}^{4} \boldsymbol{\phi}_s ABX_{t-s} + \boldsymbol{\epsilon}_t, \tag{4.1}$$

where $\mathbf{y}_t$ is a $n \times 1$ vector of endogenous dependent variables (market returns), ABX_{t-s} is the s^{th} lagged value of the ABX index assumed exogenous to the VAR system, $\boldsymbol{\beta}_s$ is a $n \times n$ matrix of coefficients in the systems of equations, $\boldsymbol{\phi}_s$ is a $n \times 1$ vector of coefficients of the lagged ABX index

[21] Forbes and Rigobon (2002) utilise VAR models to estimate the cross-market correlations between the returns of the shocked market and other markets during the crisis subperiod and the full sample. The authors adjust the cross-market conditional correlations estimated for heteroscedasticity and document little evidence of contagion during the 1997 East Asian crisis, the 1994 Mexican Peso crisis and the 1987 US stock market crash.

[22] I have also experimented with other lag orders and obtained qualitatively similar results to those associated with the four-lag order structure.

[23] Relaxing this assumption and treating the ABX index returns as an endogenous variable does not change the interpretation of the findings since the purpose of this analysis is to identify contagion specifically transmitted from the structured finance market to the international markets in an uni-directional manner.

returns, and $\boldsymbol{\epsilon}_t$ is a $n \times 1$ vector of innovations that are uncorrelated with their own lagged values and all right-hand side variables.

Since I have five ABX indices for my analysis, five VAR models are estimated and reported for each subperiod; that is, 20 VAR models estimated over the four subperiods in each country. Within each country's VAR model, I will include weekly returns of the composite equity market, the financial equity, and the government bond indices of the subject country as endogenous variables. I will also include a latent variable in my VAR models that captures the variations of the composite equity markets in the remaining four G5 countries using principal component analysis (PCA).

4.4.1 Data and crisis subperiods

Table 4.2 summarises and describes my data set. My data are collected from Datastream and are based on weekly Wednesday-to-Wednesday returns of the G5 international market indices to avoid any potential calendar day bias and abnormal trading patterns. The G5 countries include the US, UK, France, Germany and Japan and represent the five largest global economies. My sample includes observations between 25 January 2006 and 28 December 2011, and covers the entire subprime crisis and subsequent global financial crisis.

Consistent with the contagion literature, I will split the sample period into four subperiods, as discussed in Chapter 2. There are no exact dates that best define the crisis outbreak and, hence, the definition of crisis subperiods contains a certain degree of subjectivity. Despite that, the criteria of subperiod selection is based on historical events and market performance. Following Longstaff (2010), I will define the year 2006 (49 obs) as the pre-crisis subperiod, which is characterised by no significant shocks in the US structured finance and the international markets, and I will define the year 2007 (51 obs) as the subprime crisis subperiod, during which the US structured finance market started to decline sharply. As the crisis went global and was characterised by numerous corporate bankruptcies and bailouts, the period of 2008Q1 to 2009Q1 (i.e. from 2 January 2008 to 25 March 2009, 65 obs) is defined as the global crisis subperiod. Lastly, I will include a post-crisis window with data observations between 2 September 2009 and 28 December 2011 (122 observations) to facilitate comparison across the subperiods. The observations between April 2009 and August 2009 are omitted from the sample because the ABX BBB and BBB- indices were considerably stale, thus creating near singularity problems in regressions when using daily returns in subsequent sections.

4.4.2 Endogenous variables

The endogenous variables used in this study can be written as $\mathbf{y}_t^{(i)} = [EQ_t^{(i)}, FEQ_t^{(i)}, GOV_t^{(i)}, PCA_t^{(i)}]'$ where i refers to the i^{th} country in the G5 countries. The variables EQ, FEQ and GOV denote the weekly returns of the international market composite, financial equity, and government bond indices of the G5 countries while the variable PCA are the factor scores (the first principal component) from the PCA that capture the variations in the remaining four international equity market composite index returns. For the underlying data series, I will use the FTSE Global Government 10+ year bond clean price indices for government bond markets, the domestic composite equity indices for the broad equity markets, and the Datastream-calculated financial price indices for the performance of the financial equity markets.

Table 4.3 reports the full sample and subsample means and standard deviations of the endogenous variables used in my analysis. Panels A to C report the summary statistics of the weekly returns of the equity market composite, financial equity, and government bond indices, respectively. The full sample statistics show that the financial equity indices have the lowest mean returns and the highest volatilities while the government bond indices have the highest average weekly returns with the lowest standard deviations. The subsample statistics show that, during the pre-crisis subperiod, the composite equity and the financial equity indices were largely free of significant shocks while the government bond markets underperformed. The financial stocks of the G5 countries largely started to fall during the subprime crisis and declined dramatically during the global crisis subperiod with high volatilities. The equity market composite indices remained largely stable during the subprime crisis and have had negative average returns and considerable volatilities during the global crisis. In addition, the international government bond markets outperformed their equity counterparts during the global crisis subperiod, which is consistent with possible 'flight-to-safety'. During the post-crisis subperiod, I can observe no obvious patterns in the indices while largely all markets yielded positive mean returns with high volatilities.

4.4.3 Latent variables - principal component analysis

From an international market perspective, shocks might have transmitted in multiple directions and sequentially; that is, from the US structured finance market to the US domestic markets and then to the international markets. To this end, I will use PCA to extract the latent principal components that underlie the overall variation in the international equity markets. The factor scores of the first principal component extracted are then included as endogenous variables in each VAR model to control for possible spillovers of shocks from the international markets to the subject market.

For each country, I include the weekly returns of the remaining four countries' equity market composite indices as inputs to the PCA and use the factor scores of the first principal component as endogenous variables in my analysis. For instance, the principal component variable for the US VAR model is computed by using the returns of the market composite indices of the UK, France, Germany and Japan as inputs to the PCA. Kaiser's significance rule is used to determine the number of significant principal components such that any components with eigenvalues greater than one are statistically significant and retained. Table 4.4 presents the eigenvalues of the PCA and the percentage of variance explained by the first principal component for each country. Only one principal component has been identified and retained for each country. The first principal components of the G5 countries explain more than 80 per cent of the variance of the equity market returns in each market. The communalities measure the proportion of each variable's variance explained by the principal components. The statistics show that the principal components explain the variance of the European market returns reasonably well and less satisfactorily for the Japanese market.

4.5 Empirical findings

I report the country VAR(4) model results for the G5 countries in Tables 4.5 - 4.9, grouped by the crisis subperiods. I report the sums of factor loadings on the lagged ABX index returns and the R^2 for each of the VAR models. The F-tests place restrictions on the ABX factor loadings and test the null hypothesis that $h_0 : \phi_{j,1}^{(i)} = \phi_{j,2}^{(i)} = \phi_{j,3}^{(i)} = \phi_{j,4}^{(i)} = 0$, where j refers to the j^{th} endogenous variables of the i^{th} country VAR model. Significant F-statistics suggest that at least one of the lagged ABX index returns significantly predict (Granger-causality) the contemporaneous international market returns, which is consistent with my definition of contagion.

4.5.1 The pre-crisis subperiod

As shown in my summary statistics, 2006 was largely free from significant shocks and high volatilities. All international equity markets showed signs of stability and growth during this subperiod.

The findings of this one-year pre-crisis window reveal the degree of interdependencies between the US structured finance and the international markets during tranquil market conditions.

These results are in line with my expectation of finding little evidence of predictive power in the lagged ABX index returns over the international market returns. The cross-market linkages between the structured finance market and the international markets were in general weak prior to the subprime crisis. The weak relation documented is reasonable because the structured finance market was not widely known before the outbreak of the subprime crisis, and the structured finance securities were in general complex and nontransparent. It was essentially difficult to predict ex ante the scope and severity of the negative consequences if these securities went insolvent. These results are consistent with those of Longstaff (2010), who finds little interdependence between the ABX indices and the other US domestic markets in 2006.

4.5.2 The subprime crisis subperiod

The subprime crisis subperiod contains all of the observations in year 2007 and is characterised by an increasing threat of subprime mortgage delinquencies and several waves of write-downs in relation to the troubled subprime ABS portfolios among numerous financial institutions. Both the equity market composite and financial equity indices in the G5 countries started to fall sharply in mid-2007.

In the US VAR models, I find strong evidence of contagion from the ABX indices to the US equity and government bond markets, as evinced by the highly significant F-statistics across the ABX index variants. First, the results show that the declines in the ABX indices translated into subsequent higher US government bond market returns, which is consistent with possible 'flight-to-safety' from equity into safer US Treasury bonds during the crisis. In addition, I find significant F-statistics in the three lowest-rated ABX models in explaining the US S&P500 composite index returns. As for the financial equity sector, the lagged returns of all ABX indices, except the ABX AAA index, are highly significant in predicting US financial index returns. In addition, I document significant findings in the ABX AA, A and BBB models in explaining the principal component variable.

Next, I will focus on the results of the international country VAR models. My results are in general significant and consistent with my expectation that the past performance of the ABX indices explain significantly the international equity and government bond market returns. In particular, I document significant predictive power in largely all the ABX indices (with a positive impact) over the composite equity and financial index returns in the G5 countries except in the ABX BBB- models for the UK and German financial indices, and in the AAA model for the Japanese financial index. I also find that the international government bond index returns are significantly predicted (with negative sums of ABX factor loadings) by the lagged ABX index returns across all of the ABX models. Negative shocks in the ABX indices translated into subsequent increases in the international government bond markets and declines in the international equity markets, which is consistent with the existence of flights between domestic equity and government bonds. The R^2 in the VAR models of the financial indices and the government bond indices consistently increased compared to those of the pre-crisis subperiod, suggesting higher explanatory power and better model fit.

4.5.3 The global crisis subperiod

The global crisis subperiod includes the 65 observations between January 2008 and March 2009 and is characterised by the financial institutions' continual losses in relation to their subprime mortgage related businesses, severe funding and market illiquidity, and the international stock market crashes after the Lehman Brothers' collapse in September 2008. The international equity markets performed poorly throughout 2008 and plunged in 2009Q1.

The results of the US VAR models are largely insignificant and the R^2 are in general lower. The predictive power of the ABX indices largely disappeared, as evinced by the insignificant F-statistics. Consistent with the findings of Longstaff (2010), the spillovers of shocks from the US structured finance market to other domestic US markets have become remarkably weaker in this subperiod.

The international evidence is qualitatively similar to those of the US VAR models in that most of the predictive power in the lagged ABX index returns vanished, except for a few markets. The exceptions include the significant results in the financial indices (with negative impact) and in the three highest-rated ABX models of the government bond markets (with negative impact) in the G5 countries. The empirical findings reveal that the predictive power of the ABX indices has become weaker and that the international markets were, to a lesser extent, subjected to the shocks from the US structured finance market during the global financial crisis phase. Nonetheless, I still document evidence of possible 'flight-to-safety' from domestic equity into government bonds, as shown by the significant and negative sums of factor loadings in the government bond market VAR functions.

4.5.4 The post-crisis subperiod

The post-crisis subperiod starts from September 2009 to December 2011 and consists of 123 weekly observations. It partly covers the ongoing crisis in relation to the troubles of European sovereign debt markets. Although the European sovereign debt crisis is not the focus of this investigation, I will include this window to facilitate comparison across the crisis subperiods and to test whether there was still evidence of contagion from the structured finance market to the international markets after the global financial crisis.

In the US VAR models, I find marginally significant predictive power (with negative impact) in the two lowest-rated ABX indices over the US equity market composite and financial index returns. In addition, I find some evidence of predictive power in the ABX AAA model (with negative impact) over the government bond index returns. Overall, the findings are less significant than those in the global crisis subperiod, which is consistent with my expectation of no contagion.

The international evidence is again similar to those of the US VAR models and is in general insignificant, particularly when referring to the French, German and Japanese VAR models. Despite the significant F-statistics in a few UK and French VAR models, the predictive power of the ABX indices has become largely non-existent after the global financial crisis.

4.5.5 Discussions

My empirical findings provide reasonably strong evidence of contagion travelling from the US structured finance market to all G5 equity markets during the subprime crisis. Financial stocks were, to a larger extent, subject to the spillovers of shocks from the US structured finance market, which is consistent with the fact that numerous financial institutions have suffered substantial insolvency risks as a result of the huge losses they suffered in relation to their subprime ABS portfolios during the subprime crisis. In addition, the financial institutions' funding shortage and financial constraints might have reinforced market illiquidity, which in turn translated into heightened risk aversion and declines in prices in the international markets (see Brunnermeier and Pedersen, 2009). Another transmission mechanism relates to investors' obligated liquidation of cross-market investments in meeting funding requirements and to the subsequent higher selling pressures in foreign asset markets (for the role of hedge funds during the recent crisis, see Boyson et al. (2010) and Ben-David et al. (2012)).

I have also documented strong US and international evidence of 'flight-to-safety' from equity into government bonds, as evinced by the significant positive and negative sums of ABX factor loadings in the lagged returns of the equity and government bond indices, respectively. Facing higher systematic insolvency risks and trading costs, investors might switch from equity into safer and more liquid government bonds, which in effect increased the prices of the government bonds and pushed the stock prices down. 'Flight-to-safety' might be motivated from a market liquidity consideration in that investors prefer actively traded government bonds to illiquid assets to ensure that the positions can be liquidated readily so that they can fulfil their funding needs.

4.6 How did contagion transmit during the subprime mortgage crisis?

Having documented solid evidence of contagion, in the following sections I will evaluate the transmission mechanisms of contagion as it passed from the US structured finance market to the international markets. I will also seek to reveal the dynamics of 'flight-to-safety' between the domestic equity and government bond markets. To this end, I will use a similar VAR(4) model framework as in the previous sections, with identical crisis subperiods, to model the relationship between a number of liquidity, credit risk, conditional correlation variables and the ABX index returns. The endogenous variables are written as: $\mathbf{y}_t = [RATIO^{(i)}, IRSS^{(i)}, CORR^{(i)}]$, where $RATIO^{(i)}$ is the trading ratio of financial stocks relative to the overall market, $IRSS^{(i)}$ is the IRSS, and $CORR^{(i)}$ is the estimated conditional correlations between the domestic equity and government bond index returns of the i^{th} country.

4.6.1 Trading ratios

Following Longstaff (2010), I will compute a trading ratio that measures the intensity of trading activities in the financial equity market relative to the overall market. The trading ratio is calculated by dividing the aggregate dollar trading volume of a financial equity index by the aggregate dollar trading volume of the market composite index. Higher trading intensity in financial stocks during the subprime crisis is consistent with portfolio rebalancing by institutional investors for risk adjustments and 'flight-to-safety' purposes. My objective is to test whether the trading intensity can be predicted (or Granger-caused) by the past performance of the ABX indices. The trading ratio is written as:

$$RATIO_{it} = \frac{\sum_{j=1}^{5} FinVol_{ij,t-1}}{\sum_{j=1}^{5} AlleqVol_{ij,t-1}}, \tag{4.2}$$

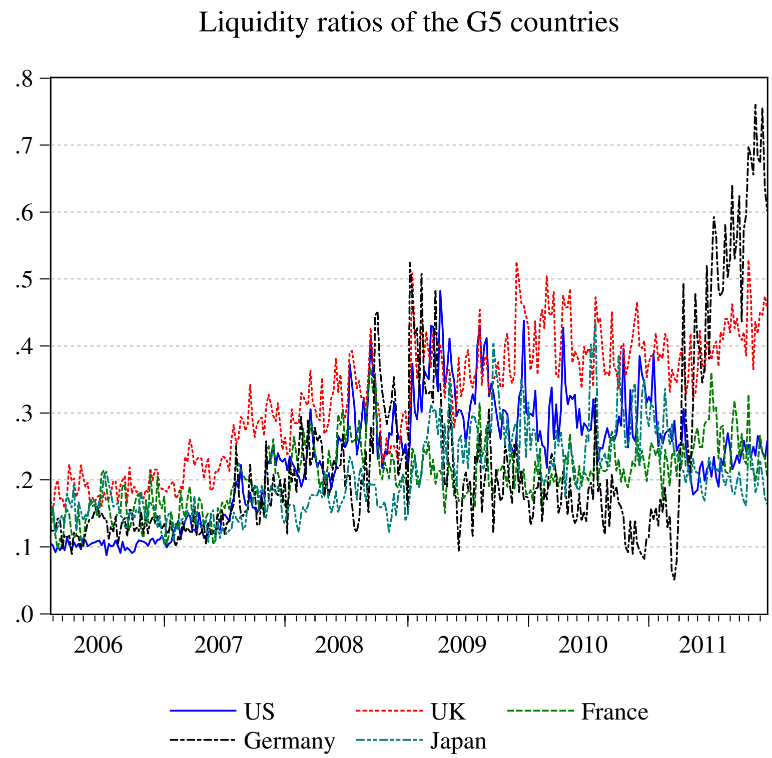
where $FinVol_{ij,t-1}$ refers to the daily trading volume in market value of the financial index in country i on trading day j of week $t-1$, and $AlleqVol_{ij,t-1}$ refers to the daily trading volume in market value of the market composite index in country i on trading day j of week $t-1$.

Fig. 4-3 plots the trading ratios of the G5 countries. The ratios for the G5 countries started to increase from 2007 onwards and soared during the global crisis subperiod. Although the trading ratios remained considerably high during the post-crisis subperiod, the German ratio fell to lower levels in mid-2009 and soared again from 2011Q2 to the end of my sample period. Table 4.10 shows that the means and standard deviations of the ratios were considerably higher during the crisis relative to the pre-crisis levels. The correlations of the trading ratios increased during the subprime crisis, suggesting that the higher trading intensity in the international markets are likely to be driven by some common causes. Since the stationarity of the trading ratios was rejected, the first differences of the trading ratios are used as endogenous variables in the VAR models.

4.6.2 Interest rate swap spreads (IRSS)

In the literature, a number of empirical studies examine the determinants of IRSS and in general follow two main streams. The first stream of research refers to the analysis of liquidity convenience yield curves while the second research direction mainly discusses swap spreads in terms of credit and counterparty default risks (see Brown et al., 1994; Grinblatt, 2001). Liu et al. (2006) show that the US interest rate swap spreads have both default risk and market illiquidity components in which strong time variation in these components over the period 1988 to 2002 have been documented. Moreover, Hui and Lam (2008) find that the Hong Kong IRSS were determined by credit risks during the period July 2002 to September 2007, and by liquidity preference during the later period

Figure 4-3: The trading ratios of the G5 countries



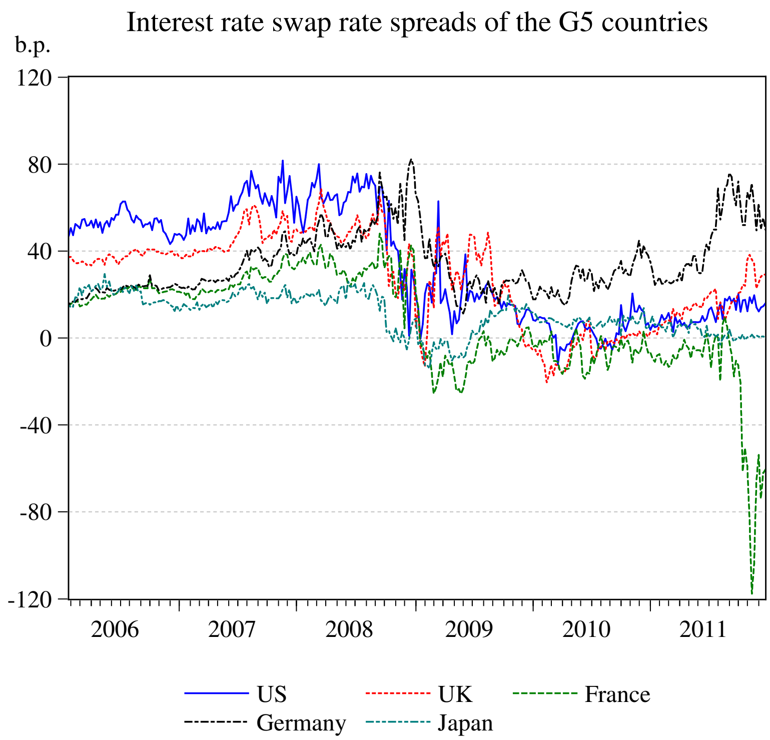
This figure plots the trading ratios of the G5 countries. The ratios are computed by dividing the aggregate weekly trading volume in market value of the financial index (using the Datastream-calculated financial price indices) by the aggregate weekly trading volume in market value of the equity market composite index. It measures the trading intensity of financial stocks relative to the overall market over time.

between September 2007 to April 2008.[24] The empirical evidence lends support to the viewpoint that the IRSS contains risk components that reflect the levels of market wide credit and market illiquidity risks and are, therefore, appropriate for my analysis.

I collected weekly Wednesday quotes of 10-year interest rate swap middle rates for the G5 countries from Datastream, and obtained the spreads by subtracting the corresponding 10-year government bond yields from the interest rate swap rates. Fig. 4-4 plots the weekly IRSS for

[24]According to the authors, the liquidity preference refers more specifically to the strong demand of short-term exchange traded bills for liquidity purposes.

Figure 4-4: The interest rate swap spreads (IRSS) of the G5 countries



This figure plots the IRSS (in basis points) of the G5 countries. The spreads are computed by subtracting the 10-year government bond yields from the interest rate swap middle rates for each subject country.

the G5 countries. The IRSS started to widen in the second half of 2007, which is suggestive of heightened credit and illiquidity risks, and peaked at the end of 2008 shortly after the collapse of Lehman Brothers. The spreads have narrowed and become negative for most G5 countries towards the end of the global crisis subperiod and during the post-crisis subperiod, except for the German IRSS, which has widened and peaked at 75.9 basis points in 2011Q3. The French IRSS narrowed and declined sharply at the end of 2011. Table 4.11 shows that the mean IRSS was larger and more volatile during the crises. To ensure stationarity, I took the first differences of the IRSS and sought to test whether the shocks from the ABX indices translated into higher credit and illiquidity risks during the recent crisis as a test of the validity of the risk premia transmission channel.

4.6.3 Conditional correlations

In the previous sections, I document strong evidence of 'flight-to-safety' in the international markets during the subprime crisis and the global financial crisis. Following a widely-adopted approach in the literature (see, for example, De Goeij and Marquering, 2004; Li, 2003; Baur and Lucey, 2009), I have studied the estimated conditional correlations between the weekly returns of domestic equity and government bond indices to examine the dynamics of the 'flight-to-safety' phenomenon during the recent financial crisis.

I adopt a MGARCH diagonal VECH model to estimate the dynamics between the returns of the domestic equity market composite and government bond indices in each G5 country and have obtained a series of conditional correlations for each pair of returns. I assume a VECH specification in which the variance-covariance matrix is modelled as in the following autoregressive process:

$$\begin{aligned} \text{vech}(\mathbf{H}_t) &= \mathbf{C} + \mathbf{A}\text{vech}(\boldsymbol{\Xi}_{t-1}\boldsymbol{\Xi}'_{t-1}) + \mathbf{B}\text{vech}(\mathbf{H}_{t-1}) \\ \boldsymbol{\Xi}_t|\mathcal{I}_{t-1} &\sim N(0, \mathbf{H}_t). \end{aligned} \tag{4.3}$$

With the restricted form developed by Bollerslev et al.(1988), matrix A and B are assumed to be diagonal such that:

$$\mathbf{H}_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{bmatrix}, \boldsymbol{\Xi}_t = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}, \mathbf{C} = \begin{bmatrix} c_{11} \\ c_{21} \\ c_{31} \end{bmatrix}, \mathbf{A} = \begin{bmatrix} \alpha_{11} & 0 & 0 \\ 0 & \alpha_{22} & 0 \\ 0 & 0 & \alpha_{33} \end{bmatrix},$$
$$\mathbf{B} = \begin{bmatrix} \beta_{11} & 0 & 0 \\ 0 & \beta_{22} & 0 \\ 0 & 0 & \beta_{33} \end{bmatrix}.$$

The conditional variances for my two asset returns in each country follow a GARCH(1,1) formulation, characterised by:

$$h_{ijt} = w_{ij} + \alpha_{ij} u_{i,t-1} u_{j,t-1} + \beta_{ij} h_{ij,t-1} \qquad \text{for } i, j = 1, 2. \tag{4.4}$$

where w_{ij}, α_{ij}, and β_{ij} are parameters to be estimated while $u_{i,t-1}$ and $u_{j,t-1}$ refer to the regression residuals of asset i and j at time $t-1$, respectively.

Fig. 4-5 plots the time-varying conditional correlations of the domestic equity and government bond market index returns of the G5 countries estimated using the MGARCH diagonal VECH model. The conditional correlations of the G5 countries are in general negative during the pre-crisis subperiod and have become more negative during the subprime crisis subperiod, except for the Japanese correlations in which strong time variations and positive spikes were present. Towards the end of year 2008, the conditional correlations became less negative, reflecting a higher degree of market comovements between the G5 domestic stock and government bond markets. The correlations largely remained negative after the crisis, except for the occasional spikes in the Japanese and German series. As shown in Table 4.12, the subsample mean correlations largely became more negative during the subprime crisis and less negative during the global financial crisis. The summary statistics suggest possible 'flight-to-safety' during the subprime crisis subperiod and higher market comovements (contagion) between the domestic equity and government bond markets during the global crisis subperiod. The conditional correlation series are included as endogenous variables in the VAR models to test whether the lagged ABX index returns have predicted the changes in comovements between domestic equity and government bond market returns during the crisis.

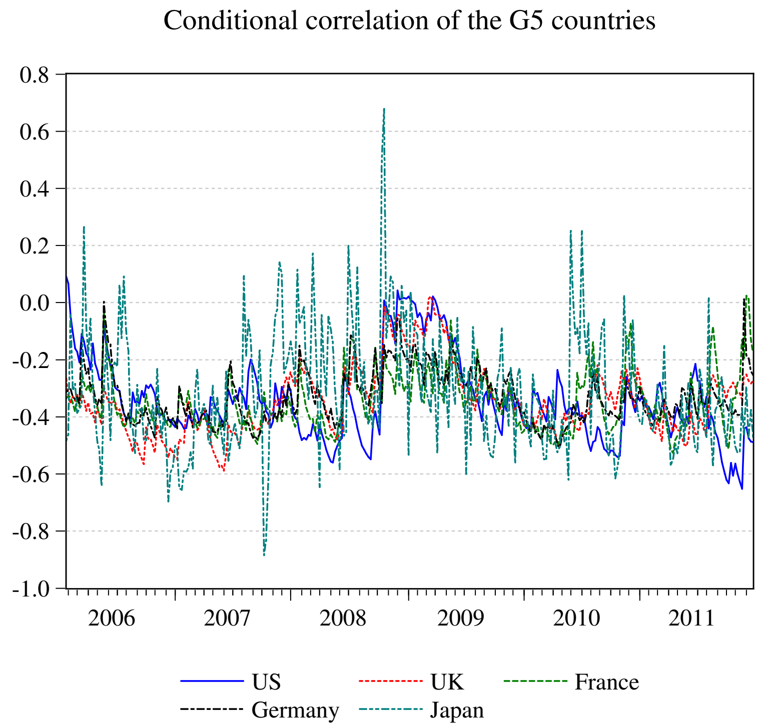
4.6.4 Empirical findings: The trading ratios, IRSS and conditional correlations VAR models

Tables 4.13 - 4.17 present the findings of the VAR(4) models with the trading ratios, IRSS and conditional correlations as endogenous variables and the lagged ABX index returns as exogenous regressors. The sums of ABX factor loadings and the R^2 of each VAR function are reported. The F-tests are based on the null hypothesis that the ABX factor loadings are jointly equal to zero: $h_0 : \phi_{j,1}^{(i)} = \phi_{j,2}^{(i)} = \phi_{j,3}^{(i)} = \phi_{j,4}^{(i)} = 0$.

Pre-crisis subperiod

During the pre-crisis subperiod, I find limited predictive power in the ABX indices over changes of trading ratios, IRSS and conditional correlations, except in the German trading ratios and the Japanese IRSS and correlation VAR models. Although I document some significant results in the US conditional correlations and the UK trading ratios and IRSS, my findings show that the lagged ABX index returns do not explain much of the variations in the changes of trading ratios, IRSS and

Figure 4-5: The conditional correlations between the weekly returns of the domestic equity market composite and government bond indices of the G5 countries



This figure plots the conditional correlations estimated using a MGARCH(1,1) diagonal VECH model between the weekly returns of the domestic equity market composite indices and the FTSE global government 10+ year bond clean price indices for each G5 country.

conditional correlations prior to the subprime crisis, which is consistent with my previous findings of no contagion during this subperiod.

Subprime crisis subperiod

During the subprime crisis subperiod, my findings are highly significant and consistent across the ABX models. First, significant predictive power (negative impact) in the ABX indices over the changes of trading intensity in US financial stocks are present, which is consistent with the findings in Longstaff (2010). Declines in the subprime RMBS valuations translates into an elevated level of trading activity among financial stocks, which is consistent with investors' portfolio rebalancing and possible 'flight-to-safety'. Second, I find significant negative sums of ABX factor loadings in the three lowest-rated ABX models for the US IRSS. In other words, the widening of the US IRSS and heightening credit risks during the subprime crisis are predicted by the past performance of the ABX indices, lending empirical support to the risk premia channel. On the other hand, the findings of the US conditional correlations are largely insignificant.

The empirical findings for the international market VAR models are remarkably significant, except in the German correlations and the Japanese trading ratios models. I document significant negative (positive) relations between the ABX index returns and the changes of trading ratios in the UK and France (Germany). As for the IRSS, the results are highly significant across the ABX models and the G5 countries in that shocks from the ABX indices translated into the widening of IRSS in the G5 countries in weeks. These results suggest that the heightening levels of credit risk and market illiquidity in the international markets were associated with the shocks from the structured finance market consistent with contagion transmission via changes in risk premia. In addition, the conditional correlations were related negatively with the ABX index returns for the UK, French and Japanese VAR models and positively related with the ABX index returns for the German ABX AAA and AA models. The declines in the ABX indices during the subprime crisis subperiod led to increases (decreases) in the changes of correlation in the UK, France and Japan (Germany). In other words, the ABX shocks led to a higher degree of market comovements (i.e. contagion) between the domestic equity and government bond markets in the UK, France and Japan and a higher degree of 'flight-to-safety' in the German markets.

Global crisis subperiod

Consistent with my findings in the previous section, my findings of the US VAR models are largely insignificant, except for the US trading ratios. The higher trading intensity in the US financial stocks are predicted by the past performance of the US structured finance market during the global financial crisis. Apart from this, the findings of the US IRSS and conditional correlations are largely insignificant.

The findings for the international markets are largely insignificant with a few exceptions, such as: the UK IRSS (negative relation in the ABX AA and A indices), German trading ratios (positive relation in ABX AA and BBB- indices), and the Japanese IRSS (negative relation in ABX AA and

A indices and positive relation in ABX AAA index).

Post-crisis subperiod

In this subperiod, the ABX model results are in general insignificant and the significant predictive power in the ABX indices over the changes in US trading ratios during the global crisis no longer existed. The R^2 are notably lower, which is in line with my expectation of little or limited explanatory power.

As for the international markets, the predictive power of the ABX indices largely weakened and became insignificant after the global crisis. The ABX indices no longer contained important market information that predicted the international market returns during the post-crisis subperiod.

4.6.5 Discussions

In summary, my VAR analysis based on weekly data shows that past returns of the ABX indices significantly predict (Granger-causality) changes in the trading activities of financial stocks, IRSS and conditional correlations, especially during the subprime crisis. In particular, the negative shocks in the ABX indices translated into subsequent higher trading intensity in the domestic financial stocks in the US, UK, France and lower trading intensity in Germany. The higher trading intensity in financial stocks is consistent with portfolio rebalancing and 'fire sales' of assets due to funding liquidity constraints and increasing risk aversion.

More remarkably, my findings show that the widening of the G5 IRSS during the subprime crisis is significantly predicted by the ABX index returns. Taken together with the significant findings of contagion from the US structured finance market to the international markets in Section 4.5, I present strong evidence in support of the contagion transmission via increases in credit and market illiquidity risks. My findings also show that the negative shocks in the ABX indices translated into subsequent higher comovements between domestic stock and government bond markets in the UK, France and Japan during the subprime crisis. I find evidence that shocks from the ABX indices encouraged 'flight-to-safety' in the German markets, as evinced by the positive relation between the lagged ABX index returns and the German conditional correlations. The evidence that the declines in the ABX indices led to contagion in both the domestic equity and government bond markets is somewhat contrary to my previous VAR results, in which the negative shocks from the ABX indices translated into lower future stock market and higher government bond market performance.

Nonetheless, my graphical analysis of the conditional correlations and the empirical results (as shown in Tables 4.5 - 4.9) both lead me to conclude that the 'flight-to-safety' between the domestic and government bond markets existed during the subprime crisis. However, the results in my liquidity and credit risk VAR models are to be interpreted with caution. First, the fact that the correlations are first-differenced means that I can only evaluate the relation between the past ABX index returns and the changes in correlations. The interpretation is limited to testing whether the past returns of the ABX indices 'encourage' or 'discourage' the 'flight-to-safety' phenomenon. For instance, assuming that the ABX indices have declined, the ABX factor loadings are negative and the conditional correlation (level data) was -0.50 at time $t-1$, the negative relation dictates that the decline in the ABX indices translates into a positive change in conditional correlation, say an increase of 0.10. The conditional correlation at t would become $-0.50 + 0.10 = -0.40$. In other words, the 'flight-to-safety' may still exist despite the negative relation documented between the lagged ABX index returns and the changes in conditional correlations. In this sense, I conclude with caution that the negative shocks from the ABX indices 'discouraged' flights in the UK, France and Japan and 'encouraged' flights in the German markets while the 'flight-to-safety' phenomenon was in general present in the G5 countries during the recent crisis.

4.7 Empirical investigation on contagion - daily data

Another widely-acknowledged working definition of contagion focuses on the role of the arrival of new market information in shock transmission. This definition relates closely to the EMH in that price discovery of efficient markets is in general immediate and rapid in adjusting to new market information. Contagion may occur in a fast and immediate manner via the arrival of information. Engle et al. (1990) show that the volatilities in foreign exchange markets spread across intra-daily market segments, while Dooley and Hutchison (2009) show empirically that the US financial and real economic news impacted on the daily changes in emerging markets' CDS spreads. Evans (2011) shows that the intra-daily jumps in the US futures market are associated with US macroeconomic news announcements. Connolly and Wang (2003) show that the market comovements of the domestic overnight returns in the US, UK and Japanese stock markets are significantly explained by foreign (US, UK and Japanese) equity market returns, but not by public economic fundamentals. The empirical evidence suggests that contagion may arise in a relatively fast and immediate manner within trading days.

In the literature, the information contagion transmission channel refers to the mechanism by which a shocked market signals new market information that affects the asset prices in other markets. Kaminsky et al. (2003) contend that shocks transmit through the arrival of negative economic news and immediately affect the collateral values in other markets. King and Wadhwani (1990) present a rational expectation equilibrium model that explains contagion as the result of market agents' attempts to infer equity values based on imperfect information about certain events. Their model implies that idiosyncratic changes in one market may affect other markets as a result of information asymmetries and result in the subsequent comovement of market volatilities. Shocks transmitted via the information transmission mechanism should be 'fast and furious' with instantaneous adverse market comovement (Kaminsky et al., 2003).

Thus far, my empirical results are consistent with Longstaff (2010) in that the significant predictive power of the lagged ABX index returns on US and international market returns is identified over a weekly frequency. I would contend that the significant contagion from the ABX indices over this frequency is inconsistent with the information transmission mechanism. Nonetheless, the predictive power of the ABX indices does not rule out the possible existence of short-lived spillovers of shocks within trading days. I will fill this gap by examining contagion from the ABX indices to the G5 international markets using daily data frequency.

4.7.1 Methodologies

In this section, I apply the same VAR model framework as in earlier sections and study the dependencies between the ABX indices and the international market indices in the G5 countries. To detect significant short-lived contagion within one trading week, I use five lags (equivalent to one trading week) and estimate the following VAR(5) model with n endogenous variables:

$$\mathbf{y}_t = \boldsymbol{\alpha}_0 + \sum_{s=1}^{5} \boldsymbol{\beta}_s \mathbf{y}_{t-i} + \sum_{k=1}^{4} \sum_{s=1}^{5} \boldsymbol{\phi}_{s,k} d_k ABX_{t-s} + \boldsymbol{\epsilon}_t, \tag{4.5}$$

where $\mathbf{y}_t$ is a $n \times 1$ vector of endogenous dependent variables (daily returns of the domestic broad equity, financial equity, and government bond indices, and a daily PCA latent factor variable constructed in the same manner as in Section 4.4.3), $\boldsymbol{\beta}_s$ is an $n \times n$ matrix of coefficients, ABX_{t-s} is the s^{th} lagged ABX index returns, $\boldsymbol{\phi}_{s,k}$ is an $n \times 1$ vector of coefficients for the lagged ABX index returns, d_k is a crisis dummy variable denoting the k^{th} crisis subperiod, and $\boldsymbol{\epsilon}_t$ is an $n \times 1$ vector of innovations that are uncorrelated with their own lagged values and all right-hand side variables.

The main difference between the current VAR model framework and the previous model given by Equation 4.1 is that I introduce crisis dummy variables and estimate one VAR model for each country using the full sample period instead of estimating a VAR model separately for each subperiod. I will then test for the block predictive power (Granger-causality) of the lagged ABX index returns over the international market returns using standard F-tests of joint significance. Significant F-statistics suggest that the G5 market returns cannot be explained fully by its own country-specific factors and that the past idiosyncratic shocks of the ABX indices have a significant impact on the international market returns observed over subsequent trading days.

4.7.2 Data and summary statistics

My daily data consists of 1385 observations and covers the period between 19 January 2006 and 31 December 2011. The endogenous variables used in the VAR models include the daily returns of the domestic broad equity, financial equity and government bond indices and the PCA variable and can be written as $\mathbf{y}_t = [EQ_t^{(i)}, FEQ_t^{(i)}, GOV_t^{(i)}, PCA_t^{(i)}]'$.

To account for the time differentials between the international market open and close times, I follow Forbes and Rigobon (2002) and compute the two-day rolling average returns (or changes) for each of the variables. In addition, the daily observations between 1 April 2009 and 31 August 2009 are excluded from the current analysis because the ABX indices were considerably stale with a number of consecutive zero returns that cause near-singularity problems in OLS regressions. Nevertheless, the main focus of the current investigation is on the subprime and global crisis subperiods and, hence, the omission of these observations has a limited impact on my main findings.

Crisis dummy variables

Crisis dummy variables denoted by d_k, where $k = \{1,...,4\}$, are introduced to allow changes in the ABX factor loadings across the crisis subperiods. Unity is assigned to observations within the specified crisis subperiod, and zero otherwise. While the pre-crisis, subprime and global crisis subperiods are defined with the exact same dates as in earlier analysis, the post-crisis subperiod starts from 1 September 2009 to 30 December 2011 and covers part of the ongoing European sovereign debt crisis.

Summary statistics

Table 4.18 reports the full sample (Panel A) and subsample (Panel B - D) summary statistics of the two-day rolling average returns of the ABX indices. In Panel A, the mean daily two-day rolling average ABX index returns are negative with larger absolute values and standard deviations towards the lower-rated ABX indices. The full sample unconditional correlation between the AAA and AA indices is as high as 0.834 while the correlation between the BBB and BBB- indices is 0.804. In Panel B - D, the mean returns of the pre-crisis subperiod are positive with low volatilities, while those of the subprime and global crisis subperiods are all negative with higher volatilities. All pairs of correlations among the ABX indices increased during the subprime crisis and remained at considerably higher levels throughout the global crisis. In the post-crisis subperiod, mean returns are largely positive with lower correlation except for that between the AAA and AA indices.

Table 4.19 reports the summary statistics of the endogenous variables used in the daily VAR models. Panels A to C contain the full sample, and subsample means and standard deviations of the daily returns of the G5 equity market composite, financial and government bond indices, respectively. Similar to their weekly counterparts (see Section 4.3), I find negative average returns in the G5 countries' equity indices (most notably in the financial indices) and positive average government bond index returns. The subsample statistics show that the international financial indices started to decline during the subprime crisis subperiod and crashed during the global crisis with increased volatilities. In addition, the average returns of the equity market composite indices were negative during the global crisis, reflecting the significant downward pressure on stock prices. By contrast, the international government bond indices yielded negative average returns during the pre-crisis and subprime crisis subperiod, and positive returns during the global and post-crisis subperiods.

Similar to the analysis in earlier sections, I include PCA factor scores in the VAR model to account for possible spillover effects across the international equity markets. Table 4.20 reports the statistics (eigenvalues, percentage of variances explained by each principal component and the communalities) of the PCA using the international equity market composite index returns (two-day rolling averages) as inputs. Only one principal component has been extracted for each subject country. The communalities scores show that, for each subject market, the first principal component explains the variations in the European stock markets better than the Japanese stock market in general. Overall, the high percentage of variances explained and the communality scores suggest that the first principal components capture the variations in the international stock markets reasonably well and are, therefore, included in the daily VAR models.

4.7.3 Empirical findings

The main objective of my analysis is to identify any significant predictive power in the daily lagged ABX index returns over the international market returns. I expect little or limited predictive power during the pre-crisis and the post-crisis subperiods, and increases in explanatory power during the subprime and global crisis subperiods. Again, standard F-tests of joint equality on the ABX factor loadings are reported with null hypothesis: $h_0 : \phi^{(i)}_{j,1} = \phi^{(i)}_{j,2} = \phi^{(i)}_{j,3} = \phi^{(i)}_{j,4} = \phi^{(i)}_{j,5} = 0$, where $\phi_{j,s}$ refers to the factor loadings of the s^{th} lagged ABX index return on the j^{th} endogenous variable VAR for country i. Tables 4.21 - 4.25 report the sums of ABX factor loadings grouped by the crisis dummy variables; that is, the sum of the ABX factor loadings that are interacted with the same crisis dummy variable, and the R^2 of each equation in the VAR models.

Pre-crisis subperiod

My findings of the pre-crisis subperiod are largely insignificant, which is consistent with my expectations and with the weekly VAR results that were presented previously. In addition, the reported ABX factor loadings on the G5 equity and government bond index functions are in general negative, except in the Japanese financial index return equations.

Subprime crisis subperiod

In this subperiod, the empirical results of the US VAR models are in general less significant than their weekly counterparts. While the sums of ABX factor loadings are largely positive, they are in general insignificant in explaining the US equity and financial equity market returns. However, the lagged ABX index returns explain (with negative impact) significantly the contemporaneous US government bond index returns across the ABX models. The declines in the ABX indices translated into higher returns in the US government bond market, which is once again suggestive of a possible 'flight-to-safety' phenomenon. Collectively, the evidence suggests that the US government bond markets were more subject to short-lived shocks from the ABX indices and tend to react more rapidly to the past daily ABX index returns than the US equity composite and financial equity sector.

As for the international markets, the empirical results are highly significant and consistent across the G5 countries. First, I have identified significant predictive power (positive relation) in largely all ABX indices (except the AAA model in the UK and Germany, and the AAA and AA models in France and Japan) over the international equity market returns. Second, the three lowest-rated ABX models over the international financial index returns are highly significant (positive relation) in the UK, France and Germany. Similarly to their US counterparts, significant and negative ABX factor loadings are documented in the international government bond market VAR models. The declines in the ABX indices translated into increases in the international government bond market returns within trading days. The results once again suggest a possible 'flight-to-safety' into the safer international government bond markets, which is driven by the negative shocks from the US structured finance market.

Global crisis subperiod

Despite the less significant results in the US VAR models during the subprime crisis, the ABX index returns significantly predicted the US market composite, financial (only in the ABX AAA and AA models), government bond index returns and the PCA factor scores. The significant sums of the ABX factor loadings in the US equity indices are all positive while those in the US government bond indices are negative. In other words, shocks in the ABX indices translated into lower equity market returns and higher government bond market returns in the US during the global crisis subperiod.

While the significant ABX predictive power over the international market returns largely remains, the results on the international government bond indices are in general less significant. By contrast, the international equity market index returns in the UK, French, and the German VAR models are significantly predicted (with positive impact) by past ABX index returns, with qualitatively similar findings to those observed in the subprime crisis subperiod. My empirical findings lend support to the existence of short-lived spillovers of shocks from the ABX indices to the US equity and government bond market, and to the G5 international equity markets.

Post-crisis subperiod

In line with my expectations, and consistent with my previous weekly frequency VAR findings, the daily VAR results in the post-crisis subperiod are largely insignificant for both US and international markets. The predictive power of the ABX indices over the international market returns largely disappeared in that the US structured finance market did not convey any important market information to the international markets during this period.

Summary

In summary, my empirical investigation documents strong evidence of short-lived spillover effects from the US structured finance market to the domestic US markets and to the international markets. For the US daily VAR models, I have detected significant contagion from the ABX indices to the government bond indices (negative impact) during the subprime crisis, and to both equity (positive impact) and government bond markets (negative impact) during the global crisis subperiod. For the G5 country daily VAR models, I have identified significant contagion from the ABX indices to the international equity and government bond markets during the subprime crisis, and to the equity markets during the global financial crisis. The findings of short-lived spillover effects provide empirical support to the contention that contagion might have transmitted via the arrival of market information, which is in contrast to the conclusion of Longstaff (2010). The evidence in this chapter supports the notion that the ABX indices were important risk barometers during the recent crisis and contained important information regarding the state of the economy that can be exploited by market participants.

4.8 Controlling for simultaneous contagion from other major US markets

In the following sections, I check the robustness of my findings and include a set of additional exogenous variables in the daily VAR models to account for possible simultaneous spillovers of shocks originating from other major US markets. More precisely, I include the two-day rolling average daily returns of various major US markets as exogenous variables in addition to the lagged ABX index returns (i.e. in Equation 4.1, the scalar ABX index return has been replaced by a vector of exogenous US market variables). The VAR(5) model can be written as:

$$\mathbf{y}_t = \boldsymbol{\alpha}_0 + \sum_{s=1}^{5} \boldsymbol{\beta}_s \mathbf{y}_{t-i} + \sum_{k=1}^{4} \sum_{s=1}^{5} \boldsymbol{\phi}_{s,k} d_k \mathbf{x}_{t-s} + \boldsymbol{\epsilon}_t, \tag{4.6}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous dependent variables (daily returns of domestic broad equity, financial equity, and government bond indices), $\boldsymbol{\beta}_s$ is an $n \times n$ matrix of coefficients, $\mathbf{x}_{t-s}$ is an 6×1 vector of US market returns:

$$\mathbf{x}_{t-s} = [ABX_{t-s}, S\&P500_{t-s}, MOODY_{t-s}, USGOV_{t-s}, ABCP_{t-s}, PCA_{t-s}]',$$

$\boldsymbol{\phi}_{s,k}$ is an $n \times 6$ matrix of coefficients for the exogenous regressors, d_k is a dummy variable denoting the k^{th} crisis subperiod, and $\boldsymbol{\epsilon}_t$ is an $n \times 1$ vector of innovations that are uncorrelated with their own lagged values and all right-hand side variables.

Apart from the ABX index returns, I include the two-day rolling average returns of the US S&P 500 composite index ($S\&P500$), the Datastream-calculated US 10-year government bond index ($USGOV$), Moody's BAA yield spreads ($MOODY$), ABCP ($ABCP$) yield spreads, and the PCA factor scores (PCA) as exogenous variables. In this model specification, I effectively control for the possible impact of the past performance of US equity, corporate bond, government bond and asset-backed money markets on international market returns during the recent crisis.

4.8.1 Empirical findings

Tables 4.26 - 4.29 report the sums of the factor loadings of the exogenous variables (grouped by crisis dummy variables) and the R^2 associated with the daily VAR models. Panels A to E report the findings of the ABX AAA, AA, A, BBB and BBB- models, respectively.

First, after controlling for the other major US market variables, the significant predictive power of the ABX indices over the international markets in general persists. During the subprime crisis subperiod, I document significant ABX factor loadings in all G5 countries, except for Japan. Interestingly, while the ABX factor loadings on the international equity and government bond markets are in general consistent with my previous findings (i.e. the daily VAR models), I find two distinct patterns of significant findings in the two highest and the three lowest-rated ABX models over the government bond index returns. Specifically, I find positive ABX factor loadings in the G5 government bond markets in the AAA and AA models, and negative factor loadings in the A, BBB and BBB- models. These results are consistent with my summary statistics that the two highest-rated and three lowest-rated ABX indices are considerably correlated with each other. In other words, declines in the ABX AAA and AA indices translated into subsequent declines in both international equity and government bond markets while the negative shocks in the ABX A, BBB and BBB- indices translated into declines in the international equity and increases in the government bond markets, which is evidence of 'flight-to-safety'. The predictive power of the three-lowest rated ABX models largely disappeared in the global crisis subperiod. The evidence suggests that the two highest-rated and the three lowest-rated ABX indices represented different sources of risks, with the two investment-graded ABX AAA and AA indices still predicting the international markets during the global financial crisis subperiod. One possible explanation is that the three lowest-rated ABX indices might have become stale and were inactively traded as investors avoided trading these extremely risky and opaque structured finance products during the crisis.

Second, I document significant and positive relations between the lagged S&P 500 composite index returns and the international market returns in almost all G5 countries and throughout my sample period. In particular, I find evidence that the significant sums of S&P 500 factor loadings on the international equity returns have increased (in absolute terms) during the subprime and global crisis subperiods. In addition, I find significant predictive power in the lagged S&P 500 composite index returns over the French government bond index returns during the subprime crisis (negative relation, evidence of 'flight-to-safety') and over the Japanese government bond index returns (positive relation, evidence of contagion) during the global financial crisis subperiod. In addition, the lagged US government bond index returns significantly predicted the UK, French and German equity index returns during the pre-crisis and post-crisis subperiods, and over the Japanese equity index returns during the post-crisis subperiod. Note that my findings suggest a change in dependencies between the US government bond index and the international markets across the non-crisis and crisis subperiods. The international equity markets largely followed (negative relation) the past returns of the US government bond market during the normal tranquil period. Moreover, when the subprime crisis unfolded, the international equity markets were no longer driven by the US government bond market and the correlation between the US and international government bond indices increased significantly.

Next, I focus on the significant predictive power of the past changes of the Moody's BAA corporate bond yield and the ABCP yield spreads over the international market returns. As a proxy for market wide default risk in the US financial system, the findings of the Moody's BAA yield spreads are less significant than the other US market variables and are mixed across the ABX models. During the subprime crisis, I document a marginally significant predictive power (with negative relation) in the lagged changes of the Moody's BAA yield spreads over the UK and French equity market returns in the ABX AA and A models, as well as over the Japanese equity market returns, in largely all ABX models. Moreover, I find some significant and positive relations between Moody's BAA spreads and German financial index returns in the ABX A and BBB- models. In contrast, the ABCP yield spreads are highly significant in explaining the European equity market returns across the ABX models. I find evidence of increases in the predictive power of the ABCP yield spreads during the crisis, which are characterised by negative factor loadings in the UK, French and German equity composite index returns during the subprime crisis. Interestingly, during the global crisis, the widening of the ABCP yield spreads during the global crisis stage translated into higher subsequent financial index returns in the European countries. In addition, I also find that the widening of ABCP yield spreads led to subsequent declines and increases in the French and Japanese government bond market returns, respectively, during the global crisis. The predictive power of the ABCP yield spreads largely disappeared in the post-crisis subperiod.

4.8.2 Discussions

My findings based on the daily VAR with exogenous US market variables are largely consistent with my previous findings in that I document the significant predictive power in the ABX indices over the international market returns. Interestingly, my results show that the past performances of the US equity market composite index, government bond index, corporate bond yield spreads, and asset-backed money market yield spreads significantly predict the international market returns. Meanwhile, the developed international markets were shown to be rather integrated. My findings highlight the important role played by the US markets in signalling market information to the international markets and support the view that investors might have acted upon the past US market information throughout the entire sample period.

By including various major US market variables in the daily VAR models, the significant predictive power in the ABX indices still persists, which is consistent with contagion travelling from the US structured finance market to the international markets. These findings are in general consistent with Longstaff (2010) and provide strong support for contagion via the information transmission channel.

4.9 Correlation coefficient analysis

To further check the robustness of the findings of my VAR models, I follow Forbes and Rigobon (2002) and test explicitly the changes in correlation coefficients between the contemporaneous ABX index returns and the international market returns. The authors propose a relatively stringent definition of contagion in that only significant increases in correlation after controlling for interdependence are considered to be evidence of contagion. The authors propose a heteroscedasticity adjusted test for correlation that detects any significant increases in correlation coefficients between the international markets and takes into account the normal level of interdependence.

4.9.1 Measuring correlations and correction for heteroscedasticity

To understand the intuition behind the correlation analysis, let us assume that there is a linear factor model:

$$y_{i,t} = \alpha_t + \beta_t y_{j,t} + \varepsilon_t, \tag{4.7}$$

where $y_{i,t}$ refers to the returns of market i and β_t is the coefficient of the market j return variable.

If there is a change in the relationship between markets i and j (e.g. the occurrence of a financial crisis), then the coefficient β_t should be statistically different before and after the changes. However, as pointed out by Forbes and Rigobon (2002), this simple test of contagion on the coefficients is complicated by the fact that volatilities have usually increased during the crisis; that is, a bias induced by heteroscedasticity. The empirical tests are framed so that, instead of testing for the changes in coefficients, the correlation coefficients are examined across crisis subperiods. Noting that, since there may be structural changes in the variances between high and low volatility subperiods, the authors show that during periods of high volatilities in market, i, the conditional correlation between markets i and j will be higher regardless of the changes in unconditional correlations. To mitigate this bias, the authors propose a correction of heteroscedasticity to the correlation coefficients as follows:

$$\rho_{adj} = \frac{\rho^*}{\sqrt{1 + \delta[1 - (\rho^*)^2]}}, \tag{4.8}$$

where

$$\delta = \frac{\sigma_{ii}^h}{\sigma_{ii}^l} - 1. \tag{4.9}$$

The ρ_{adj} is the heteroscedasticity-adjusted unconditional correlation coefficient while ρ^* is the conditional correlation coefficient. δ is the relative increase in variances during the crisis with σ_{ii}^h and σ_{ii}^l as the variances of returns of market i during high and low volatilities periods, respectively. The hypothesis test of contagion for each pair of crisis and non-crisis markets is specified as follows:

- $h_0 : \rho_{adj}^h \leq \rho_{adj}^l$

- $h_1 : \rho_{adj}^h > \rho_{adj}^l$

4.9.2 Empirical methodologies

Forbes and Rigobon (2002) point out that the limitation of the correlation coefficient analysis is that the assumption requires that there is no endogeneity between the market returns; that is, there are no feedback effects from market j to i (where i is the original shocked market). To this end, the authors control for the effects of common global shocks and include the interest rates of the US, the domestic markets, and the shocked markets in their empirical tests. Practically, the authors fit VAR models to each pair of market returns, include the interest rate variables as exogenous regressors in the models, extract the variance-covariance matrices of the VAR residuals to obtain the conditional correlation coefficients, and then correct the correlation coefficients for heteroscedasticity.

I follow the authors and fit VAR models to the pairs of market returns using the two-day rolling-average daily market returns and five lags, written as:

$$\mathbf{y_t} = \boldsymbol{\alpha}_t + \sum_{s=1}^{5} \mathbf{y_{t-s}} + \sum_{s=1}^{5} \mathbf{x_{t-s}} + \eta_t, \tag{4.10}$$

$$\mathbf{y_t} = [y_t^{(ABX)}, y_t^{(j)}]', \tag{4.11}$$

$$\mathbf{x_t} = [i_t^{(US)}, i_t^{(j)}]', \tag{4.12}$$

where $\mathbf{y_t}$ is a 2×1 vector of market returns containing the ABX index returns ($y_t^{(ABX)}$) and the international market returns ($y_t^{(j)}$, which includes the returns of the international equity market composite index, financial index and government bond index of each G5 country), $\mathbf{x_{t-s}}$ is a 2×1 vector of lagged changes of the US interest rates and the interest rates of the remaining G5 countries.

I follow Forbes and Rigobon (2002) and estimate the VAR models of each ABX and international market index pair for the full sample and the crisis subperiods. The full sample and crisis subsample conditional correlations are estimated and corrected for heteroscedasticity, as discussed above. According to Dungey and Zhumabekova (2001), formal t-tests of unconditional correlations across the full sample and crisis subsample can be formulated by applying the Fisher transformation on the adjusted correlation coefficients, and calculating the respective means and standard deviations, as follows:

$$\bar{\rho}_{adj}^{i} = \frac{1}{2}\ln(\frac{1+\rho_{adj}^{i}}{1-\rho_{adj}^{i}}), \tag{4.13}$$

where the standard deviation is computed as:

$$s_i = \sqrt{\frac{1}{n_i - 3}}. \tag{4.14}$$

Here n_i refers to the number of observations in a crisis subperiod; for example, the high-volatility sample. The two-sample t-test can be written as:

$$t\text{-stat} = \frac{\bar{\rho}_{adj}^{h} - \bar{\rho}_{adj}^{l}}{\sqrt{s_h^2 + s_l^2}}, \tag{4.15}$$

where s_h^2 and s_l^2 refers to the standard deviations of the unconditional correlation coefficients of the high-volatility subsample and the full sample, respectively. As pointed out by Dungey and Zhumabekova (2001), the Fisher transformation is an asymptotic result and is valid in general with at least 50 observations. Hence, my crisis subsamples, which exceed 50 observations in each subperiod, is sufficient to generate consistent test statistics.

4.9.3 Empirical findings

Tables 4.30, 4.31 and 4.32 report the empirical findings of the correlation coefficient analysis (between the international market and the US structured finance market). The conditional and unconditional (heteroscedasticity-adjusted) correlation coefficients and the standard deviations of the international markets are reported along with the t-statistics of the two-sample mean equality tests (with Fisher transformation).

First, my findings of the international equity markets show that the unconditional correlation coefficients are in general higher during the subprime crisis subperiod across the ABX indices and in the G5 countries (except for Japan). The correlations between the international equity markets and the US structured finance market were smaller during the global crisis subperiod relative to the subprime crisis subperiod. My test statistics reject significantly my hypothesis of no increases in correlation coefficients in all G5 European countries during the subprime crisis subperiod, they also reject my hypothesis that the correlation coefficients are significantly higher than those of the full period, which is consistent with contagion as defined by Forbes and Rigobon (2002). The test statistics for comparison between the full and global crisis subperiods are in general insignificant in that no evidence of contagion has been documented.

Second, as shown in Table 4.31, the results of the international financial equity markets are qualitatively similar to those of the broad equity markets. Although the conditional correlations across the subprime and global crisis subperiods are similar, the unconditional correlations of all G5 countries (except for Japan) are in general higher in the subprime crisis subperiod. Once again, the test statistics show that the unconditional correlations are significantly higher in the subprime crisis subperiod than the full period, while the findings on the global crisis subperiod are in general insignificant. In other words, I document contagion as it travelled from the US structured finance market to the European financial equity markets during the subprime crisis subperiod, which is consistent with the findings from my VAR analysis.

Lastly, the findings of the international government bond markets show that the unconditional correlations of the subprime crisis subperiods of all G5 countries (except Japan) are in general more negative than those of the full sample across ABX indices. The contagion test statistics for all G5 government bond markets are insignificant, which is consistent with no significant increases in correlations. The results are consistent with my expectation and with my previous VAR results in which evidence of 'flight-to-safety' has been documented. Alternatively, the one-sided tests can be interpreted in an opposite way in that the correlations between the ABX index returns and the G5 international government bond index returns (except for Japan) are significantly lower than those in the full sample period.

4.10 Conclusions

Following the approach of Longstaff (2010), this chapter offers a comprehensive empirical investigation of contagion travelling from the US subprime structured finance market to the G5 international markets during the recent 2007 to 2009 financial crisis. One major contribution is that I document strong evidence of substantial increases in cross-market linkages between the US structured finance market and a number of international equity and government bond markets during the subprime and global crisis, over both weekly and daily frequencies, which is consistent with the existence of contagion.

First, in my weekly VAR models, significant predictive power (Granger-causality) in the lagged ABX index returns over the US and G5 equity and government bond market returns is documented during the subprime crisis subperiod. The declines in the ABX prices during the subprime crisis translated into subsequent declines in the US and the G5 international equity market returns. Second, in the liquidity and credit risk VAR models, I find that the lagged ABX index returns predict (Granger-caused) the changes in trading intensity of domestic financial stocks, IRSS, and conditional correlations between the weekly returns of domestic equity and government bond markets. The results show that the shocks from the ABX indices translated into higher levels of trading activities in the US, UK and French financial stocks, which is consistent with possible 'flight-to-safety' and portfolio rebalancing. In addition, the significant predictive power in the lagged ABX index returns over the changes in the IRSS lends support to the risk premia transmission channel. As for the conditional correlations, the declines in the ABX indices translated into higher comovements between the domestic equity and government markets in all G5 countries, except for Germany. Nonetheless, the conditional correlations remained largely negative throughout the subprime and global crisis subperiods, which is consistent with the 'flight-to-safety' phenomenon.

Longstaff (2010) identifies significant contagion travelling from the US structured finance market to various US domestic financial markets over a weekly frequency and interpret the findings as inconsistent with the information transmission channel. In contrast to his conclusion, my empirical findings, which are based on daily data, present strong evidence of significant increases in cross-market linkages between the US structured finance market and international markets during the subprime crisis, which is consistent with the existence of short-lived contagion (as defined by Kaminsky et al., 2003). The evidence suggests that shocks from the structured finance market might have propagated to the international markets within trading days and via the arrival of economic information that occurred in a 'fast and furious' manner.

My daily VAR analysis with exogenous US market variables shows that the G5 international financial markets are, in general, considerably integrated with the major US markets, particularly with the US equity and government bond markets throughout the entire sample period. One major implication is that the US markets represented important sources of market information and consistently conveyed important economic information to the G5 international equity and government markets. I find evidence of contagion travelling from the S&P 500 composite index to the international markets, as evinced by the increases in factor loadings (cross-market linkages) during the subprime and global crisis subperiods. Overall, my empirical findings are robust in that the significant predictive power of the ABX index returns over the international market returns persists, even after accounting for possible simultaneous spillover effects from other major US markets into international markets.

As mentioned in a number of studies, ABCPs were extensively issued to finance the issuance of structured finance products in off-balance sheet SIVs. The ABCP yield spreads are widely-acknowledged as one of the major contagion variables during the recent subprime and global financial crises, which reflects the stress levels in the US money market and the degree of funding illiquidity (see Frank et al., 2008; Brunnermeier, 2009; Boyson et al., 2010; and Longstaff, 2010). Longstaff (2010) finds that the declines in the ABX indices translated into wider ABCP yield spreads, lending support to contagion transmission via funding illiquidity. My daily VAR analysis shows that the daily (two-day rolling-averages) changes in ABCP yield spreads predict (Granger-caused) the international equity market returns during the subprime and global crisis subperiods.

In particular, the widening of the US ABCP yield spreads translated into subsequent declines in the international equity markets, which is consistent with the existence of short-lived contagion and in support of the funding liquidity transmission channel.

In the last part of my empirical investigation, I follow Forbes and Rigobon (2002) and apply correlation coefficient analysis with heteroscedasticity correction between pairs of international markets and the US structured finance market index returns. My findings on the international broad equity and financial equity indices are similar in that I document significant increases in unconditional correlation coefficients during the subprime crisis subperiod compared to the full sample period. As for the government bond markets, my findings suggest that there were significant decreases in correlation coefficients between the international government bond market and the US structured finance market during the subprime crisis, which is consistent with a possible 'flight-to-safety' phenomenon.

Overall, this chapter has presented an empirical investigation of contagion within an international market context. It facilitates systematic comparison of contagion experienced by various types of asset markets in the G5 developed countries and provides implications for my understanding of the contagion transmission channels and the 'flight-to-safety' phenomenon during the subprime and the subsequent global crisis. This study also documents the important role of the US structured finance market in contagion and shows that the ABX indices were an important class of risk barometers and a major source of market information during the recent crisis.

Table 4.1: Summary statistics - the ABX indices (weekly)

This table contains a descriptive summary of the weekly returns (based on Wednesday quotes) of the five ABX indices. The summary statistics are organised and presented according to the crisis subperiods: Year 2006 (49 observations, from 25th January 2006 to 27 December 2006) refers to the tranquil pre-crisis subperiod; Year 2007 (51 observations, from 3rd January 2007 to 26th December 2007) refers to the subprime crisis subperiod; Year 2008-9 (65 observations) refers to the global crisis subperiod that covers the period from 2nd January 2008 to 25th March 2009; and Year 2009-2011 is the post-crisis subperiod that spans 2nd September 2009 to 28th December 2011 (122 observations). The table also reports the unconditional correlations between the ABX indices. The p-values of the Augmented Dickey Fuller (ADF) tests and the Phillips-Perron (PP) tests of non-stationarity are reported.

Panel A: Full sample

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	-0.048	0.000	11.520	-16.173	2.248	0.000	0.000	AAA	1.000	-	-	-	-
AA	-0.339	0.000	30.176	-30.581	5.043	0.000	0.000	AA	0.824	1.000	-	-	-
A	-0.668	-0.010	21.686	-22.199	5.436	0.000	0.000	A	0.435	0.561	1.000	-	-
- BBB	-0.886	0.000	19.365	-39.969	5.216	0.000	0.000	BBB	0.358	0.402	0.710	1.000	-
BBB-	-0.863	0.000	15.069	-31.649	4.685	0.000	0.000	BBB-	0.361	0.404	0.625	0.897	1.000

Panel B: Pre-crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	0.002	0.000	0.090	-0.030	0.021	0.000	0.000	AAA	1.000	-	-	-	-
AA	0.012	0.010	0.130	-0.110	0.043	0.000	0.000	AA	0.297	1.000	-	-	-
A	0.005	0.010	0.150	-0.229	0.073	0.000	0.000	A	0.410	0.657	1.000	-	-
BBB	0.009	0.040	0.457	-0.408	0.196	0.000	0.000	BBB	0.419	0.521	0.707	1.000	-
BBB-	0.011	0.055	0.594	-0.681	0.310	0.000	0.000	BBB-	0.353	0.575	0.697	0.841	1.000

Panel C: Subprime crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	-0.135	0.000	3.779	-5.275	1.091	0.000	0.000	AAA	1.000	-	-	-	-
AA	-0.321	-0.020	6.889	-10.233	2.384	0.000	0.000	AA	0.869	1.000	-	-	-
A	-0.932	-0.186	21.686	-22.199	6.140	0.000	0.000	A	0.572	0.804	1.000	-	-
BBB	-2.056	-1.092	19.365	-39.969	8.285	0.000	0.000	BBB	0.716	0.779	0.881	1.000	-
BBB-	-2.334	-1.465	15.069	-31.649	7.038	0.000	0.000	BBB-	0.682	0.689	0.739	0.928	1.000

Panel D: Global crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	-0.540	-0.099	11.520	-16.173	3.964	0.000	0.000	AAA	1.000	-	-	-	-
AA	-2.354	-0.725	10.949	-30.581	7.447	0.000	0.000	AA	0.867	1.000	-	-	-
A	-3.052	-2.473	19.166	-21.273	8.597	0.000	0.000	A	0.530	0.732	1.000	-	-
BBB	-3.228	-1.304	8.319	-25.726	7.521	0.000	0.000	BBB	0.455	0.572	0.739	1.000	-
BBB-	-3.009	-1.808	5.422	-26.890	6.896	0.000	0.000	BBB-	0.446	0.556	0.657	0.899	1.000

Panel E: Post-crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	0.133	0.106	6.270	-3.299	1.363	0.000	0.000	AAA	1.000	-	-	-	-
AA	0.342	0.309	19.168	-10.087	4.156	0.000	0.000	AA	0.810	1.000	-	-	-
A	0.381	0.000	17.258	-12.485	3.891	0.000	0.000	A	0.270	0.322	1.000	-	-
BBB	0.393	0.283	7.911	-4.934	2.081	0.000	0.000	BBB	-0.084	-0.035	0.266	1.000	-
BBB-	0.339	0.143	8.205	-4.414	1.914	0.000	0.000	BBB-	-0.007	0.073	0.234	0.567	1.000

Table 4.2: Data description and transformation

This table contains a summary of data description, full title of the time series used, country, data type and data transformation applied (whether the data are first-difference or log first-difference) (Source: Datastream).

Variables	**Country**	**Full Name of the Series**	**Data Transformation**	**Source**
ABX.HE.06-1 indices	US	ABX AAA, AA, A, BBB and BBB- indices	Log first difference	Reuters
Conditional correlations	US	MGARCH estimation	First difference	-
Conditional correlations	UK	MGARCH estimation	First difference	-
Conditional correlations	France	MGARCH estimation	First difference	-
Conditional correlations	Germany	MGARCH estimation	First difference	-
Conditional correlations	Japan	MGARCH estimation	First difference	-
S&P 500	US	S&P 500 composite - price index	Log first difference	Datastream
FTSE 100	UK	FTSE 100 - price index	Log first difference	Datastream
CAC 40	France	FRANCE CAC 40 - price index	Log first difference	Datastream
DAX 30	Germany	DAX 30 performance - price index	Log first difference	Datastream
Nikkei 225	Japan	NIKKEI 225 stock average - price index	Log first difference	Datastream
US DS DS financial index	US	US-DS financials - price index	Log first difference	Datastream
UK DS DS financial index	UK	UK-DS financials - price index	Log first difference	Datastream
France DS financial index	France	France-DS financials - price index	Log first difference	Datastream
Germany DS financial index	Germany	Germany-DS financial Svs(3) -price index	Log first difference	Datastream
Japan DS financial index	Japan	Japan-DS financials - price index	Log first difference	Datastream
Government bond index returns	US	FTSE Global Government US 10+ Y clean price index	Log first difference	Datastream
Government bond index returns	UK	FTSE Global Government UK 10+ Y clean price index	Log first difference	Datastream
Government bond index returns	France	FTSE Global Government France 10+ Y clean price index	Log first difference	Datastream
Government bond index returns	Germany	FTSE Global Government Germany 10+ Y clean price index	Log first difference	Datastream
Government bond index returns	Japan	FTSE Global Government Japan 10+ Y clean price index	Log first difference	Datastream
Interest rate swap spreads	US	US interest rate swap 10Y Mid. Rate minus US 10Y Treasury bond yields	First difference	Datastream
Interest rate swap spreads	UK	UK interest rate swap 10Y Mid. Rate minus UK 10Y Gov. bond yields	First difference	Datastream
Interest rate swap spreads	France	France interest rate swap 10Y Mid. Rate minus France 10Y Gov. bond yields	First difference	Datastream
Interest rate swap spreads	Germany	Germany interest rate swap 10Y Middle Rate minus Germany 10Y Treasury bond yields	First difference	Datastream
Interest rate swap spreads	Japan	Japan interest rate swap 10Y Middle Rate minus Japan 10Y Treasury bond yields	First difference	Datastream
Moody BAA corporate bond yield spreads	US	US CORP bonds Moodys' seasoned BAA (D) - middle rate minus US T-bills one-month	First difference	Datastream
PCA factor loadings	US	PCA using International equity market returns as inputs	Level	-
PCA factor loadings	UK	PCA using International equity market returns as inputs	Level	-
PCA factor loadings	France	PCA using International equity market returns as inputs	Level	-
PCA factor loadings	Germany	PCA using International equity market returns as inputs	Level	-
PCA factor loadings	Japan	PCA using International equity market returns as inputs	Level	-

Table 4.3: Summary statistics - endogenous variables

This table reports the summary statistics of the endogenous variables used in the weekly VAR models. Panels A to C report the full sample and subsample means and standard deviations of the weekly returns of the equity market composite, financial equity and government bond indices respectively.

Variables	**Full sample**		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Panel A: Equity market composite indices										
S&P 500	-0.007	2.819	0.225	1.206	0.093	2.060	-0.938	4.093	0.298	2.676
FTSE 100	-0.009	2.780	0.199	1.673	0.071	2.289	-0.781	3.939	0.240	2.569
CAC 40	-0.142	3.300	0.305	2.006	0.026	2.218	-1.020	4.283	0.041	3.428
DAX 30	0.022	3.438	0.414	2.203	0.368	2.187	-0.983	4.699	0.217	3.424
NIKKEI 225	-0.193	3.438	0.236	2.441	-0.184	2.529	-0.943	5.161	-0.005	2.997
Panel B: Financial equity indices										
US	-0.222	4.475	0.310	1.356	-0.327	3.323	-1.500	7.210	0.213	3.797
UK	-0.248	4.316	0.302	1.820	-0.350	3.158	-1.534	6.761	0.182	3.751
France	-0.302	4.990	0.457	2.543	-0.362	3.402	-1.415	7.183	-0.037	4.856
Germany	-0.194	3.739	0.419	2.201	-0.055	2.456	-1.225	5.584	0.011	3.437
Japan	-0.442	4.473	-0.077	3.035	-0.474	3.977	-1.064	7.219	-0.273	3.306
Panel C: Government bond indices										
US	0.074	1.378	-0.073	0.873	0.030	0.964	0.167	1.672	0.098	1.502
UK	0.040	1.400	-0.182	0.915	-0.036	0.958	0.065	2.111	0.132	1.266
France	-0.004	1.325	-0.156	0.966	-0.145	0.902	0.081	1.706	0.060	1.366
Germany	0.040	1.529	-0.159	1.098	-0.159	1.000	0.095	2.034	0.155	1.548
Japan	0.034	0.729	-0.021	0.684	0.042	0.714	0.076	0.886	0.030	0.676

Table 4.4: Principal component analysis (PCA) of the equity market composite index returns

This table contains a summary of the PCA for the G5 countries. For each subject country, the remaining four countries' equity market composite index returns are used as inputs for the PCA to obtain the first principal component and its corresponding factor scores. The eigenvalues of the first component, the percentage of variances explained, and the commonalities are reported here.

Subject Country	Eigenvalues	% of Var. explained	Communalities				
			US	UK	France	Germany	Japan
US	3.392	84.81%	-	0.889	0.944	0.909	0.650
UK	3.303	82.56%	0.819	-	0.930	0.898	0.655
France	3.255	83.38%	0.841	0.895	-	0.868	0.651
Germany	3.312	82.80%	0.848	0.905	0.911	-	0.648
Japan	3.625	90.64%	0.847	0.920	0.951	0.907	-

Table 4.5: Empirical results - US ABX VAR models (weekly)

This table reports the results of my weekly VAR models for the US domestic markets. There are in total five ABX indices included in my VAR estimation, corresponding to credit ratings of AAA, AA, A, BBB and BBB- in the underlying RMBS deals, respectively. Five VAR models are estimated for each subperiod and a total of 20 VAR models are estimated for each country for all four subperiods. In each VAR function, the dependent variable is written as a function of its own lags and the exogenous lagged ABX index returns and can be written as $\mathbf{y}_t = \alpha_0 + \sum_{s=1}^{4} \boldsymbol{\beta}_s \mathbf{y}_{t-s} + \sum_{s=1}^{4} \boldsymbol{\phi}_s ABX_{t-s} + \boldsymbol{\epsilon}_t$. I report the (net) sum of the ABX factor loadings and the R^2 of each VAR function in the VAR systems. The 1%, 5% and 10% significance levels of the F-tests of joint significance of the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i)} = \phi_{j,2}^{(i)} = \phi_{j,3}^{(i)} = \phi_{j,4}^{(i)} = 0$, are reported and denoted by superscripts ***, **, and * respectively. The endogenous variables include the weekly returns of the broad equity (S&P 500), financial equity (Fin), the government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		Pre-crisis		Subprime		Global		Post-crisis	
US	ABX	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2
S&P 500	AAA	11.23	0.45	2.23	0.41	-0.91^{**}	0.35	-0.03	0.16
	AA	-19.38	0.43	1.08	0.41	-0.41	0.32	-0.14	0.20
	A	-20.63	0.55	0.42^{***}	0.52	-0.14	0.30	-0.09	0.18
	BBB	-1.11	0.47	0.25^{***}	0.49	-0.07	0.30	-0.39^{**}	0.20
	BBB-	-0.97	0.41	0.32^{***}	0.47	-0.09	0.28	-0.39^{*}	0.21
Fin	AAA	28.82	0.44	2.26	0.50	-1.47	0.39	-0.22	0.22
	AA	-14.76	0.42	1.26^{***}	0.56	-0.59	0.36	-0.29	0.25
	A	-21.80^{*}	0.56	0.55^{***}	0.63	-0.15	0.34	-0.15	0.23
	BBB	-3.11	0.50	0.34^{***}	0.62	0.01^{*}	0.36	-0.67^{*}	0.25
	BBB-	-2.09	0.45	0.43^{***}	0.60	0.02	0.34	-0.67^{**}	0.25
Gov	AAA	-29.66	0.24	-0.95^{*}	0.35	-0.23^{*}	0.47	-0.01^{**}	0.12
	AA	-26.71^{***}	0.37	-0.46^{**}	0.39	-0.16	0.48	0.01	0.12
	A	1.91	0.21	-0.19^{***}	0.49	-0.07	0.46	-0.01	0.11
	BBB	0.63	0.17	-0.14^{***}	0.51	-0.09	0.47	0.13	0.14
	BBB-	-0.09	0.19	-0.17^{***}	0.53	-0.10	0.47	0.17	0.12
PCA	AAA	6.05^{*}	0.47	0.27	0.40	-0.13	0.36	0.03	0.11
	AA	-6.94	0.35	0.23^{*}	0.43	-0.10	0.38	-0.05	0.13
	A	-11.04^{*}	0.52	0.10^{**}	0.49	-0.02	0.43	-0.04	0.12
	BBB	-1.00	0.40	0.05^{***}	0.52	0.04	0.39	-0.07	0.14
	BBB-	-0.63	0.31	0.06	0.47	0.04	0.37	-0.12^{**}	0.16

Table 4.6: Empirical results - UK ABX VAR models (weekly)

This table reports the results of my weekly VAR models for the UK financial markets. There are in total five ABX indices included in my VAR model estimation, corresponding to credit ratings of AAA, AA, A, BBB and BBB- in the underlying RMBS deals, respectively. Five VAR models are estimated for each subperiod and a total of 20 VAR models are estimated for each country for all four subperiods. In each VAR function, the dependent variable is written as a function of its own lags and the exogenous lagged ABX index returns and can be written as $\mathbf{y}_t = \alpha_0 + \sum_{s=1}^{4} \boldsymbol{\beta}_s \mathbf{y}_{t-s} + \sum_{s=1}^{4} \boldsymbol{\phi}_s ABX_{t-s} + \boldsymbol{\epsilon}_t$. I report the (net) sum of the ABX factor loadings and the R^2 of each VAR function in the VAR systems. The 1%, 5% and 10% significance levels of the F-tests of joint significance of the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i)} = \phi_{j,2}^{(i)} = \phi_{j,3}^{(i)} = \phi_{j,4}^{(i)} = 0$, are reported and denoted by superscripts ***, **, and *, respectively. The endogenous variables include the weekly returns of the UK equity market composite (FTSE 100), financial equity (Fin), and government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		Pre-crisis		Subprime		Global		Post-crisis	
UK	ABX	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2
FTSE 100	AAA	9.64	0.44	1.71**	0.56	−0.22	0.37	−0.02	0.14
	AA	−0.45	0.36	0.78***	0.58	−0.18	0.40	−0.18	0.17
	A	−23.39	0.48	0.31***	0.64	−0.08	0.44	−0.11	0.14
	BBB	−4.63	0.45	0.14***	0.62	−0.02	0.38	−0.23	0.16
	BBB-	−1.63	0.38	0.15***	0.61	−0.06	0.39	−0.19	0.17
Fin	AAA	18.76	0.44	1.40*	0.57	−0.37*	0.48	−0.07	0.19
	AA	−12.89	0.34	0.75**	0.57	−0.32***	0.50	−0.27	0.23
	A	−33.62**	0.55	0.32***	0.63	−0.21***	0.54	−0.17	0.20
	BBB	−6.98*	0.47	0.14**	0.61	−0.06	0.49	−0.32	0.21
	BBB-	−3.18	0.41	0.17	0.59	−0.11	0.48	−0.36	0.22
Gov	AAA	−33.04	0.28	−0.54*	0.54	−0.26***	0.48	−0.06*	0.19
	AA	−18.43	0.27	−0.29	0.52	−0.20***	0.57	−0.03	0.18
	A	−0.17	0.21	−0.12*	0.53	−0.10	0.44	−0.02	0.17
	BBB	0.12	0.25	−0.08*	0.52	−0.07	0.44	0.02	0.19
	BBB-	−1.01	0.24	−0.09	0.52	−0.07	0.43	0.05***	0.20
PCA	AAA	4.92*	0.52	0.45**	0.54	−0.15	0.36	−0.03	0.18
	AA	1.01	0.41	0.24**	0.52	−0.08	0.39	−0.07*	0.21
	A	−7.91	0.51	0.10***	0.58	−0.04	0.43	−0.06	0.18
	BBB	−1.48	0.52	0.06***	0.55	−0.02	0.37	−0.05	0.18
	BBB-	−0.49	0.43	0.08**	0.54	−0.02	0.35	−0.07	0.21

Table 4.7: Empirical results - France ABX VAR models (weekly)

This table reports the results of my weekly VAR models for the French financial markets. There are in total five ABX indices included in my VAR model estimation, corresponding to credit ratings of AAA, AA, A, BBB and BBB- in the underlying RMBS deals respectively. Five VAR models are estimated for each subperiod and a total of 20 VAR models are estimated for each country for all four subperiods. In each VAR function, the dependent variable is written as a function of its own lags and the exogenous lagged ABX index returns and can be written as $\boldsymbol{y}_t = \alpha_0 + \sum_{s=1}^{4} \boldsymbol{\beta}_s \boldsymbol{y}_{t-s} + \sum_{s=1}^{4} \boldsymbol{\phi}_s ABX_{t-s} + \boldsymbol{\epsilon}_t$. I report the (net) sum of the ABX factor loadings and the R^2 of each VAR function in the VAR systems. The 1%, 5% and 10% significance levels of the F-tests of joint significance of the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i)} = \phi_{j,2}^{(i)} = \phi_{j,3}^{(i)} = \phi_{j,4}^{(i)} = 0$, are reported and denoted by superscripts ***, **, and * respectively. The endogenous variables include the weekly returns of the French equity market composite (CAC 40), financial equity (Fin), and government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
France	ABX	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2
CAC 40	AAA	40.47*	0.51	3.06***	0.48	−1.05	0.43	0.26**	0.22
	AA	17.61	0.41	1.08***	0.46	−0.35	0.41	−0.10	0.22
	A	−24.54	0.52	0.49***	0.53	−0.10	0.42	−0.11	0.20
	BBB	0.42	0.40	0.25***	0.50	0.03	0.36	−0.04	0.20
	BBB-	1.36	0.36	0.21**	0.43	0.14	0.36	−0.24	0.21
Fin	AAA	53.40*	0.38	2.95**	0.52	−1.68**	0.51	0.32**	0.22
	AA	25.97	0.30	1.31***	0.53	−0.42	0.45	−0.10*	0.22
	A	−34.01*	0.44	0.63***	0.61	−0.16	0.44	−0.12	0.20
	BBB	−0.22	0.28	0.31***	0.60	0.06	0.40	0.01	0.20
	BBB-	1.58	0.27	0.26*	0.53	0.24	0.40	−0.22	0.20
Gov	AAA	−66.99	0.33	−0.94*	0.41	−0.25**	0.35	−0.07	0.07
	AA	−27.32***	0.33	−0.29**	0.40	−0.16***	0.42	0.00	0.09
	A	−2.47	0.18	−0.14***	0.49	−0.07	0.28	0.05	0.09
	BBB	−0.16	0.18	−0.13***	0.53	−0.09	0.34	0.13	0.09
	BBB-	−0.37	0.18	−0.15***	0.53	−0.12	0.37	0.15	0.08
PCA	AAA	12.12*	0.47	1.03***	0.47	−0.37	0.43	0.07	0.18
	AA	4.57	0.36	0.39***	0.49	−0.14*	0.42	−0.03	0.18
	A	−6.77	0.48	0.18***	0.60	−0.05	0.39	−0.03	0.17
	BBB	0.04	0.41	0.09***	0.55	−0.01	0.34	−0.05	0.17
	BBB-	0.46	0.37	0.08***	0.47	0.00	0.34	−0.10	0.18

Table 4.8: Empirical results - Germany ABX VAR models (weekly)

This table reports the results of my weekly VAR models for the German financial markets. There are in total five ABX indices included in my VAR model estimation, corresponding to credit ratings of AAA, AA, A, BBB and BBB- in the underlying RMBS deals, respectively. Five VAR models are estimated for each subperiod and a total of 20 VAR models are estimated for each country for all four subperiods. In each VAR function, the dependent variable is written as a function of its own lags and the exogenous lagged ABX index returns and can be written as $\boldsymbol{y}_t=\alpha_0+\sum_{s=1}^{4}\boldsymbol{\beta}_s\boldsymbol{y}_{t-s}+\sum_{s=1}^{4}\boldsymbol{\phi}_s ABX_{t-s}+\boldsymbol{\epsilon}_t$. I report the (net) sum of the ABX factor loadings and the R^2 of each VAR function in the VAR systems. The 1%, 5% and 10% significance levels of the F-tests of joint significance of the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i)} = \phi_{j,2}^{(i)} = \phi_{j,3}^{(i)} = \phi_{j,4}^{(i)} = 0$, are reported and denoted by superscripts ***, **, and *, respectively. The endogenous variables include the weekly returns of the German equity market composite (DAX 30), financial equity (Fin), and government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
Germany	ABX	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2
DAX 30	AAA	16.31	0.57	0.54**	0.58	−0.63	0.35	0.08	0.17
	AA	−9.07	0.56	0.66***	0.59	−0.46**	0.40	−0.14	0.18
	A	−23.03*	0.64	0.21***	0.59	−0.16*	0.43	−0.14	0.16
	BBB	−3.01	0.61	0.09***	0.60	−0.04	0.33	0.00	0.17
	BBB-	−1.66	0.54	0.10**	0.55	−0.01	0.32	−0.17	0.18
Fin	AAA	53.88*	0.57	0.17*	0.56	−1.42***	0.54	0.01	0.15
	AA	−6.59	0.49	0.69***	0.60	−0.80***	0.59	−0.15	0.17
	A	−32.43**	0.64	0.20**	0.60	−0.32***	0.53	−0.14	0.16
	BBB	−3.57	0.56	0.08***	0.60	−0.18	0.44	0.03	0.16
	BBB-	−2.62	0.51	0.08	0.56	−0.18	0.43	−0.13	0.17
Gov	AAA	−43.37	0.48	−0.23	0.26	−0.22	0.39	−0.13	0.14
	AA	−11.45	0.45	−0.21	0.29	−0.07**	0.43	−0.03	0.15
	A	−0.99	0.35	−0.07	0.35	−0.03	0.33	0.01	0.17
	BBB	0.42	0.39	−0.08**	0.40	−0.07	0.39	0.04	0.15
	BBB-	−0.33	0.37	−0.12***	0.43	−0.09	0.42	0.09	0.17
PCA	AAA	13.66**	0.47	0.52**	0.54	−0.26	0.32	0.05	0.13
	AA	2.76	0.39	0.38***	0.60	−0.16**	0.37	−0.04	0.14
	A	−6.75	0.50	0.13***	0.63	−0.06**	0.37	−0.04	0.14
	BBB	−0.85	0.45	0.07***	0.59	−0.03	0.26	−0.04	0.14
	BBB-	−0.32	0.38	0.06***	0.54	−0.03	0.26	−0.07	0.15

Table 4.9: Empirical results - Japan ABX VAR models (weekly)

This table reports the results of my weekly VAR models for the Japanese financial markets. There are in total five ABX indices included in my VAR model estimation, corresponding to credit ratings of AAA, AA, A, BBB and BBB- in the underlying RMBS deals, respectively. Five VAR models are estimated for each subperiod and a total of 20 VAR models are estimated for each country for all four subperiods. In each VAR function, the dependent variable is written as a function of its own lags and the exogenous lagged ABX index returns and can be written as $\mathbf{y}_t=\alpha_0+\sum_{s=1}^{4}\boldsymbol{\beta}_s\mathbf{y}_{t-s}+\sum_{s=1}^{4}\boldsymbol{\phi}_s ABX_{t-s}+\boldsymbol{\epsilon}_t$. I report the (net) sum of the ABX factor loadings and the R^2 of each VAR function in the VAR systems. The 1%, 5% and 10% significance levels of the F-tests of joint significance of the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i)} = \phi_{j,2}^{(i)} = \phi_{j,3}^{(i)} = \phi_{j,4}^{(i)} = 0$, are reported and denoted by superscripts ***, **, and *, respectively. The endogenous variables include the weekly returns of the Japanese equity market composite (Nikkei 225), financial equity (Fin), and government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
Japan	ABX	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2
Nikkei 225	AAA	33.79	0.27	1.71**	0.50	−0.40	0.27	0.19	0.17
	AA	38.30	0.35	1.18***	0.54	−0.14	0.28	−0.04	0.16
	A	−26.44	0.32	0.56***	0.69	−0.10	0.26	−0.19	0.20
	BBB	−2.33	0.34	0.34***	0.63	0.15	0.28	0.06	0.17
	BBB-	0.21	0.25	0.33***	0.60	0.12	0.28	−0.14	0.18
Fin	AAA	71.41	0.33	−0.54	0.51	0.26	0.35	0.33	0.18
	AA	67.67***	0.43	0.62**	0.53	0.18	0.37	0.00	0.18
	A	−24.04	0.33	0.41***	0.60	−0.01	0.34	−0.08	0.20
	BBB	1.77	0.36	0.23***	0.63	0.32**	0.39	0.28	0.17
	BBB-	1.92	0.30	0.28***	0.59	0.30**	0.38	0.17	0.18
Gov	AAA	−23.38**	0.41	−0.16	0.28	−0.01**	0.34	−0.10	0.16
	AA	−11.69	0.31	−0.09	0.27	−0.07**	0.38	−0.02	0.18
	A	5.89	0.23	−0.04***	0.40	−0.03***	0.37	0.01	0.16
	BBB	0.71	0.26	−0.05*	0.34	−0.01	0.31	0.11	0.19
	BBB-	0.10	0.23	−0.08***	0.39	−0.03	0.33	0.12*	0.18
PCA	AAA	−1.54	0.51	0.33	0.40	−0.16	0.36	0.02	0.16
	AA	−1.94	0.47	0.26**	0.44	−0.06	0.36	−0.04	0.18
	A	−9.33**	0.71	0.11***	0.56	−0.02	0.36	−0.03	0.17
	BBB	−0.83	0.53	0.07***	0.52	0.03**	0.39	−0.02	0.17
	BBB-	−0.31	0.47	0.07***	0.49	0.03	0.38	−0.03	0.19

Table 4.10: Summary statistics - trading ratios

This table contains the summary statistics of the trading ratios (level) of the G5 countries. The ratios are computed by dividing the aggregate weekly trading volume in market value of the financial equity sector (using the Datastream-calculated financial price indices) by the aggregate weekly trading volume in market value for the broader equity market for each country. It measures the intensity of trading activities in financial stocks relative to the overall market. Panels A to E report the full sample, pre-crisis, subprime crisis, global crisis and post-crisis subsample statistics, respectively. The means, medians, maximums, minimums, standard deviations and the correlation matrices are reported. In addition, the p-values of the Augmented Dickey Fuller (ADF) tests and the Phillips-Perron (PP) tests of non-stationarity are reported for the full sample and crisis subsamples.

Panel A: Full sample

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.233	0.242	0.482	0.087	0.089	0.110	0.010	US	1.000	-	-	-	-
UK	0.322	0.336	0.529	0.153	0.093	0.189	0.021	UK	0.765	1.000	-	-	-
France	0.206	0.207	0.368	0.097	0.049	0.000	0.000	France	0.563	0.630	1.000	-	-
Germany	0.225	0.177	0.760	0.051	0.140	0.916	0.111	Germany	0.252	0.481	0.476	1.000	-
Japan	0.204	0.192	0.436	0.104	0.062	0.001	0.000	Japan	0.673	0.631	0.315	0.072	1.000

Panel B: Pre-crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.103	0.104	0.116	0.087	0.007	0.000	0.000	US	1.000	-	-	-	-
UK	0.186	0.183	0.223	0.153	0.018	0.000	0.000	UK	0.089	1.000	-	-	-
France	0.150	0.149	0.214	0.097	0.030	0.002	0.002	France	0.190	-0.045	1.000	-	-
Germany	0.130	0.128	0.162	0.090	0.017	0.000	0.000	Germany	0.068	-0.013	0.406	1.000	-
Japan	0.156	0.156	0.212	0.115	0.021	0.005	0.004	Japan	0.103	-0.156	0.255	0.075	1.000

Panel C: Subprime crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.157	0.147	0.252	0.099	0.041	0.685	0.754	US	1.000	-	-	-	-
UK	0.245	0.235	0.342	0.172	0.044	0.651	0.320	UK	0.809	1.000	-	-	-
France	0.172	0.169	0.261	0.104	0.037	0.043	0.060	France	0.817	0.774	1.000	-	-
Germany	0.149	0.138	0.258	0.100	0.035	0.002	0.002	Germany	0.721	0.672	0.708	1.000	-
Japan	0.147	0.142	0.191	0.104	0.025	0.015	0.017	Japan	0.560	0.602	0.394	0.456	1.000

Panel D: Global crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.271	0.259	0.430	0.187	0.060	0.143	0.179	US	1.000	-	-	-	-
UK	0.322	0.315	0.509	0.224	0.059	0.019	0.033	UK	0.636	1.000	-	-	-
France	0.237	0.236	0.368	0.156	0.045	0.021	0.024	France	0.389	0.417	1.000	-	-
Germany	0.264	0.240	0.524	0.120	0.093	0.006	0.009	Germany	0.341	0.295	-0.059	1.000	-
Japan	0.184	0.177	0.313	0.121	0.039	0.484	0.545	Japan	0.722	0.625	0.140	0.225	1.000

Panel E: Post-crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.287	0.274	0.482	0.178	0.057	0.020	0.000	US	1.000	-	-	-	-
UK	0.396	0.390	0.529	0.277	0.047	0.000	0.000	UK	-0.048	1.000	-	-	-
France	0.223	0.217	0.361	0.151	0.037	0.000	0.000	France	-0.251	0.248	1.000	-	-
Germany	0.268	0.194	0.760	0.051	0.174	0.978	0.237	Germany	-0.383	0.320	0.431	1.000	-
Japan	0.250	0.239	0.436	0.162	0.054	0.000	0.000	Japan	0.369	-0.128	-0.188	-0.423	1.000

Table 4.11: Summary statistics - interest rate swap spreads (IRSSs)

This table contains the summary statistics of the IRSSs (level) of the G5 countries. The IRSSs are computed by subtracting the corresponding 10-year government bond yields from the 10-year interest rate swap middle rates for each G5 country. The IRSSs reflect the level of credit risks and market illiquidity in the G5 financial markets. Panels A to E report the full sample, pre-crisis, subprime crisis, global crisis and post-crisis subsample statistics, respectively. The means, medians, maximums, minimums, standard deviations and the correlation matrices are reported. In addition, the p-values of the Augmented Dickey Fuller (ADF) tests and the Phillips-Perron (PP) tests of non-stationarity are reported for the full sample and the crisis subsamples.

Panel A: Full sample													
ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.337	0.268	0.815	-0.122	0.253	0.641	0.463	US	1.000	-	-	-	-
UK	0.275	0.346	0.685	-0.204	0.208	0.175	0.180	UK	0.863	1.000	-	-	-
France	0.074	0.120	0.480	-1.176	0.239	0.630	0.607	France	0.721	0.535	1.000	-	-
Germany	0.347	0.295	0.823	0.113	0.149	0.110	0.077	Germany	0.114	0.231	0.062	1.000	-
Japan	0.110	0.121	0.294	-0.140	0.090	0.267	0.170	Japan	0.729	0.510	0.662	-0.181	1.000

Panel B: Pre-crisis subperiod													
ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.527	0.531	0.628	0.432	0.042	0.131	0.130	US	1.000	-	-	-	-
UK	0.374	0.375	0.409	0.334	0.023	0.440	0.522	UK	-0.128	1.000	-	-	-
France	0.202	0.211	0.277	0.145	0.030	0.208	0.237	France	0.231	0.729	1.000	-	-
Germany	0.220	0.228	0.288	0.151	0.027	0.088	0.091	Germany	0.183	0.629	0.933	1.000	-
Japan	0.198	0.206	0.294	0.125	0.039	0.546	0.264	Japan	0.479	-0.457	-0.233	-0.090	1.000

Panel C: Subprime crisis subperiod													
ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.597	0.596	0.815	0.451	0.092	0.321	0.130	US	1.000	-	-	-	-
UK	0.459	0.441	0.612	0.366	0.073	0.412	0.395	UK	0.841	1.000	-	-	-
France	0.258	0.247	0.387	0.179	0.054	0.709	0.703	France	0.818	0.847	1.000	-	-
Germany	0.319	0.296	0.490	0.223	0.073	0.674	0.674	Germany	0.840	0.876	0.975	1.000	-
Japan	0.180	0.180	0.248	0.123	0.034	0.451	0.176	Japan	0.778	0.813	0.723	0.747	1.000

Panel D: Global crisis subperiod													
ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.513	0.621	0.800	-0.004	0.218	0.666	0.561	US	1.000	-	-	-	-
UK	0.409	0.480	0.685	-0.130	0.181	0.262	0.248	UK	0.796	1.000	-	-	-
France	0.254	0.321	0.480	-0.256	0.179	0.680	0.732	France	0.554	0.606	1.000	-	-
Germany	0.510	0.487	0.823	0.324	0.117	0.107	0.127	Germany	-0.234	0.015	0.515	1.000	-
Japan	0.117	0.174	0.260	-0.140	0.114	0.557	0.557	Japan	0.828	0.747	0.664	-0.107	1.000

Panel E: Post-crisis subperiod													
ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	0.099	0.092	0.384	-0.122	0.079	0.025	0.016	US	1.000	-	-	-	-
UK	0.114	0.093	0.485	-0.204	0.164	0.330	0.364	UK	0.727	1.000	-	-	-
France	-0.118	-0.069	0.095	-1.176	0.194	0.180	0.275	France	-0.197	-0.358	1.000	-	-
Germany	0.327	0.277	0.759	0.113	0.147	0.546	0.434	Germany	0.269	0.274	-0.397	1.000	-
Japan	0.052	0.060	0.196	-0.103	0.056	0.254	0.080	Japan	-0.234	-0.466	0.375	-0.293	1.000

Table 4.12: Summary statistics - conditional correlations between domestic equity and government bond indices' weekly returns

This table contains the summary statistics of the conditional correlations (level) estimated using a MGARCH(1,1) model with diagonal VECH specification between the weekly returns of the domestic equity and government bond indices of the G5 countries. Panels A to E report the full sample, pre-crisis, subprime crisis, global crisis and post-crisis subsample statistics, respectively. The means, medians, maximums, minimums, standard deviations and the correlation matrices are reported. In addition, the p-values of the Augmented Dickey Fuller (ADF) tests and the Phillips-Perron (PP) tests of non-stationarity are reported for the full sample and the crisis subsamples.

Panel A: Full sample

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	-0.338	-0.368	0.090	-0.652	0.147	0.003	0.003	US	1.000	-	-	-	-
UK	-0.345	-0.354	0.023	-0.588	0.122	0.022	0.029	UK	0.483	1.000	-	-	-
France	-0.346	-0.367	0.024	-0.526	0.100	0.000	0.000	France	0.329	0.575	1.000	-	-
Germany	-0.331	-0.352	0.012	-0.509	0.094	0.000	0.000	Germany	0.489	0.712	0.762	1.000	-
Japan	-0.312	-0.343	0.678	-0.885	0.207	0.000	0.000	Japan	0.244	0.358	0.182	0.277	1.000

Panel B: Pre-crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	-0.265	-0.296	0.090	-0.426	0.125	0.068	0.062	US	1.000	-	-	-	-
UK	-0.419	-0.420	-0.266	-0.565	0.079	0.220	0.304	UK	0.794	1.000	-	-	-
France	-0.353	-0.382	-0.037	-0.438	0.081	0.038	0.038	France	0.624	0.657	1.000	-	-
Germany	-0.330	-0.351	0.003	-0.474	0.100	0.102	0.112	Germany	0.598	0.749	0.934	1.000	-
Japan	-0.328	-0.372	0.264	-0.696	0.195	0.008	0.007	Japan	0.167	0.401	0.228	0.337	1.000

Panel C: Subprime crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	-0.359	-0.368	-0.199	-0.442	0.059	0.073	0.073	US	1.000	-	-	-	-
UK	-0.435	-0.428	-0.262	-0.588	0.074	0.589	0.511	UK	0.281	1.000	-	-	-
France	-0.393	-0.401	-0.234	-0.495	0.054	0.023	0.016	France	-0.081	0.294	1.000	-	-
Germany	-0.393	-0.408	-0.206	-0.478	0.058	0.100	0.100	Germany	-0.029	0.268	0.833	1.000	-
Japan	-0.372	-0.394	0.141	-0.885	0.220	0.029	0.030	Japan	0.412	0.379	-0.302	-0.168	1.000

Panel D: Global crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	-0.295	-0.397	0.043	-0.561	0.213	0.818	0.818	US	1.000	-	-	-	-
UK	-0.226	-0.244	0.023	-0.479	0.131	0.568	0.600	UK	0.857	1.000	-	-	-
France	-0.317	-0.318	-0.127	-0.487	0.097	0.025	0.028	France	0.574	0.678	1.000	-	-
Germany	-0.260	-0.246	-0.057	-0.440	0.095	0.038	0.044	Germany	0.686	0.805	0.877	1.000	-
Japan	-0.172	-0.183	0.678	-0.646	0.232	0.000	0.000	Japan	0.244	0.246	0.148	0.188	1.000

Panel E: Post-crisis subperiod

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		US	UK	France	Germany	Japan
US	-0.375	-0.381	0.008	-0.652	0.124	0.015	0.020	US	1.000	-	-	-	-
UK	-0.341	-0.343	-0.041	-0.503	0.096	0.005	0.005	UK	0.325	1.000	-	-	-
France	-0.340	-0.353	0.024	-0.526	0.114	0.008	0.004	France	0.180	0.568	1.000	-	-
Germany	-0.341	-0.355	0.012	-0.509	0.082	0.025	0.001	Germany	0.355	0.632	0.694	1.000	-
Japan	-0.349	-0.373	0.251	-0.620	0.165	0.000	0.000	Japan	0.155	0.137	0.216	0.158	1.000

Table 4.13: Liquidity and credit risks VAR model results - US

This table reports the sums of the ABX factor loadings of my weekly US liquidity and credit risks VAR models grouped by crisis subperiods. With the same VAR model framework of Equation 4.1, the same exogenous lagged ABX index returns and identical crisis subsamples, I include sets of liquidity and credit risks related endogenous variables in the analysis. The trading ratios are computed by dividing the weekly aggregate trading volume in market value of the Datastream calculated financial price index by the weekly aggregate trading volume in market value of the Datastream calculated market price index for each country. The IRSSs refer to the yield differentials between the interest rate swap middle rate and the corresponding 10-year government bond yield (or middle rate) quoted weekly. The conditional correlation refers to the estimated correlation coefficients between the weekly returns of the Datastream calculated equity market composite index and the FTSE global government bond clean price index for each country, using MGARCH(1,1) diagonal VECH models. The superscripts ***, ** and * denote the statistical significance of the F-tests of joint significance of the ABX factor loadings at the 1%, 5% and 10% levels, respectively.

y_t		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
US	ABX	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2
Trading ratios	AAA	0.284	0.53	−0.016***	0.51	−0.007***	0.40	−0.003	0.25
	AA	0.020	0.49	−0.008***	0.64	−0.002**	0.41	−0.001	0.25
	A	0.013	0.49	−0.005***	0.66	−0.002***	0.50	−0.000	0.24
	BBB	−0.007	0.49	−0.003***	0.62	−0.002***	0.38	−0.000	0.24
	BBB-	0.001	0.47	−0.003***	0.60	−0.002***	0.39	−0.000	0.26
IRSS	AAA	0.450	0.35	−0.022	0.46	0.007	0.38	−0.003	0.23
	AA	0.153	0.35	−0.011	0.48	0.000	0.37	−0.001	0.22
	A	−0.174	0.36	−0.005***	0.62	0.000	0.33	−0.001	0.23
	BBB	−0.081	0.42	−0.000**	0.56	0.002	0.32	−0.003	0.23
	BBB-	−0.047***	0.51	−0.000*	0.56	0.002	0.33	−0.003	0.22
Conditional correlation	AAA	2.892**	0.38	−0.006	0.34	−0.055	0.35	0.011	0.21
	AA	2.637	0.41	−0.005	0.36	−0.024*	0.34	0.006	0.23
	A	0.331	0.30	−0.003*	0.40	−0.002	0.20	0.010	0.28
	BBB	0.064**	0.35	−0.004	0.40	0.001	0.20	0.012	0.22
	BBB-	0.110**	0.39	−0.004	0.36	−0.002	0.21	0.017**	0.25

Table 4.14: Liquidity and credit risks VAR model results - UK

This table reports the sums of the ABX factor loadings of my weekly UK liquidity and credit risks VAR models grouped by crisis subperiods. With the same VAR model framework of Equation 4.1, the same exogenous lagged ABX index returns and identical crisis subsamples, I include sets of liquidity and credit risks related endogenous variables in the analysis. The trading ratios are computed by dividing the weekly aggregate trading volume in market value of the Datastream calculated financial price index by the weekly aggregate trading volume in market value of the Datastream calculated market price index for each country. The IRSSs refer to the yield differentials between the interest rate swap middle rate and the corresponding 10-year government bond yield (or middle rate) quoted weekly. The conditional correlation refers to the estimated correlation coefficients between the weekly returns of the Datastream calculated equity market composite index and the FTSE global government bond clean price index for each country, estimated using MGARCH(1,1) diagonal VECH models. The superscripts ***, ** and * denote the statistical significance of the F-tests of joint significance of the ABX factor loadings at the 1%, 5% and 10% levels, respectively.

y_t		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
UK	ABX	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2
Trading ratios	AAA	−0.396	0.47	0.005*	0.43	−0.003	0.34	0.000	0.30
	AA	0.001*	0.49	0.001**	0.42	−0.001	0.30	0.001	0.30
	A	−0.084*	0.46	−0.000***	0.46	−0.001	0.29	−0.000	0.31
	BBB	0.021	0.45	−0.000**	0.48	0.000	0.26	0.000	0.34
	BBB-	0.017	0.45	−0.001***	0.54	0.000	0.27	−0.002	0.31
IRSS	AAA	−0.173	0.42	−0.000***	0.47	−0.013	0.23	0.005	0.15
	AA	−0.065**	0.41	−0.004***	0.47	−0.007*	0.28	−0.000	0.13
	A	0.023**	0.40	−0.003***	0.37	−0.004*	0.23	−0.001	0.16
	BBB	−0.001	0.40	−0.000***	0.32	−0.004	0.19	−0.001	0.13
	BBB-	0.006	0.38	0.000	0.26	−0.005	0.18	0.001	0.13
Conditional correlation	AAA	1.308	0.22	−0.070***	0.59	−0.035	0.43	−0.008	0.20
	AA	2.199*	0.30	−0.021	0.56	−0.016***	0.41	−0.001	0.20
	A	0.617	0.21	−0.011**	0.59	0.000	0.24	0.002	0.20
	BBB	0.128	0.20	−0.009***	0.65	0.002	0.24	−0.009	0.21
	BBB-	0.081	0.21	−0.010***	0.65	0.000	0.25	−0.012	0.22

Table 4.15: Liquidity and credit risks VAR model results - France

This table reports the sums of the ABX factor loadings of my weekly French liquidity and credit risks VAR models grouped by crisis subperiods. With the same VAR model framework of Equation 4.1, the same exogenous lagged ABX index returns and identical crisis subsamples, I include sets of liquidity and credit risks related endogenous variables in the analysis. The trading ratios are computed by dividing the weekly aggregate trading volume in market value of the Datastream calculated financial price index by the weekly aggregate trading volume in market value of the Datastream calculated market price index for each country. The IRSSs refer to the yield differentials between the interest rate swap middle rate and the corresponding 10-year government bond yield (or middle rate) quoted weekly. The conditional correlation refers to the estimated correlation coefficients between the weekly returns of the Datastream calculated equity market composite index and the FTSE global government bond clean price index for each country, estimated using MGARCH(1,1) diagonal VECH models. The superscripts ***, ** and * denote the statistical significance of the F-tests of joint significance of the ABX factor loadings at the 1%, 5% and 10% levels, respectively.

y_t		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
France	ABX	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2	$\sum_{s=1}^{4} \phi_{j,s}$	R^2
Trading ratios	AAA	0.116	0.54	-0.007^{***}	0.44	-0.001	0.23	0.004	0.34
	AA	0.186	0.58	-0.007^{***}	0.47	-0.001	0.22	0.000	0.33
	A	-0.007^{**}	0.63	-0.006^{***}	0.46	-0.002	0.28	0.000	0.33
	BBB	-0.056	0.61	-0.003	0.38	-0.001	0.25	0.001	0.34
	BBB-	-0.034	0.60	-0.003	0.36	-0.002	0.25	0.000	0.32
IRSS	AAA	-0.393	0.27	-0.023^{***}	0.47	-0.005	0.39	0.014	0.28
	AA	0.039	0.20	-0.009^{***}	0.45	-0.003	0.36	0.006	0.31
	A	-0.009	0.25	-0.004^{***}	0.49	-0.002	0.25	0.007^{**}	0.28
	BBB	0.002	0.32	-0.002^{***}	0.43	-0.002	0.22	0.015	0.28
	BBB-	0.001	0.30	-0.002^{**}	0.41	-0.002	0.26	0.017	0.29
Conditional correlation	AAA	0.191	0.33	-0.012^{**}	0.56	-0.019	0.34	-0.005	0.42
	AA	0.878	0.37	-0.007	0.56	-0.009^{*}	0.37	0.000	0.41
	A	0.652	0.38	-0.002^{*}	0.56	-0.002	0.26	-0.000	0.42
	BBB	0.013	0.35	-0.000^{**}	0.56	0.000	0.24	-0.005	0.42
	BBB-	-0.012	0.32	-0.001	0.55	-0.001	0.25	-0.007	0.42

Table 4.16: Liquidity and credit risks VAR model results - Germany

This table reports the sums of the ABX factor loadings of my weekly German liquidity and credit risks VAR models grouped by crisis subperiods. With the same VAR model framework of Equation 4.1, the same exogenous lagged ABX index returns and identical crisis subsamples, I include sets of liquidity and credit risks related endogenous variables in the analysis. The trading ratios are computed by dividing the weekly aggregate trading volume in market value of the Datastream calculated financial price index by the weekly aggregate trading volume in market value of the Datastream calculated market price index for each country. The IRSSs refer to the yield differentials between the interest rate swap middle rate and the corresponding 10-year government bond yield (or middle rate) quoted weekly. The conditional correlation refers to the estimated correlation coefficients between the weekly returns of the Datastream calculated equity market composite index and the FTSE global government bond clean price index for each country, estimated using MGARCH(1,1) diagonal VECH models. The superscripts ***, ** and * denote the statistical significance of the F-tests of joint significance of the ABX factor loadings at the 1%, 5% and 10% levels, respectively.

y_t		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
Germany	ABX	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2
Trading ratios	AAA	−0.652*	0.61	0.022***	0.58	0.009	0.23	−0.010	0.28
	AA	0.055	0.57	0.006***	0.71	0.007*	0.35	−0.007***	0.33
	A	0.094***	0.65	0.001***	0.70	0.003	0.24	−0.008***	0.34
	BBB	−0.028***	0.60	0.000***	0.65	0.001	0.22	−0.008	0.28
	BBB-	−0.006**	0.57	0.000**	0.55	0.002*	0.24	−0.012	0.28
IRSS	AAA	0.209	0.31	−0.013***	0.34	−0.003	0.33	0.000	0.20
	AA	0.135	0.36	−0.011***	0.27	−0.002	0.30	0.000	0.20
	A	−0.032	0.32	−0.005***	0.41	−0.003*	0.31	−0.001	0.20
	BBB	0.003	0.38	−0.002***	0.32	−0.003	0.28	−0.005	0.20
	BBB-	0.003	0.37	−0.002***	0.32	−0.004	0.33	−0.003	0.19
Conditional correlation	AAA	0.498	0.38	0.019***	0.61	−0.021	0.31	−0.011	0.28
	AA	1.955	0.40	0.001*	0.58	−0.011**	0.36	−0.002	0.29
	A	0.570	0.36	0.002	0.52	−0.002	0.21	−0.004	0.28
	BBB	0.099	0.35	0.002	0.57	−0.001	0.19	−0.013*	0.31
	BBB-	0.042	0.31	0.002	0.56	−0.002	0.21	−0.015	0.30

Table 4.17: Liquidity and credit risks VAR model results - Japan

This table reports the sums of the ABX factor loadings of my weekly Japanese liquidity and credit risks VAR models grouped by crisis subperiods. With the same VAR model framework of Equation 4.1, the same exogenous lagged ABX index returns and identical crisis subsamples, I include sets of liquidity and credit risks related endogenous variables in the analysis. The trading ratios are computed by dividing the weekly aggregate trading volume in market value of the Datastream calculated financial price index by the weekly aggregate trading volume in market value of the Datastream calculated market price index for each country. The IRSSs refer to the yield differentials between the interest rate swap middle rate and the corresponding 10-year government bond yield (or middle rate) quoted weekly. The conditional correlation refers to the estimated correlation coefficients between the weekly returns of the Datastream calculated equity market composite index and the FTSE global government bond clean price index for each country, estimated using MGARCH(1,1) diagonal VECH models. The superscripts ***, ** and * denote the statistical significance of the F-tests of joint significance of the ABX factor loadings at the 1%, 5% and 10% levels, respectively.

y_t		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
Japan	ABX	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2	$\sum_{s=1}^{4}\phi_{j,s}$	R^2
Trading ratios	AAA	0.612**	0.60	0.000	0.35	−0.003***	0.44	0.002	0.19
	AA	0.149**	0.63	0.003	0.36	−0.001***	0.38	0.001*	0.23
	A	−0.222	0.58	0.000	0.38	−0.001	0.33	−0.003	0.18
	BBB	−0.004	0.53	0.000	0.36	0.000	0.26	0.002	0.16
	BBB-	−0.005	0.53	−0.001	0.36	0.000	0.27	0.003	0.18
IRSS	AAA	0.837***	0.51	−0.013***	0.61	0.003***	0.35	0.001	0.33
	AA	0.352*	0.51	−0.004***	0.59	−0.000**	0.36	0.000	0.33
	A	0.310	0.48	−0.002*	0.49	−0.001***	0.39	0.001	0.34
	BBB	0.073**	0.51	−0.001	0.48	−0.001	0.29	0.002	0.34
	BBB-	0.061*	0.55	−0.001	0.48	−0.001	0.25	0.003	0.35
Conditional correlation	AAA	−4.755**	0.50	−0.248	0.44	−0.004	0.29	−0.036	0.13
	AA	4.237**	0.61	−0.037	0.38	−0.004	0.30	−0.005	0.12
	A	−2.444***	0.54	−0.019***	0.47	0.001	0.33	0.010	0.14
	BBB	0.541	0.52	−0.015***	0.47	0.001	0.30	0.052*	0.22
	BBB-	0.274	0.47	−0.014***	0.46	−0.001	0.28	0.048***	0.25

Table 4.18: Summary statistics - the ABX indices (daily)

This table contains the summary statistics of the daily returns (two-day rolling averages) of the five ABX indices. The means, medians, maximums, minimums, standard deviations, the p-values of the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests are reported grouped by crisis subperiods: Year 2006 (239 observations, from 19 January 2006 to 29 December 2006) refers to the tranquil pre-crisis subperiod; Year 2007 (251 observations, from 2 January 2007 to 31 December 2007) refers to the subprime crisis subperiod; Year 2008-9 (312 observations, from 2 January 2008 to 31 March 2009) refers to the global crisis subperiod; and Year 2009-2011 is defined as the post-crisis subperiod (583 observations) that spans 1 September 2009 to 30 December 2011. The data points between the period of 1 April 2009 to 31 August 2009 are excluded from the analysis. The table reports the unconditional correlations between the ABX indices.

Panel A: Full sample

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	-0.021	0.000	5.777	-5.394	0.620	0.000	0.000	AAA	1.000	-	-	-	-
AA	-0.096	0.000	10.836	-9.778	1.384	0.000	0.000	AA	0.834	1.000	-	-	-
A	-0.147	0.000	8.445	-9.118	1.571	0.000	0.000	A	0.499	0.592	1.000	-	-
BBB	-0.195	0.000	8.804	-11.606	1.507	0.000	0.000	BBB	0.373	0.398	0.617	1.000	-
BBB-	-0.192	0.000	9.599	-11.696	1.387	0.000	0.000	BBB-	0.401	0.427	0.585	0.804	1.000

Panel B: Pre-crisis subperiod (19th Jan 2006 - 29th Dec 2006, 239 obs.)

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	0.000	0.000	0.035	-0.045	0.008	0.000	0.000	AAA	1.000	-	-	-	-
AA	0.002	0.000	0.105	-0.060	0.016	0.000	0.000	AA	0.243	1.000	-	-	-
A	0.001	0.000	0.080	-0.090	0.021	0.000	0.000	A	0.255	0.548	1.000	-	-
BBB	0.004	0.000	0.327	-0.214	0.070	0.000	0.000	BBB	0.117	0.293	0.573	1.000	-
BBB-	0.004	0.005	0.263	-0.214	0.090	0.005	0.000	BBB-	0.146	0.343	0.529	0.799	1.000

Panel C: Subprime crisis subperiod (2nd Jan 2007 - 31st Dec 2007, 251 obs.)

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	-0.027	0.000	1.696	-1.996	0.326	0.000	0.000	AAA	1.000	-	-	-	-
AA	-0.068	-0.005	3.868	-3.864	0.745	0.000	0.000	AA	0.817	1.000	-	-	-
A	-0.199	-0.021	8.445	-6.239	1.755	0.000	0.000	A	0.671	0.808	1.000	-	-
BBB	-0.437	-0.130	8.804	-10.473	2.155	0.001	0.000	BBB	0.662	0.732	0.862	1.000	-
BBB-	-0.488	-0.193	9.599	-8.406	2.027	0.000	0.000	BBB-	0.644	0.678	0.792	0.916	1.000

Panel D: Global crisis subperiod (2nd Jan 2008 - 31st Mar 2009, 312 obs.)

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	-0.120	-0.009	5.777	-5.394	1.127	0.000	0.000	AAA	1.000	-	-	-	-
AA	-0.505	-0.402	10.836	-9.778	2.164	0.000	0.000	AA	0.869	1.000	-	-	-
A	-0.643	-0.456	7.584	-9.118	2.418	0.000	0.000	A	0.556	0.718	1.000	-	-
BBB	-0.667	-0.322	5.788	-11.606	2.154	0.000	0.000	BBB	0.456	0.527	0.652	1.000	-
BBB-	-0.626	-0.181	5.179	-11.696	1.926	0.000	0.000	BBB-	0.485	0.553	0.596	0.841	1.000

Panel E: Post-crisis subperiod (1st Sept 2009 - 30th Dec 2011, 583 obs.)

ABX	Mean	Median	Maximum	Minimum	Stdev	ADF p	PP p		AAA	AA	A	BBB	BBB-
AAA	0.027	0.017	3.046	-1.736	0.424	0.000	0.000	AAA	1.000	-	-	-	-
AA	0.072	0.028	9.454	-5.140	1.299	0.000	0.000	AA	0.817	1.000	-	-	-
A	0.080	0.018	5.584	-5.787	1.105	0.000	0.000	A	0.299	0.310	1.000	-	-
BBB	0.080	0.000	4.321	-2.766	0.825	0.000	0.000	BBB	-0.016	0.001	0.052	1.000	-
BBB-	0.089	0.000	4.084	-2.969	0.765	0.000	0.000	BBB-	0.107	0.131	0.163	0.273	1.000

Table 4.19: Summary statistics - endogenous variables (daily)

This table reports the summary statistics of the endogenous variables used in my daily VAR models. Panels A to C report the full sample and subsample means and standard deviations of the (two-day rolling average) daily returns of the equity market composite, financial equity and government bond indices of the G5 countries, respectively.

Variables	**Full sample**		**Pre-crisis**		**Subprime**		**Global**		**Post-crisis**	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Panel A: Equity market composite indices										
S&P 500	-0.030	1.010	0.044	0.448	0.018	0.643	-0.224	1.619	0.024	0.857
FTSE 100	-0.022	0.991	0.034	0.509	0.005	0.736	-0.164	1.524	0.020	0.860
CAC 40	-0.049	1.137	0.065	0.628	-0.001	0.738	-0.224	1.590	-0.023	1.142
DAX 30	-0.017	1.093	0.085	0.664	0.074	0.691	-0.218	1.541	0.009	1.074
NIKKEI 225	-0.058	1.196	0.040	0.825	-0.053	0.795	-0.180	1.884	-0.036	0.970
Panel B: Financial equity indices										
US	-0.091	1.594	0.065	0.476	-0.072	0.914	-0.350	2.828	-0.024	1.124
UK	-0.088	1.387	0.056	0.579	-0.101	0.930	-0.268	2.271	-0.044	1.130
France	-0.094	1.570	0.098	0.734	-0.090	0.950	-0.279	2.234	-0.075	1.597
Germany	-0.064	1.185	0.081	0.635	-0.011	0.708	-0.270	1.748	-0.036	1.136
Japan	-0.107	1.447	-0.020	1.063	-0.111	1.218	-0.215	2.280	-0.082	1.045
Panel C: Government bond indices										
US	0.021	0.386	-0.014	0.212	0.018	0.289	0.040	0.538	0.026	0.381
UK	0.018	0.306	-0.024	0.187	0.009	0.204	0.041	0.414	0.025	0.313
France	0.004	0.267	-0.018	0.180	-0.009	0.190	0.025	0.332	0.006	0.286
Germany	0.013	0.283	-0.020	0.179	-0.007	0.199	0.033	0.360	0.024	0.300
Japan	0.009	0.157	-0.002	0.173	0.011	0.156	0.009	0.185	0.012	0.132

Table 4.20: Principal component analysis (PCA) of the equity market returns (daily)

This table contains a summary of the PCA for the G5 countries. For each subject country, the daily returns (two-day rolling averages) of the remaining four countries' equity market composite indices are used as inputs for the PCA to obtain the principal components and the corresponding factor scores. The eigenvalues of the first component, the percentage of variances explained and the commonalities are reported here.

Subject Country	Eigenvalues	% of Var. explained	Communalities				
			US	UK	France	Germany	Japan
US	3.221	80.53%	-	0.898	0.937	0.895	0.491
UK	3.018	75.45%	0.740	-	0.907	0.901	0.470
France	2.972	74.31%	0.748	0.873	-	0.881	0.469
Germany	3.010	75.24%	0.729	0.894	0.908	-	0.478
Japan	3.516	87.60%	0.760	0.904	0.937	0.915	-

Table 4.21: Empirical results - daily US VAR models

This table reports the results of my VAR models for the US financial markets using daily data. To account for the fact that international markets have different opening and closing times, I follow Forbes and Rigobon (2002) and use the two-day rolling-average returns in my analysis. Similar to the weekly VAR analysis, all five ABX indices, which correspond to credit ratings of the AAA, AA, A, BBB and BBB- RMBS deals, are included in my VAR models. In each VAR equation, the dependent variable is written as a function of its own lags and the lagged ABX index returns: $\mathbf{y}_t = \boldsymbol{\alpha}_0 + \sum_{s=1}^{5} \boldsymbol{\beta}_s \mathbf{y}_{t-s} + \sum_{k=1}^{4} \sum_{s=1}^{5} \boldsymbol{\phi}_{s,k} d_k ABX_{t-s} + \boldsymbol{\epsilon}_t$. I report the (net) sums of the ABX factor loadings and the R^2 of each VAR function. The 1%, 5% and 10% levels of significance of the F-tests of joint significance of the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i,k)} = \phi_{j,2}^{(i,k)} = \phi_{j,3}^{(i,k)} = \phi_{j,4}^{(i,k)} = \phi_{j,5}^{(i,k)} = 0$ (where $\phi_{j,s}^{(i,k)}$ refers to the factor loading of the s^{th} ABX lagged returns on the function of the j^{th} endogenous variable of country i in the k^{th} crisis subperiod), are reported and are denoted by superscripts ***, **, and *, respectively. The endogenous variables include the daily returns of the US equity market composite (S&P 500), financial equity (Fin), and government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		**Pre-crisis (k=1)**		**Subprime (k=2)**		**Global (k=3)**		**Post (k=4)**	
US	ABX	$\sum_{s=1}^{5} \phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5} \phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5} \phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5} \phi_{j,s}^{k}$	R^2
S&P 500	AAA	−3.827**	0.40	−0.048	0.40	0.067***	0.40	−0.242**	0.40
	AA	−0.194**	0.41	0.010	0.41	0.029***	0.41	−0.062	0.41
	A	−2.882	0.38	0.023	0.38	−0.007	0.38	−0.037	0.38
	BBB	−0.423	0.39	0.040	0.39	0.038**	0.39	−0.018	0.39
	BBB-	−0.192	0.39	0.047**	0.39	0.035*	0.39	−0.006	0.39
Fin	AAA	2.011	0.39	0.107	0.39	0.191***	0.39	−0.326*	0.39
	AA	0.649	0.39	0.063	0.39	0.097***	0.39	−0.086	0.39
	A	−2.567	0.36	0.062	0.36	0.046	0.36	−0.064	0.36
	BBB	−0.304	0.38	0.077	0.38	0.119	0.38	−0.019	0.38
	BBB-	−0.039	0.37	0.100**	0.37	0.116	0.37	−0.002	0.37
Gov	AAA	−4.423	0.43	−0.136***	0.43	−0.038**	0.43	0.026	0.43
	AA	−2.562**	0.43	−0.035	0.43	−0.026*	0.43	0.020	0.43
	A	−0.629	0.43	−0.033**	0.43	−0.010***	0.43	−0.012	0.43
	BBB	−0.150	0.43	−0.040***	0.43	−0.034*	0.43	0.011	0.43
	BBB-	−0.169	0.43	−0.041***	0.43	−0.036	0.43	0.038	0.43
PCA	AAA	−9.514**	0.54	0.036	0.54	0.000**	0.54	−0.247	0.54
	AA	−0.100	0.55	0.037	0.55	0.004***	0.55	−0.075*	0.55
	A	−4.509	0.54	0.036	0.54	−0.016*	0.54	−0.001	0.54
	BBB	−0.562	0.54	0.025*	0.54	−0.005**	0.54	−0.045	0.54
	BBB-	−0.021	0.54	0.021**	0.54	0.001	0.54	0.000	0.54

Table 4.22: Empirical results - daily UK VAR models

This table reports the results of my VAR models for the UK financial markets using daily data. To account for the fact that international markets have different opening and closing times, I follow Forbes and Rigobon (2002) and use the two-day rolling-average returns in my analysis. Similar to the weekly VAR analysis, all five ABX indices, which correspond to credit ratings of the AAA, AA, A, BBB and BBB- RMBS deals, are included in my VAR models. In each VAR equation, the dependent variable is written as a function of its own lags and the lagged ABX index returns: $\mathbf{y}_t = \boldsymbol{\alpha}_0 + \sum_{s=1}^{5} \boldsymbol{\beta}_s \mathbf{y}_{t-i} + \sum_{k=1}^{4} \sum_{s=1}^{5} \boldsymbol{\phi}_{s,k} d_k ABX_{t-s} + \boldsymbol{\epsilon}_t$. I report the (net) sums of the ABX factor loadings and the R^2 of each VAR function. The 1%, 5% and 10% levels of significance of the F-tests of joint significance of the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i,k)} = \phi_{j,2}^{(i,k)} = \phi_{j,3}^{(i,k)} = \phi_{j,4}^{(i,k)} = \phi_{j,5}^{(i,k)} = 0$ (where $\phi_{j,s}^{(i,k)}$ refers to the factor loading of the s^{th} ABX lagged returns on the function of the j^{th} endogenous variable of country i in the k^{th} crisis subperiod), are reported and are denoted by superscripts ***, **, and *, respectively. The endogenous variables include the daily returns of the UK equity market composite (FTSE 100), financial equity (Fin), and government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		Pre-crisis (k=1)		Subprime (k=2)		Global (k=3)		Post (k=4)	
UK	ABX	$\sum_{s=1}^{5} \phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5} \phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5} \phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5} \phi_{j,s}^{k}$	R^2
FTSE 100	AAA	−2.962	0.44	0.341	0.44	0.096***	0.44	−0.170	0.44
	AA	−0.044	0.45	0.094**	0.45	0.052***	0.45	−0.056	0.45
	A	−5.125**	0.44	0.082***	0.44	0.033**	0.44	−0.014	0.44
	BBB	−0.750	0.44	0.078***	0.44	0.068**	0.44	−0.061	0.44
	BBB-	−0.378	0.44	0.087***	0.44	0.059**	0.44	−0.008	0.44
Fin	AAA	2.088	0.45	0.226	0.45	0.002*	0.45	−0.292	0.45
	AA	0.325	0.46	0.011	0.46	0.044***	0.46	−0.083	0.46
	A	−5.029**	0.45	0.080***	0.45	0.041	0.45	−0.015	0.45
	BBB	−0.797	0.46	0.082***	0.46	0.076*	0.46	−0.064	0.46
	BBB-	−0.458	0.45	0.093***	0.45	0.050	0.45	0.037	0.45
Gov	AAA	−1.846	0.46	−0.011**	0.46	0.009*	0.46	0.056	0.46
	AA	−0.937	0.47	0.000**	0.47	0.002**	0.47	0.021	0.47
	A	−0.102	0.46	−0.019***	0.46	−0.001	0.46	−0.013	0.46
	BBB	−0.147	0.47	−0.022***	0.47	−0.010	0.47	0.013	0.47
	BBB-	−0.189	0.47	−0.019***	0.47	−0.010	0.47	0.022	0.47
PCA	AAA	−8.496***	0.50	0.076	0.50	0.017*	0.50	−0.218	0.50
	AA	−1.695	0.51	0.027	0.51	0.014***	0.51	−0.063*	0.51
	A	−4.602**	0.49	0.040*	0.49	−0.005	0.49	−0.013	0.49
	BBB	−0.964	0.50	0.041***	0.50	0.028	0.50	−0.061	0.50
	BBB-	−0.441	0.50	0.042***	0.50	0.032	0.50	−0.029	0.50

Table 4.23: Empirical results - daily French VAR models

This table reports the results of my VAR models for the French financial markets using daily data. To account for the fact that international markets have different opening and closing times, I follow Forbes and Rigobon (2002) and use the two-day rolling-average returns for my analysis. Similar to the weekly VAR analysis, all five ABX indices, which correspond to credit ratings of the AAA, AA, A, BBB and BBB- RMBS deals, are included in my VAR models. In each VAR equation, the dependent variable is written as a function of its own lags and the exogenous lagged ABX index returns: $\mathbf{y}_t=\boldsymbol{\alpha}_0+\sum_{s=1}^{5}\boldsymbol{\beta}_s\mathbf{y}_{t-i}+\sum_{k=1}^{4}\sum_{s=1}^{5}\boldsymbol{\phi}_{s,k}d_kABX_{t-s}+\boldsymbol{\epsilon}_t$. I report the (net) sums of the ABX factor loadings and the R^2 of each VAR function. The 1%, 5% and 10% levels of significance of the F-tests of joint significance of the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i,k)}=\phi_{j,2}^{(i,k)}=\phi_{j,3}^{(i,k)}=\phi_{j,4}^{(i,k)}=\phi_{j,5}^{(i,k)}=0$ (where $\phi_{j,s}^{(i,k)}$ refers to the factor loading of the s^{th} ABX lagged returns on the function of the j^{th} endogenous variable of country i in the k^{th} crisis subperiod), are reported and are denoted by superscripts ***, **, and *, respectively. The endogenous variables include the daily returns of the French equity market composite (CAC 40), financial equity (Fin), and government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		**Pre-crisis (k=1)**		**Subprime (k=2)**		**Global (k=3)**		**Post (k=4)**	
France	ABX	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2
CAC 40	AAA	−6.555	0.44	0.223	0.44	0.082**	0.44	−0.258*	0.44
	AA	−1.920	0.45	0.069	0.45	0.060***	0.45	−0.102**	0.45
	A	−4.719	0.44	0.056*	0.44	0.050**	0.44	−0.017	0.44
	BBB	−1.032	0.44	0.046***	0.44	0.083***	0.44	−0.099	0.44
	BBB-	−0.576	0.44	0.058***	0.44	0.080**	0.44	−0.003	0.44
Fin	AAA	−3.320	0.47	−0.058	0.47	0.057**	0.47	−0.383	0.47
	AA	−0.286	0.48	−0.024	0.48	0.082***	0.48	−0.138*	0.48
	A	−4.087	0.48	0.057**	0.48	0.091*	0.48	0.004	0.48
	BBB	−0.472	0.47	0.058***	0.47	0.122**	0.47	−0.114	0.47
	BBB-	−0.003	0.47	0.075***	0.47	0.117*	0.47	0.067	0.47
Gov	AAA	−2.570	0.46	−0.029**	0.46	−0.004	0.46	0.049	0.46
	AA	−1.509	0.47	−0.006**	0.47	−0.001**	0.47	0.025*	0.47
	A	−0.527	0.47	−0.018**	0.47	0.000	0.47	0.006	0.47
	BBB	−0.315	0.47	−0.020***	0.47	−0.009	0.47	0.013	0.47
	BBB-	−0.263	0.47	−0.020***	0.47	−0.007	0.47	0.031***	0.47
PCA	AAA	−8.502**	0.50	0.128	0.50	0.030*	0.50	−0.171*	0.50
	AA	−0.905	0.51	0.050*	0.51	0.019***	0.51	−0.048**	0.51
	A	−4.671**	0.50	0.044**	0.50	−0.002	0.50	−0.016	0.50
	BBB	−0.816	0.50	0.043***	0.50	0.034	0.50	−0.072	0.50
	BBB-	−0.300	0.50	0.047***	0.50	0.038	0.50	−0.026	0.50

Table 4.24: Empirical results - daily German VAR models

This table reports the results of my VAR models for the German financial markets using daily data. To account for the fact that international markets have different opening and closing times, I follow Forbes and Rigobon (2002) and use the two-day rolling-average returns for my analysis. Similar to the weekly VAR analysis, all five ABX indices, which correspond to credit ratings of the AAA, AA, A, BBB and BBB- RMBS deals, are included in my VAR models. In each VAR equation, the dependent variable is written as a function of its own lags and the lagged ABX index returns: $\mathbf{y}_t=\boldsymbol{\alpha}_0+\sum_{s=1}^{5}\boldsymbol{\beta}_s\mathbf{y}_{t-i}+\sum_{k=1}^{4}\sum_{s=1}^{5}\boldsymbol{\phi}_{s,k}d_k ABX_{t-s}+\boldsymbol{\epsilon}_t$. I report the (net) sums of the ABX factor loadings and the R^2 of each VAR function. The 1%, 5% and 10% levels of significance of the F-tests of joint significance on the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i,k)}=\phi_{j,2}^{(i,k)}=\phi_{j,3}^{(i,k)}=\phi_{j,4}^{(i,k)}=\phi_{j,5}^{(i,k)}=0$ (where $\phi_{j,s}^{(i,k)}$ refers to the factor loading of the s^{th} ABX lagged returns on the function of the j^{th} endogenous variable of country i in the k^{th} crisis subperiod), are reported and are denoted by superscripts ***, **, and *, respectively. The endogenous variables include the daily returns of the German equity market composite (DAX 30), financial equity (Fin), and government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		Pre-crisis (k=1)		Subprime (k=2)		Global (k=3)		Post (k=4)	
Germany	ABX	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2
DAX 40	AAA	−11.776*	0.44	0.208	0.44	0.103***	0.44	−0.248**	0.44
	AA	−2.826	0.45	0.064**	0.45	0.058***	0.45	−0.083**	0.45
	A	−6.298**	0.44	0.053***	0.44	0.022	0.44	−0.004	0.44
	BBB	−1.304	0.44	0.045***	0.44	0.055	0.44	−0.048	0.44
	BBB-	−0.574	0.44	0.056***	0.44	0.063	0.44	0.029	0.44
Fin	AAA	−1.659	0.48	0.006	0.48	0.004**	0.48	−0.309	0.48
	AA	0.457	0.48	−0.015	0.48	0.030***	0.48	−0.100	0.48
	A	−2.962	0.47	0.045*	0.47	0.032	0.47	0.007	0.47
	BBB	−0.250	0.47	0.050**	0.47	0.046**	0.47	−0.055	0.47
	BBB-	0.032	0.47	0.059***	0.47	0.040	0.47	0.024	0.47
Gov	AAA	−2.409	0.48	−0.028	0.48	−0.011	0.48	0.070	0.48
	AA	−1.665	0.49	−0.001***	0.49	−0.005*	0.49	0.031**	0.49
	A	−0.526	0.48	−0.019**	0.48	−0.002	0.48	−0.016	0.48
	BBB	−0.302**	0.49	−0.021***	0.49	−0.011	0.49	0.010	0.49
	BBB-	−0.261	0.49	−0.022***	0.49	−0.011	0.49	0.018	0.49
PCA	AAA	−7.038**	0.49	0.163	0.49	0.015	0.49	−0.226	0.49
	AA	0.273	0.50	0.060	0.50	0.015***	0.50	−0.058*	0.50
	A	−3.862*	0.49	0.056**	0.49	−0.011	0.49	−0.017	0.49
	BBB	−0.707	0.50	0.051***	0.50	0.019	0.50	−0.068	0.50
	BBB-	−0.184	0.49	0.052***	0.49	0.026	0.49	−0.038	0.49

Table 4.25: Empirical results - daily Japanese VAR models

This table reports the results of my VAR models for the Japanese financial markets using daily data. To account for the fact that international markets have different opening and closing times, I follow Forbes and Rigobon (2002) and use the two-day rolling-average returns for my analysis. Similar to the weekly VAR analysis, all five ABX indices, which correspond to credit ratings of the AAA, AA, A, BBB and BBB- RMBS deals, are included in my VAR estimation. In each VAR equation, the dependent variable is written as a function of its own lags and the lagged ABX index returns: $\mathbf{y}_t=\boldsymbol{\alpha}_0+\sum_{s=1}^{5}\boldsymbol{\beta}_s\mathbf{y}_{t-i}+\sum_{k=1}^{4}\sum_{s=1}^{5}\boldsymbol{\phi}_{s,k}d_k ABX_{t-s}+\boldsymbol{\epsilon}_t$. I report the (net) sum of the ABX factor loadings and the R^2 of each VAR function. The 1%, 5% and 10% levels of significance of the F-tests of joint significance of the ABX factor loadings with null hypothesis: $\phi_{j,1}^{(i,k)}=\phi_{j,2}^{(i,k)}=\phi_{j,3}^{(i,k)}=\phi_{j,4}^{(i,k)}=\phi_{j,5}^{(i,k)}=0$ (where $\phi_{j,s}^{(i,k)}$ refers to the factor loading of the s^{th} ABX lagged returns on the function of the j^{th} endogenous variable of country i in the k^{th} crisis subperiod), are reported and are denoted by superscripts ***, **, and *, respectively. The endogenous variables include the daily returns of the Japanese equity market composite (Nikkei 225), financial equity (Fin), and government bond indices (Gov) as well as a PCA latent variable (PCA).

y_t		Pre-crisis (k=1)		Subprime (k=2)		Global (k=3)		Post (k=4)	
Japan	ABX	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2	$\sum_{s=1}^{5}\phi_{j,s}^{k}$	R^2
Nikkei 225	AAA	−14.088	0.55	0.094	0.55	−0.070	0.55	0.082	0.55
	AA	1.253	0.55	0.052	0.55	−0.020	0.55	−0.005	0.55
	A	−0.860**	0.55	0.059*	0.55	0.005*	0.55	0.011	0.55
	BBB	−0.501	0.55	0.049***	0.55	0.052	0.55	−0.102	0.55
	BBB-	0.333	0.55	0.049**	0.55	0.044	0.55	−0.121	0.55
Fin	AAA	−10.662**	0.54	−0.105	0.54	0.040	0.54	−0.007	0.54
	AA	5.878	0.54	−0.047**	0.54	0.033	0.54	−0.020	0.54
	A	2.778**	0.55	0.032	0.55	0.039**	0.55	0.003	0.55
	BBB	0.641	0.55	0.015***	0.55	0.089**	0.55	−0.016	0.55
	BBB-	0.943*	0.55	0.015*	0.55	0.085	0.55	−0.083	0.55
Gov	AAA	1.604	0.43	−0.097***	0.43	−0.010	0.43	0.000	0.43
	AA	−1.254**	0.43	−0.023***	0.43	−0.004	0.43	0.005	0.43
	A	0.064	0.42	−0.016***	0.42	−0.005	0.42	−0.007	0.42
	BBB	−0.212	0.43	−0.012***	0.43	−0.007***	0.43	0.012	0.43
	BBB-	−0.186**	0.43	−0.010***	0.43	−0.007*	0.43	0.021	0.43
PCA	AAA	−7.734**	0.45	0.113	0.45	0.134**	0.45	−0.255*	0.45
	AA	−0.048	0.46	0.054	0.46	0.067***	0.46	−0.067*	0.46
	A	−4.665*	0.44	0.047*	0.44	0.014	0.44	−0.025	0.44
	BBB	−0.933	0.45	0.038**	0.45	0.032	0.45	−0.055	0.45
	BBB-	−0.479	0.45	0.042***	0.45	0.041	0.45	−0.022	0.45

Table 4.26: Empirical results - daily UK VAR models with exogenous US market variables

This table reports the results of my VAR models for the UK financial markets using daily data. To account for the fact that international markets have different opening and closing times, I follow Forbes and Rigobon (2002) and use the two-day rolling-average returns for my analysis. Similar to the weekly VAR analysis, all five ABX indices, which correspond to credit ratings of the AAA, AA, A, BBB and BBB- RMBS deals, are included in my VAR models. In each VAR equation, the dependent variable is written as a function of its own lags and a few major US market variables and can be written as: $\mathbf{y}_t = \boldsymbol{\alpha}_0 + \sum_{s=1}^{5} \boldsymbol{\beta}_s \mathbf{y}_{t-i} + \sum_{k=1}^{4} \sum_{s=1}^{5} \boldsymbol{\phi}_{s,k} d_k \mathbf{x}_{t-s} + \boldsymbol{\epsilon}_t$, where $\mathbf{x_{t-s}}$ is a 6×1 vector of US market variables including the daily returns of the ABX indices, the US S&P 500 composite index, the US government bond market index, the changes in the US Moody's BAA corporate bond yield spreads and asset-backed commercial papers (ABCP) yields spreads and a PCA latent variable. I report the (net) sums of the factor loadings of the US market variables grouped by crisis subperiods and the R^2 of each VAR equation. The 1%, 5% and 10% significance levels of the F-tests of joint significance of the factor loadings with null hypothesis: $\phi_{j,1}^{(x,k)} = \phi_{j,2}^{(x,k)} = \phi_{j,3}^{(x,k)} = \phi_{j,4}^{(x,k)} = \phi_{j,5}^{(x,k)} = 0$ (where $\phi_{j,s}^{(x,k)}$ refers to the factor loading of the s^{th} ABX lagged returns on the function of the j^{th} endogenous variable of the x^{th} exogenous variables in the k^{th} crisis subperiod), are reported and are denoted by superscripts ***, **, and *, respectively. The endogenous variables include the daily returns of the UK equity market composite (FTSE 100), financial equity (Fin) and government bond indices (Gov).

y_t	$\sum_{s=1}^{5} \phi_{j,s}^{ABX,k}$				$\sum_{s=1}^{5} \phi_{j,s}^{S\%P500,k}$				$\sum_{s=1}^{5} \phi_{j,s}^{USGov,k}$				$\sum_{s=1}^{5} \phi_{j,s}^{USBAA,k}$				$\sum_{s=1}^{5} \phi_{j,s}^{USABCP,k}$				R^2
UK	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	
Panel A: ABX AAA																					
FTSE 100	−0.45	0.34	0.03***	−0.14	0.20***	0.57***	0.67***	0.57***	−0.32***	−0.15	−0.01	−0.55*	3.42**	−1.05	−2.53	4.56	1.95	−0.22*	−0.35**	−1.00	0.56
Fin	2.22	0.22	−0.14**	−0.23	0.20***	0.58***	0.97***	0.68***	−0.11***	0.04	−0.16	−0.66*	0.44**	−1.16	0.07	4.05	2.89	−0.43**	1.25***	−1.33	0.54
Gov	−2.72	0.13**	0.03***	0.04	0.02	−0.05	−0.13	−0.04	0.19	0.30***	0.15***	0.29***	−2.46	−1.59	−0.01	−0.86	−0.65	0.01	−0.15*	−1.44	0.54
Panel B:ABX AA																					
FTSE 100	−0.07	0.14***	0.01***	−0.05	0.20***	0.55***	0.69***	0.58***	−0.28***	−0.16	−0.00	−0.50*	3.49*	−1.47	−2.67	4.52	1.83	−0.25*	−0.40**	−0.95	0.56
Fin	1.61	0.04	−0.03*	−0.07	0.24***	0.55***	0.93***	0.67***	−0.10***	0.07	−0.10	−0.62*	0.27**	−1.85	−0.45	4.34	2.78	−0.31**	1.33***	−1.25	0.55
Gov	−0.65	0.05***	0.02***	0.01	0.02	−0.04	−0.14	−0.04	0.18	0.27***	0.14***	0.27***	−1.94	−1.76	0.12	−0.92	−0.62	−0.01	−0.16	−1.51	0.54
Panel C: ABX A																					
FTSE 100	−4.64*	0.10***	−0.01	−0.01	0.17***	0.51***	0.64***	0.56***	−0.24***	−0.02	0.05	−0.53*	1.38	−2.12*	−3.16*	5.19	1.31	−0.53***	−0.21**	−1.07	0.56
Fin	−4.76**	0.10***	−0.03	0.01	0.16***	0.51***	0.89***	0.64***	−0.05***	0.23	−0.11	−0.68*	−2.06*	−2.49	−0.56	5.24	2.22	−0.69***	1.54***	−1.22	0.54
Gov	−0.39	0.01**	0.01	−0.01	0.02	−0.05	−0.13	−0.04	0.19	0.25***	0.13***	0.29***	−2.25	−1.76**	0.13*	−1.14	−0.65*	0.03	−0.17	−1.71	0.53
Panel D: ABX BBB																					
FTSE 100	−0.16	0.08***	0.03	−0.09	0.19***	0.54***	0.61***	0.53***	−0.32***	0.02	0.08	−0.55*	3.52**	−1.45	−2.85*	5.51	1.72	−0.44***	−0.34*	−0.54	0.56
Fin	0.08	0.09***	−0.00	−0.08	0.18***	0.53***	0.88***	0.61***	−0.13***	0.23	−0.12	−0.71*	0.47**	−1.60	−0.16	5.51	2.86	−0.67***	1.29**	−0.78	0.54
Gov	−0.35	−0.01***	0.01	0.02	0.02	−0.04	−0.13	−0.03	0.21	0.24***	0.12***	0.29***	−2.61	−1.77**	0.14	−1.17	−0.89*	0.08	−0.16	−1.57	0.54
Panel E: ABX BBB-																					
FTSE 100	0.00	0.08***	0.03	0.00	0.20***	0.52***	0.62***	0.55***	−0.28***	0.05	0.11	−0.55*	3.66*	−0.53	−2.90*	5.28	1.83	−0.42**	−0.32*	−0.92	0.56
Fin	0.11	0.09***	−0.04	0.08	0.19***	0.51***	0.89***	0.64***	−0.10***	0.26	−0.13	−0.73*	0.17**	−0.42	−0.17	5.25	2.89	−0.65***	1.42***	−1.17	0.54
Gov	−0.25	−0.00***	0.01	0.01	0.00	−0.04	−0.13	−0.04	0.19	0.25***	0.12***	0.29***	−2.12	−1.79	0.11	−1.11	−0.85**	0.07	−0.17	−1.57	0.53

Table 4.27: Empirical results - daily French VAR models with exogenous US market variables

This table reports the results of my VAR models for the French financial markets using daily data. To account for the fact that international markets have different opening and closing times, I follow Forbes and Rigobon (2002) and use the two-day rolling-average returns for my analysis. Similar to the weekly VAR analysis, all five ABX indices, which correspond to credit ratings of the AAA, AA, A, BBB and BBB- RMBS deals, are included in my VAR models. In each VAR equation, the dependent variable is written as a function of its own lags and a few major US market variables and can be written as: $\mathbf{y}_t = \boldsymbol{\alpha}_0 + \sum_{s=1}^{5} \boldsymbol{\beta}_s \mathbf{y}_{t-i} + \sum_{k=1}^{4} \sum_{s=1}^{5} \boldsymbol{\phi}_{s,k} d_k \mathbf{x}_{t-s} + \boldsymbol{\epsilon}_t$, where $\mathbf{x_{t-s}}$ is a 6×1 vector of US market variables including the daily returns of the ABX indices, the US S&P 500 composite index, the US government bond market index, the changes in the US Moody's BAA corporate bond yield spreads and asset-backed commercial papers (ABCP) yields spreads and a PCA latent variable. I report the (net) sums of the factor loadings of the US market variables grouped by crisis subperiods (as specified by the crisis dummy variables) and the R^2 of each VAR equation. The 1%, 5% and 10% significance levels of the F-tests of joint significance on the factor loadings with null hypothesis: $\phi_{j,1}^{(x,k)} = \phi_{j,2}^{(x,k)} = \phi_{j,3}^{(x,k)} = \phi_{j,4}^{(x,k)} = \phi_{j,5}^{(x,k)} = 0$ (where $\phi_{j,s}^{(x,k)}$ refers to the factor loading of the s^{th} ABX lagged returns on the function of the j^{th} endogenous variable of the x^{th} exogenous variables in the k^{th} crisis subperiod), are reported and are denoted by superscripts ***, **, and *, respectively. The endogenous variables include the daily returns of the French equity market composite (CAC 40), financial equity (Fin), and government bond indices (Gov).

y_t	$\sum_{s=1}^{5}\phi_{j,s}^{ABX,k}$				$\sum_{s=1}^{5}\phi_{j,s}^{S\%P500,k}$				$\sum_{s=1}^{5}\phi_{j,s}^{USGov,k}$				$\sum_{s=1}^{5}\phi_{j,s}^{USBAA,k}$				$\sum_{s=1}^{5}\phi_{j,s}^{USABCP,k}$				R^2
France	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	
Panel A: ABX AAA																					
CAC 40	−1.74	0.18	−0.01***	−0.20	0.28***	0.72***	0.69***	0.54**	−0.45***	−0.30	−0.32	−0.94**	1.35	0.03	−1.20	5.83	1.55	−0.35	−0.22***	0.06	0.53
Fin	2.45	−0.13*	−0.10***	−0.27	0.10***	0.66***	1.08***	0.65*	−0.54***	−0.46	−0.58	−1.15*	−1.43*	−1.44	3.56	5.11	1.56	0.04	1.43***	2.08	0.56
Gov	−4.76*	0.07**	0.01	0.08**	0.09	−0.12**	−0.06	−0.11	0.20**	0.28***	0.14***	0.27***	−2.95	−1.60	0.46*	−0.86***	−0.42**	0.08	−0.19**	0.94	0.54
Panel B: ABX AA																					
CAC 40	0.37**	0.11*	0.01***	−0.09	0.36***	0.69***	0.71***	0.56**	−0.48***	−0.30	−0.29	−0.87**	1.81*	−0.00*	−1.35	5.52	1.57	−0.42*	−0.26***	0.11	0.54
Fin	3.38**	−0.00	0.01***	−0.11	0.21***	0.61***	1.02***	0.66*	−0.57***	−0.37	−0.47	−1.06*	−1.36*	−1.42	3.09	4.81	1.63	0.07**	1.48***	2.11	0.56
Gov	−1.69	0.02***	0.01	0.04***	0.10	−0.11**	−0.06	−0.12	0.20**	0.27***	0.13***	0.25***	−2.25	−1.68	0.56*	−0.70**	−0.44**	0.06	−0.20**	0.92	0.54
Panel C: ABX A																					
CAC 40	−2.78	0.08***	0.00	−0.01	0.31***	0.67***	0.64***	0.52**	−0.37***	−0.16	−0.21	−0.92**	0.40	−0.81*	−1.78	6.89	1.26	−0.59**	−0.07***	0.06	0.53
Fin	−2.09	0.08**	0.01	0.03	0.13***	0.56***	0.97***	0.62*	−0.44***	−0.18	−0.41	−1.13*	−2.86	−2.10	3.04	6.56	1.28	−0.29***	1.69***	2.17	0.56
Gov	−1.36	−0.01	0.01	0.01	0.09	−0.11**	−0.06	−0.10	0.20*	0.23**	0.13***	0.29***	−2.74	−1.56	0.57*	−1.33**	−0.53**	0.11	−0.22**	0.72	0.54
Panel D: ABX BBB																					
CAC 40	−0.42	0.05***	0.04	−0.11	0.30***	0.70***	0.60***	0.48*	−0.43***	−0.14	−0.16	−0.94**	1.80*	−0.38	−1.63	7.32	1.10	−0.47**	−0.17***	0.49	0.53
Fin	0.22	0.07***	0.03	−0.14	0.12***	0.60***	0.92***	0.57*	−0.48***	−0.17	−0.37	−1.16*	−0.51*	−1.42	3.03	7.12	1.53	−0.26**	1.51**	2.50	0.55
Gov	−0.58*	−0.01***	0.00	0.01	0.08	−0.11**	−0.05	−0.10	0.21**	0.21*	0.12***	0.29***	−3.07	−1.67*	0.53	−1.37***	−0.85**	0.14*	−0.19**	0.88	0.54
Panel E: ABX BBB-																					
CAC 40	−0.08	0.05***	0.03	0.01	0.30***	0.69***	0.61***	0.51*	−0.40***	−0.12	−0.15	−0.95**	2.17*	0.22	−1.67	6.96	1.39	−0.46*	−0.18***	0.26	0.53
Fin	0.72	0.07***	0.01	0.11	0.15***	0.58***	0.94***	0.61	−0.46***	−0.15	−0.39	−1.18*	−0.59*	−0.39	3.02	6.47	2.17	−0.25**	1.52**	2.13	0.55
Gov	−0.34	−0.01***	0.00	0.02	0.06	−0.10*	−0.05	−0.10	0.20**	0.21*	0.12***	0.28***	−2.33	−1.74*	0.53	−1.32***	−0.73***	0.14	−0.21**	0.63	0.54

Table 4.28: Empirical results - daily German VAR models with exogenous US market variables

This table reports the results of my VAR models for the German financial markets using daily data. To account for the fact that international markets have different opening and closing times, I follow Forbes and Rigobon (2002) and use the two-day rolling-average returns for my analysis. Similar to the weekly VAR analysis, all five ABX indices, which correspond to credit ratings of the AAA, AA, A, BBB and BBB- RMBS deals, are included in my VAR models. In each VAR equation, the dependent variable is written as a function of its own lags and a few major US market variables and can be written as: $\mathbf{y}_t = \boldsymbol{\alpha}_0 + \sum_{s=1}^{5} \boldsymbol{\beta}_s \mathbf{y}_{t-i} + \sum_{k=1}^{4} \sum_{s=1}^{5} \boldsymbol{\phi}_{s,k} d_k \mathbf{x}_{t-s} + \boldsymbol{\epsilon}_t$, where $\mathbf{x_{t-s}}$ is a 6×1 vector of US market variables including the daily returns of the ABX indices, the US S&P 500 composite index, the US government bond market index, the changes in the US Moody's BAA corporate bond yield spreads and asset-backed commercial papers (ABCP) yields spreads and a PCA latent variable. I report the (net) sums of the factor loadings of the US market variables grouped by crisis subperiods (as specified by the crisis dummy variables) and the R^2 of each VAR equation. The 1%, 5% and 10% significance levels of the F-tests of joint significance on the factor loadings with null hypothesis: $\phi_{j,1}^{(x,k)} = \phi_{j,2}^{(x,k)} = \phi_{j,3}^{(x,k)} = \phi_{j,4}^{(x,k)} = \phi_{j,5}^{(x,k)} = 0$ (where $\phi_{j,s}^{(x,k)}$ refers to the factor loading of the s^{th} ABX lagged returns on the function of the j^{th} endogenous variable of the x^{th} exogenous variables in the k^{th} crisis subperiod), are reported and are denoted by superscripts ***, **, and *, respectively. The endogenous variables include the daily returns of the German equity market composite (DAX 30), financial equity (Fin), and government bond indices (Gov).

y_t	$\sum_{s=1}^{5} \phi_{j,s}^{ABX,k}$				$\sum_{s=1}^{5} \phi_{j,s}^{S\%P500,k}$				$\sum_{s=1}^{5} \phi_{j,s}^{USGov,k}$				$\sum_{s=1}^{5} \phi_{j,s}^{USBAA,k}$				$\sum_{s=1}^{5} \phi_{j,s}^{USABCP,k}$				R^2
Germany	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	
Panel A: ABX AAA																					
DAX 30	−3.82	0.22	−0.02***	−0.15	0.22***	0.47***	0.77***	0.26	−0.39***	−0.65	−0.03	−0.77*	1.68*	3.21	−3.69	5.61	1.97	−0.34	−0.52*	−2.94	0.53
Fin	3.37	−0.06***	−0.14***	−0.14	−0.02**	0.31***	0.76***	0.23	−0.02***	−0.44	0.28	−0.77*	−0.32	1.82	−4.29**	3.89	2.78	−0.12*	0.81***	1.22	0.56
Gov	−4.28**	0.08**	0.02	0.05	0.06	−0.09	−0.07	−0.04	0.26**	0.31***	0.19***	0.35***	−3.15	−1.61	0.31	−1.17	−0.53**	0.03	−0.16	−0.95	0.55
Panel B: ABX AA																					
DAX 30	−0.76	0.11***	−0.00***	−0.06	0.27***	0.46***	0.79***	0.27	−0.44***	−0.67	−0.01	−0.72*	2.77*	3.11	−3.72	5.53	1.94	−0.39**	−0.53**	−2.68	0.53
Fin	2.51	−0.02*	−0.05***	−0.05	0.03**	0.27***	0.72***	0.24	−0.07***	−0.40	0.29	−0.72*	−0.40	1.79	−4.70	3.80	2.66*	−0.03*	0.83***	1.27	0.56
Gov	−1.71	0.04***	0.01	0.03**	0.07	−0.08	−0.07	−0.05	0.25*	0.30***	0.18***	0.33***	−2.49	−1.69	0.38	−1.05	−0.52**	0.00	−0.17	−0.98	0.56
Panel C: ABX A																					
DAX 30	−3.32*	0.07***	−0.02	0.01	0.21***	0.44***	0.71***	0.26	−0.34***	−0.57	0.07	−0.74*	0.97*	2.68	−4.43	6.39	1.61	−0.56**	−0.32	−2.60	0.52
Fin	−1.48	0.04**	−0.02	0.02	−0.05***	0.24***	0.64***	0.23	0.01***	−0.29	0.36	−0.75*	−1.41	1.61*	−4.91*	4.66	2.47	−0.28**	1.03***	1.50	0.55
Gov	−1.22	−0.00*	0.01	−0.02	0.06	−0.09	−0.07	−0.03	0.26*	0.27**	0.18***	0.35***	−2.92	−1.63	0.40	−1.42	−0.61**	0.06	−0.19	−1.07	0.56
Panel D: ABX BBB																					
DAX 30	−0.31	0.05***	0.02	−0.08	0.22***	0.47***	0.70***	0.22	−0.36***	−0.53	0.15	−0.73*	2.71**	3.13	−4.23	6.58	1.62	−0.50**	−0.42	−2.33	0.53
Fin	0.71	0.04**	−0.01	−0.09	−0.05**	0.27***	0.64***	0.19	0.01***	−0.29	0.40	−0.74*	1.17	1.90	−4.80	4.84	3.10	−0.33***	0.85***	1.48	0.55
Gov	−0.59*	−0.01***	0.00	0.02*	0.05	−0.09	−0.06	−0.03	0.27**	0.25*	0.16***	0.35***	−3.32	−1.67	0.40	−1.54	−0.97**	0.10	−0.16	−1.04	0.56
Panel E: ABX BBB-																					
DAX 30	0.13	0.05***	0.04	0.04	0.24***	0.46***	0.69***	0.26	−0.35***	−0.52	0.17	−0.76*	3.06*	3.71	−4.26	6.42	1.99	−0.48**	−0.44*	−2.43	0.52
Fin	0.60	0.05***	−0.02	0.07	−0.00**	0.27***	0.65***	0.22	0.01***	−0.27	0.36	−0.77*	0.04	2.58*	−4.65	4.56	3.16	−0.30**	0.90***	1.46	0.55
Gov	−0.36	−0.01***	0.01	0.01	0.04	−0.08	−0.06	−0.03	0.26	0.25*	0.17***	0.35***	−2.63	−1.79	0.40	−1.46	−0.85**	0.10	−0.19	−1.15	0.55

Table 4.29: Empirical results - daily Japanese VAR models with exogenous US market variables

This table reports the results of my VAR models for the Japanese financial markets using daily data. To account for the fact that international markets have different opening and closing times, I follow Forbes and Rigobon (2002) and use the two-day rolling-average returns for my analysis. Similar to the weekly VAR analysis, all five ABX indices, which correspond to credit ratings of the AAA, AA, A, BBB and BBB- RMBS deals, are included in my VAR models. In each VAR equation, the dependent variable is written as a function of its own lags and a few major US market variables and can be written as: $\mathbf{y}_t = \boldsymbol{\alpha}_0 + \sum_{s=1}^{5} \boldsymbol{\beta}_s \mathbf{y}_{t-i} + \sum_{k=1}^{4} \sum_{s=1}^{5} \boldsymbol{\phi}_{s,k} d_k \mathbf{x}_{t-s} + \boldsymbol{\epsilon}_t$, where $\mathbf{x_{t-s}}$ is a 6×1 vector of US market variables including the daily returns of the ABX indices, the US S&P 500 composite index, the US government bond market index, the changes in the US Moody's BAA corporate bond yield spreads and asset-backed commercial papers (ABCP) yields spreads and a PCA latent variable. I report the (net) sums of the factor loadings of the US market variables grouped by crisis subperiods (as specified by the crisis dummy variables) and the R^2 of each VAR equation. The 1%, 5% and 10% significance levels of the F-tests of joint significance on the factor loadings with null hypothesis: $\phi_{j,1}^{(x,k)} = \phi_{j,2}^{(x,k)} = \phi_{j,3}^{(x,k)} = \phi_{j,4}^{(x,k)} = \phi_{j,5}^{(x,k)} = 0$ (where $\phi_{j,s}^{(x,k)}$ refers to the factor loading of the s^{th} ABX lagged returns on the function of the j^{th} endogenous variable of the x^{th} exogenous variables in the k^{th} crisis subperiod), are reported and are denoted by superscripts ***, **, and *, respectively. The endogenous variables include the daily returns of the Japanese equity market composite (Nikkei 225), financial equity (Fin), and government bond indices (Gov).

y_t	$\sum_{s=1}^{5}\phi_{j,s}^{ABX,k}$				$\sum_{s=1}^{5}\phi_{j,s}^{S\%P500,k}$				$\sum_{s=1}^{5}\phi_{j,s}^{USGov,k}$				$\sum_{s=1}^{5}\phi_{j,s}^{USBAA,k}$				$\sum_{s=1}^{5}\phi_{j,s}^{USABCP,k}$				R^2
Japan	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	
Panel A: ABX AAA																					
Nikkei 225	−10.56*	−0.24	−0.21**	0.04	0.27	0.88***	0.97***	0.33***	−0.56	−0.08	−0.53	−0.49***	21.84**	−2.41**	−1.40	−1.00	0.21	−0.31**	−0.11	−3.85	0.64
Fin	−8.30**	−0.35***	−0.10	0.02	0.02	0.92***	0.83***	0.26	−0.20	0.59	−0.54	−0.43*	23.14	−2.55	1.03	−3.14	−0.17	−0.41	0.62	−4.61	0.62
Gov	2.34**	0.00***	−0.00*	−0.01	0.12	−0.05	0.01**	−0.00	0.21***	0.15***	0.15***	0.17***	−0.01**	−0.09	−0.27	0.27	−0.22**	0.05**	0.01***	0.32	0.56
Panel B: ABX AA																					
Nikkei 225	1.95*	−0.03	−0.10	−0.01	0.16**	0.86***	0.97***	0.34***	−0.48	−0.09	−0.54	−0.47***	24.76***	−1.67**	−1.76	−1.35	0.13	−0.42*	−0.05	−3.79	0.64
Fin	6.97	−0.10**	−0.05	−0.01	−0.12	0.87***	0.84***	0.27	−0.08	0.59	−0.51	−0.40*	26.28	−1.76	0.91	−3.48	0.03	−0.44	0.66	−4.70	0.62
Gov	−0.70*	0.01***	0.00	0.00	0.12	−0.05	0.00**	−0.00	0.21***	0.15***	0.15***	0.17***	−0.61*	−0.03	−0.27	0.28	−0.25	0.05	0.00***	0.30	0.56
Panel C: ABX A																					
Nikkei 225	0.96***	0.01	−0.05	0.02	0.13**	0.87***	0.92***	0.32***	−0.45	−0.01	−0.49	−0.46***	24.12***	−1.80**	−1.45	−1.25	0.38	−0.49**	0.01	−3.82	0.64
Fin	4.31**	−0.00	−0.02	0.01	−0.16	0.88***	0.83***	0.27	−0.11	0.67	−0.47	−0.43*	26.78*	−1.83	0.81	−3.24	0.56	−0.59	0.61	−4.49	0.62
Gov	0.05*	−0.01***	−0.00	−0.01	0.12	−0.05	0.01**	−0.00	0.22***	0.13***	0.14***	0.17***	−0.56**	0.03	−0.26	0.29	−0.22*	0.08	0.01***	0.29	0.56
Panel D: ABX BBB																					
Nikkei 225	0.73	−0.00*	−0.02	−0.09	0.17*	0.87***	0.92***	0.31***	−0.54	−0.04	−0.49	−0.46***	25.88***	−1.57*	−0.99	−0.90	0.80	−0.47*	−0.09	−3.53	0.64
Fin	2.03*	−0.02	0.02**	0.02	−0.05	0.86***	0.77***	0.26	−0.21	0.58	−0.42	−0.42*	28.63*	−1.59	1.16	−3.33	1.51	−0.54	0.65	−4.61	0.63
Gov	−0.18**	−0.00**	−0.00	0.01	0.12	−0.05	0.00*	−0.00	0.22***	0.14***	0.14***	0.17***	−0.87	−0.06	−0.26	0.25	−0.40**	0.07	0.02**	0.26	0.56
Panel E: ABX BBB-																					
Nikkei 225	0.99	−0.01	−0.02	−0.08	0.18*	0.89***	0.93***	0.33***	−0.56	−0.08	−0.48	−0.47***	25.82***	−1.52**	−0.86	−1.15	1.25	−0.50**	0.03	−3.52	0.64
Fin	1.51	−0.04	0.00	−0.03	−0.04	0.89***	0.80***	0.26	−0.22	0.55	−0.42	−0.44*	26.97*	−1.88	1.09	−3.30	1.53	−0.59	0.75	−4.61	0.62
Gov	−0.17***	0.00**	0.00	0.01	0.13	−0.05	0.00**	−0.00	0.22***	0.14***	0.15***	0.17***	−0.68	−0.01	−0.24	0.27	−0.44**	0.07	0.01***	0.27	0.56

Table 4.30: Subprime and global crises - conditional and unconditional correlation coefficients on the international equity markets

This table reports the conditional correlation coefficients, standard deviations, unconditional (adjusted for heteroskedasticity following Forbes and Rigobon (2002) as shown in Equation 4.8) correlation coefficients between each G5 international broad equity market and the US structured finance market (measured by the ABX indices) of the full sample and the crisis subperiods. All the correlation coefficients have been transformed using Fisher transformation as shown in Equation 4.13 and the standard deviations (of the ABX indices) have been transformed using Equation 4.14. Reported are the statistics of the two-sample t-tests (one-sided tests, as shown in Equation 4.15) of the conditional and unconditional correlation coefficients between the full sample and the crisis subperiods, respectively. The 'Y' in the columns with header 'Contagion' report the presence of contagion when the test statistics are larger than the critical values and 'N' otherwise (for the absence of contagion). ρ_{adj}, ρ_{con} and σ refer to the (heteroskedasticity-adjusted) unconditional correlation coefficients, conditional correlation coefficients and the standard deviations of the international markets, respectively.

Broad equity markets		**Pre-crisis**			**Subprime**			**Global**			**Post-crisis**			**Full**		**Full vs Subprime (C)**		**Full vs Global (C)**		**Full vs Subprime (Adj.)**		**Full vs Global (Adj.)**	
Country	ABX	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	σ_{uncon}	t-stat	Contagion	t-stat	Contagion	t-stat	Contagion	t-stat	Contagion
US	AAA	-0.99	-0.09	0.32	0.64	0.41	0.51	0.22	0.35	1.30	0.52	0.40	0.65	0.35	0.81	1.12	N	0.08	N	5.87	**Y**	-2.14	N
	AA	-0.99	-0.13	0.32	0.57	0.36	0.51	0.27	0.40	1.30	0.44	0.40	0.65	0.37	0.81	-0.08	N	0.54	N	3.81	**Y**	-1.68	N
	A	-0.95	-0.04	0.32	0.48	0.48	0.51	0.19	0.29	1.32	0.09	0.07	0.66	0.22	0.81	4.34	**Y**	1.20	N	4.28	**Y**	-0.55	N
	BBB	0.98	0.20	0.32	0.39	0.43	0.49	0.10	0.14	1.30	-0.07	-0.06	0.66	0.12	0.81	5.08	**Y**	0.43	N	4.26	**Y**	-0.22	N
	BBB-	0.98	0.28	0.33	0.37	0.42	0.50	0.15	0.21	1.31	0.03	0.02	0.65	0.16	0.81	4.23	**Y**	0.84	N	3.32	**Y**	-0.16	N
UK	AAA	-0.50	-0.01	0.40	0.52	0.31	0.54	0.19	0.30	1.06	0.55	0.43	0.63	0.33	0.74	-0.30	N	-0.51	N	3.41	**Y**	-2.37	N
	AA	0.63	0.01	0.41	0.56	0.36	0.54	0.23	0.33	1.07	0.46	0.41	0.63	0.35	0.74	0.16	N	-0.33	N	3.95	**Y**	-2.04	N
	A	1.00	0.17	0.40	0.36	0.36	0.53	0.18	0.28	1.08	0.09	0.07	0.63	0.22	0.74	2.31	**Y**	1.11	N	2.34	**Y**	-0.54	N
	BBB	0.99	0.34	0.40	0.30	0.34	0.52	0.09	0.12	1.07	-0.03	-0.02	0.63	0.13	0.74	3.36	**Y**	-0.13	N	2.67	**Y**	-0.65	N
	BBB-	0.99	0.36	0.40	0.24	0.29	0.52	0.12	0.17	1.08	0.06	0.05	0.63	0.16	0.74	1.98	**Y**	0.23	N	1.32	N	-0.56	N
France	AAA	-0.66	-0.01	0.43	0.47	0.27	0.48	0.21	0.33	1.06	0.57	0.44	0.74	0.34	0.78	-1.15	N	-0.23	N	2.29	**Y**	-2.31	N
	AA	0.94	0.04	0.43	0.53	0.33	0.48	0.23	0.34	1.06	0.47	0.42	0.74	0.36	0.78	-0.45	N	-0.31	N	3.24	**Y**	-2.17	N
	A	0.99	0.12	0.43	0.32	0.32	0.47	0.19	0.29	1.07	0.11	0.09	0.74	0.21	0.78	1.69	**Y**	1.40	N	1.78	**Y**	-0.37	N
	BBB	0.99	0.33	0.43	0.27	0.31	0.47	0.10	0.14	1.06	-0.06	-0.04	0.74	0.11	0.78	2.97	**Y**	0.45	N	2.37	**Y**	-0.19	N
	BBB-	0.99	0.35	0.43	0.24	0.27	0.47	0.13	0.19	1.07	0.10	0.07	0.74	0.16	0.78	1.81	**Y**	0.51	N	1.20	N	-0.38	N
Germany	AAA	-0.19	0.00	0.42	0.46	0.26	0.46	0.19	0.31	1.06	0.55	0.43	0.70	0.32	0.75	-0.94	N	-0.17	N	2.46	**Y**	-2.16	N
	AA	-0.46	-0.01	0.42	0.50	0.30	0.46	0.22	0.33	1.06	0.44	0.40	0.70	0.33	0.75	-0.47	N	-0.08	N	2.96	**Y**	-1.90	N
	A	0.99	0.10	0.42	0.36	0.36	0.45	0.16	0.24	1.08	0.14	0.11	0.70	0.19	0.76	2.68	**Y**	0.99	N	2.77	**Y**	-0.48	N
	BBB	0.99	0.31	0.42	0.32	0.36	0.45	0.11	0.16	1.07	-0.03	-0.02	0.70	0.12	0.76	3.76	**Y**	0.60	N	3.01	**Y**	-0.13	N
	BBB-	0.99	0.36	0.42	0.32	0.37	0.45	0.14	0.20	1.08	0.06	0.04	0.70	0.15	0.76	3.44	**Y**	0.81	N	2.61	**Y**	-0.13	N
Japan	AAA	0.87	0.02	0.58	0.15	0.08	0.60	0.18	0.29	1.23	0.28	0.20	0.62	0.22	0.81	-2.12	N	1.24	N	-1.10	N	-0.66	N
	AA	1.00	0.26	0.60	0.11	0.06	0.60	0.18	0.27	1.22	0.21	0.18	0.61	0.21	0.80	-2.21	N	1.07	N	-1.46	N	-0.48	N
	A	1.00	0.15	0.59	0.04	0.04	0.59	0.15	0.24	1.23	0.13	0.10	0.62	0.17	0.81	-1.96	N	1.10	N	-1.94	N	-0.33	N
	BBB	0.96	0.14	0.58	0.04	0.04	0.58	0.04	0.06	1.23	-0.05	-0.04	0.62	0.06	0.81	-0.22	N	-0.02	N	-0.30	N	-0.28	N
	BBB-	0.94	0.16	0.58	0.04	0.05	0.59	0.11	0.15	1.24	-0.03	-0.02	0.62	0.10	0.81	-0.84	N	0.75	N	-0.93	N	0.04	N

Table 4.31: Subprime and global crises - conditional and unconditional correlation coefficients on the international financial equity markets

This table reports the conditional correlation coefficients, standard deviations, unconditional (adjusted for heteroscedasticity following Forbes and Rigobon (2002) as shown in Equation 4.8) correlation coefficients between each G5 international financial equity market and the US structured market (measured by the ABX indices) of the full sample and the crisis subperiods. All the correlation coefficients have been transformed using Fisher transformation as shown in Equation 4.13 and the standard deviations have been transformed using Equation 4.14. This table reports the statistics of the two-sample t-tests (one-sided tests, as shown in Equation 4.15) of the conditional and unconditional correlation coefficients between the full sample and the crisis subperiods respectively. The 'Y' in the columns with header 'Contagion' report the presence of contagion when the test statistics are larger than the critical values and 'N' otherwise (for the absence of contagion). ρ_{adj}, ρ_{con} and σ refer to the (heteroskedasticity-adjusted) unconditional correlation coefficients, conditional correlation coefficients, and the standard deviations of the international markets, respectively.

Financial equity markets		**Pre-crisis**			**Subprime**			**Global**			**Post-crisis**			**Full**		**Full vs Subprime (C)**		**Full vs Global (C)**		**Full vs Subprime (Adj.)**		**Full vs Global (Adj.)**	
Country	ABX	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	σ_{uncon}	t-stat	Contagion	t-stat	Contagion	t-stat	Contagion	t-stat	Contagion
US	AAA	-0.99	-0.10	0.35	0.67	0.43	0.68	0.20	0.32	2.21	0.55	0.43	0.88	0.34	1.27	1.62	N	-0.19	N	6.65	**Y**	-2.27	N
	AA	-0.99	-0.12	0.35	0.54	0.34	0.68	0.24	0.35	2.20	0.48	0.43	0.88	0.34	1.27	-0.10	N	0.12	N	3.63	**Y**	-1.85	N
	A	-0.38	-0.01	0.35	0.52	0.52	0.69	0.17	0.26	2.23	0.12	0.09	0.88	0.22	1.28	5.09	**Y**	0.72	N	5.06	**Y**	-0.84	N
	BBB	0.98	0.19	0.35	0.42	0.47	0.67	0.11	0.15	2.19	-0.10	-0.08	0.88	0.12	1.27	5.62	**Y**	0.53	N	4.78	**Y**	-0.18	N
	BBB-	0.98	0.28	0.35	0.38	0.43	0.68	0.14	0.20	2.21	0.04	0.03	0.88	0.16	1.27	4.45	**Y**	0.68	N	3.54	**Y**	-0.27	N
UK	AAA	-0.26	0.00	0.44	0.52	0.31	0.68	0.16	0.25	1.67	0.56	0.43	0.82	0.30	1.06	0.14	N	-0.90	N	3.90	**Y**	-2.47	N
	AA	0.99	0.09	0.45	0.57	0.37	0.69	0.17	0.24	1.67	0.47	0.43	0.82	0.31	1.06	0.95	N	-1.20	N	4.83	**Y**	-2.44	N
	A	1.00	0.20	0.44	0.40	0.40	0.67	0.16	0.25	1.68	0.12	0.09	0.82	0.21	1.06	3.07	**Y**	0.69	N	3.05	**Y**	-0.79	N
	BBB	0.99	0.37	0.44	0.34	0.39	0.66	0.09	0.12	1.67	-0.04	-0.03	0.82	0.12	1.06	4.19	**Y**	-0.08	N	3.37	**Y**	-0.61	N
	BBB-	0.99	0.38	0.44	0.30	0.35	0.66	0.10	0.14	1.68	0.07	0.05	0.82	0.15	1.07	3.13	**Y**	-0.10	N	2.30	**Y**	-0.74	N
France	AAA	0.57	0.01	0.53	0.60	0.36	0.69	0.20	0.32	1.62	0.56	0.43	1.11	0.34	1.16	0.39	N	-0.35	N	4.97	**Y**	-2.39	N
	AA	0.97	0.05	0.53	0.62	0.40	0.69	0.21	0.31	1.63	0.45	0.41	1.11	0.34	1.16	1.00	N	-0.57	N	5.42	**Y**	-2.28	N
	A	0.99	0.13	0.53	0.43	0.43	0.68	0.18	0.28	1.64	0.11	0.09	1.11	0.22	1.16	3.45	**Y**	1.12	N	3.54	**Y**	-0.58	N
	BBB	0.99	0.34	0.53	0.36	0.40	0.67	0.11	0.15	1.63	-0.07	-0.05	1.11	0.12	1.16	4.45	**Y**	0.45	N	3.64	**Y**	-0.23	N
	BBB-	0.99	0.35	0.53	0.31	0.36	0.66	0.13	0.18	1.64	0.11	0.08	1.11	0.16	1.16	3.24	**Y**	0.37	N	2.42	**Y**	-0.47	N
Germany	AAA	0.59	0.01	0.46	0.53	0.31	0.50	0.20	0.33	1.26	0.55	0.43	0.81	0.34	0.88	-0.51	N	-0.35	N	3.45	**Y**	-2.43	N
	AA	0.87	0.02	0.46	0.55	0.34	0.49	0.22	0.33	1.26	0.45	0.41	0.81	0.34	0.87	-0.04	N	-0.34	N	3.78	**Y**	-2.13	N
	A	0.99	0.13	0.45	0.43	0.43	0.49	0.17	0.27	1.27	0.13	0.10	0.81	0.21	0.88	3.61	**Y**	1.08	N	3.68	**Y**	-0.55	N
	BBB	0.99	0.33	0.46	0.34	0.39	0.49	0.12	0.17	1.27	-0.03	-0.02	0.81	0.13	0.88	4.05	**Y**	0.52	N	3.26	**Y**	-0.22	N
	BBB-	0.99	0.38	0.46	0.33	0.38	0.49	0.13	0.18	1.27	0.09	0.07	0.81	0.15	0.88	3.64	**Y**	0.48	N	2.77	**Y**	-0.40	N
Japan	AAA	0.94	0.04	0.75	0.10	0.05	0.81	0.19	0.31	1.62	0.24	0.17	0.72	0.23	1.05	-2.70	N	1.27	N	-2.02	N	-0.72	N
	AA	1.00	0.26	0.77	0.07	0.04	0.80	0.19	0.29	1.61	0.18	0.16	0.72	0.21	1.05	-2.58	N	1.27	N	-2.11	N	-0.35	N
	A	1.00	0.17	0.76	0.01	0.01	0.81	0.16	0.25	1.62	0.10	0.08	0.73	0.18	1.05	-2.50	N	1.25	N	-2.49	N	-0.28	N
	BBB	0.96	0.16	0.75	0.04	0.04	0.79	0.05	0.06	1.62	-0.05	-0.04	0.73	0.07	1.05	-0.36	N	-0.06	N	-0.43	N	-0.34	N
	BBB-	0.93	0.16	0.75	0.00	0.00	0.81	0.10	0.14	1.63	-0.04	-0.03	0.73	0.10	1.06	-1.44	N	0.70	N	-1.45	N	0.02	N

Table 4.32: Subprime and global crises - conditional and unconditional correlation coefficients on the international government bond markets

This table reports the conditional correlation coefficients, standard deviations, unconditional (adjusted for heteroscedasticity following Forbes and Rigobon (2002) as shown in Equation 4.8) correlation coefficients between each G5 international government bond market and the US structured market (measured by the ABX indices) of the full sample and the crisis subperiods. All the correlation coefficients have been transformed using Fisher transformation as shown in Equation 4.13 and the standard deviations have been transformed using Equation 4.14. Reported are the statistics of the two-sample t-tests (one-sided tests, as shown in Equation 4.15) of the conditional and unconditional correlation coefficients between the full sample and the crisis subperiods, respectively. The 'Y' in the columns with header 'Contagion' report the presence of contagion when the test statistics are larger than the critical values and 'N' otherwise (for the absence of contagion). ρ_{adj}, ρ_{con} and σ refer to the (heteroskedasticity-adjusted) unconditional correlation coefficients, conditional correlation coefficients, and the standard deviations of the international markets, respectively.

Government bond markets		**Pre-crisis**			**Subprime**			**Global**			**Post-crisis**			**Full**		**Full vs Subprime (C)**		**Full vs Global (C)**		**Full vs Subprime (Adj.)**		**Full vs Global (Adj.)**	
Country	ABX	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	ρ_{con}	σ	ρ_{adj}	σ_{uncon}	t-stat	Contagion	t-stat	Contagion	t-stat	Contagion	t-stat	Contagion
US	AAA	-0.70	-0.01	0.15	-0.46	-0.26	0.21	-0.16	-0.26	0.39	-0.29	-0.21	0.29	-0.23	0.30	-0.52	N	-0.52	N	-3.74	N	1.17	N
	AA	0.39	0.01	0.15	-0.46	-0.28	0.20	-0.21	-0.31	0.40	-0.25	-0.22	0.29	-0.24	0.30	-0.64	N	-1.19	N	-3.73	N	0.54	N
	A	0.39	0.01	0.15	-0.35	-0.35	0.20	-0.15	-0.24	0.40	-0.07	-0.05	0.29	-0.16	0.30	-2.91	N	-1.24	N	-2.90	N	0.18	N
	BBB	-0.63	-0.04	0.15	-0.28	-0.32	0.20	-0.08	-0.11	0.40	0.09	0.07	0.29	-0.07	0.30	-3.74	N	-0.53	N	-3.10	N	-0.06	N
	BBB-	0.58	0.05	0.15	-0.29	-0.34	0.20	-0.13	-0.19	0.40	0.00	0.00	0.29	-0.13	0.30	-3.22	N	-0.98	N	-2.49	N	-0.08	N
UK	AAA	-0.22	0.00	0.13	-0.45	-0.26	0.14	-0.12	-0.20	0.29	-0.27	-0.19	0.22	-0.21	0.23	-0.77	N	0.10	N	-3.95	N	1.35	N
	AA	-0.60	-0.01	0.13	-0.43	-0.26	0.14	-0.16	-0.23	0.29	-0.21	-0.19	0.22	-0.21	0.23	-0.78	N	-0.41	N	-3.58	N	0.81	N
	A	-0.99	-0.14	0.13	-0.24	-0.25	0.14	-0.12	-0.19	0.29	-0.05	-0.04	0.23	-0.12	0.23	-1.87	N	-1.14	N	-1.85	N	-0.02	N
	BBB	-0.57	-0.03	0.13	-0.19	-0.22	0.14	-0.10	-0.13	0.29	0.04	0.03	0.22	-0.08	0.23	-2.09	N	-0.86	N	-1.62	N	-0.30	N
	BBB-	0.17	0.01	0.13	-0.21	-0.25	0.14	-0.08	-0.12	0.29	0.03	0.02	0.23	-0.07	0.23	-2.72	N	-0.84	N	-2.14	N	-0.31	N
France	AAA	0.96	0.05	0.13	-0.43	-0.24	0.14	-0.10	-0.17	0.24	-0.17	-0.12	0.20	-0.15	0.20	-1.45	N	-0.32	N	-4.57	N	0.75	N
	AA	-0.67	-0.01	0.13	-0.42	-0.25	0.13	-0.15	-0.22	0.24	-0.13	-0.12	0.20	-0.17	0.20	-1.25	N	-0.95	N	-4.06	N	0.29	N
	A	-0.99	-0.13	0.13	-0.26	-0.25	0.13	-0.10	-0.15	0.24	0.00	0.00	0.20	-0.09	0.20	-2.46	N	-0.98	N	-2.51	N	-0.07	N
	BBB	-0.64	-0.04	0.13	-0.20	-0.23	0.13	-0.06	-0.09	0.24	0.00	0.00	0.20	-0.07	0.20	-2.44	N	-0.31	N	-1.98	N	0.09	N
	BBB-	-0.17	-0.01	0.13	-0.20	-0.23	0.13	-0.07	-0.11	0.24	-0.06	-0.04	0.20	-0.09	0.20	-2.09	N	-0.26	N	-1.61	N	0.24	N
Germany	AAA	0.95	0.04	0.13	-0.43	-0.24	0.14	-0.11	-0.19	0.25	-0.35	-0.25	0.20	-0.21	0.21	-0.50	N	0.36	N	-3.57	N	1.54	N
	AA	-0.94	-0.04	0.13	-0.42	-0.25	0.14	-0.16	-0.24	0.25	-0.27	-0.24	0.20	-0.23	0.20	-0.23	N	-0.20	N	-3.02	N	1.15	N
	A	-0.99	-0.14	0.13	-0.26	-0.25	0.14	-0.11	-0.18	0.25	-0.07	-0.05	0.20	-0.12	0.21	-1.97	N	-0.94	N	-2.02	N	0.16	N
	BBB	-0.83	-0.06	0.13	-0.20	-0.23	0.14	-0.06	-0.08	0.25	0.00	0.00	0.20	-0.07	0.20	-2.43	N	-0.16	N	-1.97	N	0.19	N
	BBB-	-0.44	-0.03	0.13	-0.18	-0.21	0.13	-0.06	-0.08	0.25	-0.01	-0.01	0.21	-0.06	0.21	-2.25	N	-0.33	N	-1.79	N	0.07	N
Japan	AAA	-0.43	-0.01	0.13	0.02	0.01	0.12	-0.03	-0.05	0.14	-0.13	-0.09	0.10	-0.04	0.12	0.71	N	-0.16	N	0.88	N	0.13	N
	AA	-0.61	-0.01	0.13	-0.01	0.00	0.12	-0.01	-0.02	0.14	-0.09	-0.08	0.10	-0.03	0.12	0.44	N	0.21	N	0.39	N	0.33	N
	A	-0.69	-0.01	0.13	0.04	0.04	0.12	-0.02	-0.02	0.14	-0.08	-0.06	0.10	-0.02	0.12	0.84	N	-0.08	N	0.84	N	0.06	N
	BBB	-0.75	-0.05	0.13	0.00	0.01	0.12	-0.03	-0.04	0.14	-0.04	-0.03	0.10	-0.03	0.12	0.53	N	-0.12	N	0.52	N	0.06	N
	BBB-	-0.87	-0.11	0.13	0.00	0.00	0.12	-0.04	-0.06	0.14	0.05	0.04	0.10	-0.02	0.12	0.35	N	-0.64	N	0.34	N	-0.35	N

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Chapter 5

Firm-Level Contagion: An Asset Pricing Perspective

5.1 Introduction

Financial contagion is a term that is used to describe any sudden transmission of shocks that are unexplained by fundamentals[25], which has received considerable attention among researchers and regulators. This is somewhat unsurprising given the frequency of crises in recent years. The vast majority of studies in the contagion literature follow similar research designs; that is, to first empirically detect contagion and then to examine the dynamics of contagion transmission. An important strand of the literature is filled with studies that seek to identify significant increases in market comovements between international asset markets (for correlation breakdown analysis see, for example, Baig and Goldfajn, 1999; Corsetti et al., 2001; Forbes and Rigobon, 2002; for factor models of contagion, see Boyer et al., 1999; Corsetti et al., 2005; and Dungey et al., 2005). While the majority of studies focus on the role of international markets in contagion and use aggregate market indices as units of analysis, empirical investigation into the impact of contagion on individual stocks and industry sectors has been relatively sparse in comparison to studies that analyse contagion at a macro level. To fill this gap, I use firm-level information and examine the impact of contagion on the US equity market at the individual stock and industry sector levels during the recent crisis. I

[25] This definition of contagion has been assumed in a number of studies. For studies that define contagion as 'excess comovements' see, for example, Eichengreen et al. (1996), Dornbusch et al. (2000), Forbes and Rigbon (2002), Kaminsky et al. (2003), etc.; for studies that focus on the role of fundamentals (e.g. trade linkages), see Kaminsky and Reinhart (2000); for a detailed review of contagion definitions and methodologies, see Pericoli and Sbracia (2003) and Dungey et al. (2005).

will then identify the major determinants of individual stock's exposure to the crisis-related risks associated with the US structured finance market.

Empirical analysis at firm-level is important for at least three reasons. First, it provides practical implications to investment management, especially to investors who invest primarily in domestic markets. The objectives of this chapter are to first test for the presence of contagion in the US equity market at the aggregate and industry sector levels, and then to identify the determinants of individual stock's exposure to the crisis-related risk. The identification of individual stocks that are vulnerable to the idiosyncratic shocks from the US structured finance market during the recent crisis is key to understanding investment performance and managing risk exposure during a period of market distress. Second, this chapter reveals the time variation of crisis-related risk in relation to the variation in the structured finance market, and it then examines the determinants of its time variation using three widely-acknowledged contagion variables relating to the market wide funding illiquidity and credit risks. Third, my empirical analysis facilitates comparison on the model performance of various asset pricing models and tests whether the contagion-related risk factors (the ABX factors) explain the cross-section of expected returns.

Longstaff (2010) examines contagion as it travelled from the US subprime residential RMBS market (tracked by the ABX indices) to a few major US domestic financial markets during the subprime crisis and identifies significant predictive ability in the ABX indices for the US equity, treasuries and corporate bond markets. He interprets this predictability as evidence of contagion travelling from the US structured finance market to the domestic markets. In Chapter 4, as an extension to Longstaff's (2010) investigation, I studied contagion within an international market perspective and at a higher data frequency, and document strong evidence of contagion travelling from the US structured finance market to the US equity market, and to a number of international markets. The recent 2007 to 2009 financial crisis represents a good opportunity or, as Longstaff (2010) described, 'a near-laboratory setting', for contagion research because of its clear-cut origin of shocks. One of the first shocked markets during the subprime crisis was the subprime residential mortgage market, which is characterised by its relatively small, niche and isolated nature from other major US financial markets. Contrary to the expectation that a failure in such a small and isolated market should not have massive repercussions when the crisis unfolded, a number of financial markets collapsed and the crisis later evolved into a global context characterised by severe market and funding illiquidity in late 2008. I include a sample period that covers the recent financial crisis and seek to examine the effects of contagion, specifically travelling from the US structured finance market to the US equity market. I will use the available US stock information from the Center for Research in Security Prices (CRSP) database.

In the first part of this chapter, I follow Bekaert et al. (2011) and use a multifactor asset pricing model to test for contagion in the US equity market using all available stocks from the three major US exchanges, notably: the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ Stock Market (NASDAQ). More concretely, I construct monthly innovations for the ABX indices that are orthogonal to the excess returns of the market index and include the ABX innovations as pricing factors in the model. To identify any significant increases in cross-market linkages between the structured finance market and the US equity market, I include crisis dummy variables. Through their interaction with the market and ABX factors, any significant increases in the ABX factor loadings can be reasonably interpreted as evidence of contagion. Practically, I estimate pooled regressions with standard errors clustered by industry SIC and report test diagnostics of the residual's cross-sectional dependence as measures of model fit. To study whether industry effects were dominant in my findings, I estimate industry subsample contagion models based on the 12-industry classification codes obtained from Kenneth R. French's web site.[26] In addition, I shed light on the validity of the funding liquidity and credit risk contagion transmission channel (see Chapter 3 and Chapter 4). I also interact the contagion-related instruments, which measure the levels of market wide credit, market and funding illiquidity risks in the US financial system, with the market and ABX factors in the pricing models. As a preview to the results, I find significant increases in the ABX AAA factor loadings during the subprime crisis and significantly lower ABX factor loadings during the subsequent global crisis, consistent with contagion documented by Longstaff (2010). The ABX AAA factor loadings were highly significant in both the full and industry subsample models, lending support to the conjecture that the ABX AAA index was an important source of risk during the crisis and is relevant to asset valuation. The market systematic risks are consistently lower during the subprime and global financial crisis subperiods relative to the pre-crisis subperiod in all 12 industries, except for utilities stocks. My evidence shows that the spillovers of shocks from the ABX AAA index were considerably systematic

[26]The Kenneth R. French's data library can be accessed via: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.h

and there were no apparent dominating industry effects. In addition, the contagion models with instruments show that the changes in market betas are associated with changes in TED spreads and the Moody's corporate bond yield spreads. A significant and positive relation between the changes in ABCP yield spreads and the ABX factor loadings has been identified during the crisis. In other words, I present strong evidence that the ABX factor loadings increased when funding illiquidity became more severe, which is consistent with contagion being transmitted via the funding liquidity channel (see Longstaff, 2010; and Chapter 4 of this thesis).

I will then proceed to test whether the ABX factor explains the cross-section of expected returns over the period between February 2006 and December 2011. Using a two-pass regression framework and the Generalised Least Squares (GLS) approach on the 25 Fama-French (1993) size and book-to-market ratios sorted portfolios (daily data frequency), I find that the Carhart (1997) four-factor model augmented with the orthogonalised ABX AAA factor holds with insignificant pricing errors statistics during the subprime crisis subperiod.[27] I show empirically that the spillovers of shocks from the structured finance market were systematically priced, lending support to the conjecture by Fender and Scheicher (2009) that pricing models which do not account for the market illiquidity risks and increases in risk aversion as reflected in the declining ABX prices are inappropriate.

After contagion has been identified, I reveal how the US equity market's risk exposure to the ABX indices evolved over time and will shed light on the major drivers that determined the degree of risk exposure. To gauge the degree of the individual stock's sensitivity to the ABX innovations, I estimate the Carhart (1997) four-factor model augmented with an orthogonalised ABX factor at the end of each month to obtain monthly factor loadings of each individual stock in the US Exchanges. Based on the monthly factor loadings, I create a simple statistic that measures the aggregate equity markets' exposure to the variations of the ABX indices in each month, denoted as $\kappa_{ABX,t}$. This is achieved by computing the proportion of stocks with statistically significant ABX factor loadings to the total number of available individual stocks in my sample at the end of each month. The statistical significance is determined at a threshold level of 5%.[28] The main intuition behind this statistic is that when contagion occurs, the increases in cross-market linkages between the structured finance market and the equity market shall be reflected by a larger proportion of

[27] The Carhart (1997) four-factor model refers to the Fama-French (1993) three-factor model with the addition of the momentum factor.

[28] The findings associated with a 10% significance level are qualitatively similar (untabulated).

stocks with significant ABX factor loadings. I analyse graphically and observe substantial time-variations in the $\kappa_{ABX,t}$ with occasional positive spikes during the subprime and global financial crises. The Granger-causality tests show that the exposure to the ABX AAA index was driven by average market illiquidity, LIBOR-OIS yield spreads (funding illiquidity) and value-weighted average idiosyncratic volatilities, again lending support to contagion transmission via changes in risk premia and funding illiquidity. Overall, the evidence provides additional support to the viewpoint that the ABX AAA index was an important barometer of risk during the crisis, which was closely related to market wide average illiquidity and idiosyncratic risks, this is consistent with Fender and Scheicher (2009).

In the last part of this chapter, I will investigate the determinants of the individual stock's exposure to the ABX innovations using sets of logistic, multinomial logistic and multivariate OLS regressions at the end of each crisis subperiod. My findings show that higher idiosyncratic volatilities and lower standard deviations are associated with higher levels of the stock's exposure to the ABX AAA and AA innovations while for the lower-rated ABX indices my findings are significant but with opposite signs. More importantly, a positive relation has been documented between the market betas and the ABX factor loadings at a firm level, which is robust to both cross-sectional and fixed effects panel regressions. In addition, a higher log turnover and book-to-market ratios are positively related to the exposure to the ABX innovations. However, I find little evidence of explanatory power in the firm-specific fundamental variables over the exposure to the ABX innovations, which is consistent with the definition that contagious effects were unexplained by the firm's fundamentals.

This chapter is structured as follows: Section 2 discusses the motivation of this chapter; Section 3 investigates contagion travelling from the structured finance market to the US equity market within an asset pricing framework using all stock data; Section 4 tests whether the crisis-related risk factor explains the cross-section of expected returns in the US; Section 5 presents an empirical investigation of the time variation of the crisis-related systematic risk; Section 6 examines the determinants of individual stocks' exposure to the crisis-related systematic risk; and, Section 7 concludes this chapter.

5.2 Motivation

Over the past decade, the US structured finance market has expanded rapidly and has become one of the largest fixed income markets in the US (see Weaver, 2008; and Chapter 2 of this thesis). Attracted by the relatively higher profitability, subprime mortgage-related ABSs (e.g. RMBSs and CDOs) were particularly popular among institutional investors and fund managers as tools for hedging and for risk management purposes. Structured securities were usually held in off-balance sheet SPVs or SIVs and were financed by the issuance of short-term ABCP (for more details on SIVs, see Eichengreen, 2008). When the subprime crisis unfolded, these opaque and complex structured finance securities (including the highest-rated CDO tranches) suffered severe losses and downgrades as the values of the underlying collateral (i.e. the pools of mortgage loan assets) withered amidst the increasing waves of mortgage delinquencies (for more details on tranche securitisation in CDOs, see Benmelech and Dlugosz, 2009). The buy-side of the structured markets almost disappeared and the price discovery was seriously impaired. Meanwhile, facing higher insolvency risks and higher risk aversion, nervous investors were unwilling to roll over their ABCPs resulting in a sudden disruption of funding supply and further declines in the structured finance market. A number of financial institutions revealed substantial losses in their subprime mortgage businesses and they also revealed their significant exposure to the subprime ABS-CDOs. As of February 2009, the total value of write downs in relation to the ABS-CDOs totalled $218 billion in financial institutions worldwide (Benmelech and Dlugosz, 2009). Since a number of these institutions have cross-market functionality and are of significant size in general, a number of international markets were essentially vulnerable to the spillovers of shocks from the US structured finance market.

Introduced in January 2006, the family of ABX indices (in which each ABX index tracks the performance of 20 RMBS deals) became an important type of stress indicator among investors during the subprime crisis. In Chapter 4, I have documented significant short-lived spillovers of shocks travelling from the ABX indices to a few international markets, which is consistent with shock transmission via the arrival of information. Longstaff (2010) finds that the declines in the ABX indices translated into larger trading intensity in the US financial sector relative to the broad equity market. The evidence suggests that investors might have based their investment decisions on the past information of the ABX indices and flew from the troubled financial sectors to safer assets. The significant increases in cross-market linkages documented between the US structured finance and stock markets suggest that the structured finance market represented a source of significant risk. Despite the increasing importance of the US structured finance market over recent years, to my knowledge, there is as yet no comprehensive study that investigates how the macroeconomic risk exposure to the structured finance market impacts on expected stock returns. I will fill this gap by testing contagion in the US equity market using firm-level information within an asset pricing framework.

This chapter makes a number of contributions to both the financial contagion and asset pricing literature. First, most empirical contagion studies focus on the role of international markets in contagion and in general test for significant increases in market comovements. These studies relate the transmission of shocks with investors' irrational behaviour (e.g. investors' herding) and with fundamental causes (e.g. trade linkages). They also provide implications to the effectiveness of international diversification during a crisis. However, relatively few empirical studies have examined the impact of the spillovers of shocks on individual stocks and industry sectors in the context of contagion. This chapter tests, empirically, whether: i) there is evidence of contagion in the US stock market from the US structured finance market; ii) the crisis-related risk interacts with a few credit risk, market and funding illiquidity contagion variables consistent with the contagion transmission via changes in risk premia and liquidity; iii) the ABX factors explain the cross-section of expected returns in the US stock market during the crisis; iv) the degree of exposure to the ABX innovations changes over time; and, v) there are firm-level factors that significantly determined the individual stocks' exposure to ABX innovations.

5.3 Contagion analysis using firm-level information - empirical framework

In the spirit of Bekaert et al. (2011), I formulate a two-factor asset pricing model that includes both a market risk factor and a structured finance market related ABX risk factor.[29] The former is the excess monthly returns of the valued-weighted market index obtained from French's web site while

[29]My approach differs from Bekaert et al. (2011) in that I examine contagion from the US structured finance market to the US equity market while they look for contagious effects across the international equity markets. Hence, in contrast to their uses of international equity portfolios as units of analysis, I study the monthly returns of all the available individual stocks from the three major US Exchanges. Note also that my model uses monthly data while weekly data has been used in Bekaert et al. (2011).

the latter is the orthogonalised monthly ABX innovations.[30] Five sets of results are reported and discussed, corresponding to the findings based on the ABX AAA, AA, A, BBB and BBB- factors. The two-factor pricing model is written as follows:

$$R_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_t'}\mathbf{F_t} + \gamma_{i,0}Subp_t + \eta_{i,0}Global_t + \varepsilon_{i,t}, \tag{5.1}$$

$$\boldsymbol{\beta_t} = \boldsymbol{\beta_0} + \boldsymbol{\phi_1}\mathbf{Z_t} + \boldsymbol{\xi_t}Subp_t + \boldsymbol{\zeta_t}Global_t, \tag{5.2}$$

$$\boldsymbol{\xi_t} = \boldsymbol{\xi_0} + \boldsymbol{\xi_1}\mathbf{Z_t}, \tag{5.3}$$

$$\boldsymbol{\zeta_t} = \boldsymbol{\zeta_0} + \boldsymbol{\zeta_1}\mathbf{Z_t}, \tag{5.4}$$

where $R_{i,t}$ is the excess returns of stock i in month t and $\mathbf{F_t}$ is an 2×1 vector of excess returns of the market index and the ABX indices. $Subp_t$ and $Global_t$ are crisis dummy variables with unity denoting the subprime crisis and global financial crisis subperiods, respectively, and zero otherwise. $\mathbf{Z_t}$ is an 3×1 vector of instruments of contagion variables related to the level of credit and illiquidity risks in the US financial system. The $\boldsymbol{\beta_t}$ is an 2×1 vector of time varying factor loadings (containing $\beta_{MKT,t}$ and $\beta_{ABX,t}$). The $\boldsymbol{\phi_1}$ is an 2×3 matrix of coefficients on the scaled instruments, the $\boldsymbol{\xi_1}$ and $\boldsymbol{\zeta_1}$ are 2×3 matrices of coefficients on the factor loadings scaled by the subprime crisis and global crisis dummy variables, respectively. The full sample period is January 2006 to December 2011, with the subprime crisis subperiod covering all months in 2007 and the global crisis subperiod covering the period January 2008 to March 2009 (see Section 2.5). Practically, I estimate the asset pricing models using pooled regressions in which the robust standard errors are clustered by industry SIC.[31]

5.3.1 Interdependence and contagion

Consistent with the working definition of Forbes and Rigobon (2002), contagion is defined as significant increases in market comovement after interdependence has been accounted for. To account for the interdependence between the US structured and equity market, for each set of

[30]The orthogonalised ABX factor is obtained by regressing the monthly excess returns of each ABX index on the excess returns of the value-weighted market index over the full sample period. The series of regression residuals is then included in the asset pricing model as the ABX risk factor. The orthogonalisation mitigates the potential problem of multicollinearity between the excess returns of the market and ABX indices during the crisis, and allows me to interpret the ABX factors as the portions of variation in the ABX index returns unexplained by the market index or as shocks to the ABX indices unexplained by the market index.

[31]The 12-industry classification code is obtained from French's web site.

empirical tests I first estimate an 'interdependence model', which does not include crisis dummy variables, followed by a 'contagion model', which does. With the inclusion of crisis dummy variables, the contagion model allows changes in the intercepts and factor loadings to account for structural breaks during the crisis. Significant coefficients on the crisis dummy variables suggest that the interdependence model is insufficient in explaining the variations of the dependent variables during the crisis and I expect an improvement in model fit with the inclusion of the crisis dummy variables (see Bekaert et al., 2005; Dungey et al., 2006; and Bekaert et al., 2011).

In my model, γ and η in Equation 5.1 provide a measure of contagion in the equity market, which is unexplained by the market and the ABX factors. Such findings would suggest that investors did not discriminate against the differences between stocks of various characteristics and industries and that there were shift changes in the stock returns during the crisis. This is consistent with investors' herding behaviour and possible systematic 'flights' from risky assets into safer assets.

More importantly, ξ and ζ in Equation 5.2 quantify the changes in the market betas and the ABX factor loadings during the crisis, and allow me to test explicitly for any increases in market linkages between an average stock and the structured finance market during the crisis as evidence of contagion. In addition, I follow Bekaert et al. (2011) and model the ξ and ζ as functions of a few instruments (Z) of contagion variables to evaluate the drivers that underlie the time variation of the comovement measures, and to examine the validity of the risk premia and liquidity transmission channel.

5.3.2 Contagion variables as instruments

In Equation 5.2, I allow the factor loadings to depend on the vector of instruments $\mathbf{Z_t}$ and model them as linear functions of both $\mathbf{Z_t}$ and the crisis dummy variables. In addition, as shown in Equations 5.3 and 5.4, I further interact the crisis dummy variables with the instruments $\mathbf{Z_t}$ to test whether the effects of credit and illiqudity risks on the factor loadings might have changed during the crisis.

I include three contagion variables that are positively related to credit and illiquidity risks in the US markets. The first variable is the TED spread, which is the yield differential between US three-month T-bills and three-month LIBOR, as a proxy for funding illiquidity and the level of stress in the money market. Second, I include Moody's BAA corporate bond yield spread, which is computed by subtracting the 10-year constant maturity Treasury bond yield from Moody's BAA corporate bond yield, as a proxy for the market wide credit risk in the corporate sector. The third variable refers to the ABCP yield spread, which is the yield differential between the one-month ABCP and the one-month T-bill. This reflects the level of funding illiquidity in the money market and also the health of the structured finance markets.[32]

5.3.3 Specification tests

I follow Bekaert et al. (2011) and derive a few specification tests to examine the cross-sectional dependence of the regression residuals. A good model fit of the pooled OLS regression should have residuals with negligible cross-correlations. Since the number of individual stocks are large in my sample, I focus on the excess comovements between residuals at an industry level based on the 12-industry SIC classification.

First, with N_i number of stocks within the i^{th} industry, I compute the average covariance for the i^{th} industry in month t as:

$$ACOV_{i,t} = \frac{2}{N_i(N_i-1)} \sum_{a=1}^{N_i} \sum_{b=a+1}^{N_i} (\varepsilon_{a,i,t} \times \varepsilon_{b,i,t}), \tag{5.5}$$

where $\varepsilon_{a,i,t}$ refers the residual of the a^{th} stock of the i^{th} industry in month t of Equation 5.1. Based on this average covariance measure, I compute the average covariances across the industry at each cross-section, with I denoting the average industry as follows:

$$ACOV_{I,t} = \frac{1}{12} \sum_{i=1}^{12} ACOV_{i,t}. \tag{5.6}$$

The formal test of excess comovement for an average stock can be formulated as a Chi-squared test

[32]Brunnermeier (2009) and Frank et al. (2008) point out that the financial institutions' exposure to the structured securities is often via off-balance sheet entities (e.g. the SIVs), which purchase long maturity structured finance securities or other assets with the issuance of ABCP. During the subprime crisis, the investors were reluctant to roll over the short-term ABCP given the increasing uncertainty with regard to the structured securities' valuation. This resulted in surging funding illiquidity and increasing pressure in banking institutions to absorb these entities onto their balance sheets. The ABCP spreads reflected the level of stress in the structured finance market and the money market.

with one degree of freedom:

$$EXTEST_I = \frac{[\frac{1}{T}\sum_{t=1}^{T} ACOV_{I,t}]^2}{\text{Var}(ACOV_{I,t})}, \tag{5.7}$$

I use 12 lags in computing the Newey-West (1987) variances of $ACOV_{I,t}$ to account for any potential autocorrelation in the monthly covariance measures. The critical value for a Chi-squared test with one degree of freedom is 3.84 (6.63) at the 5% (1%) level. As pointed out by Bekaert et al. (2011), it is possible that a few strong rejections in specific industries (country level, as in Bekaert et al., 2011) might not result in the rejection of the null hypothesis because I average the industry-specific comovement across all industries, therefore, I compute an alternative industry-level comovement measure (that does not average across the industry cross-sectionally) as follows:

$$ICSTAT_I = \sum_{i=1}^{12} \frac{[\frac{1}{T}\sum_{t=1}^{T} ACOV_{i,t}]^2}{\text{Var}(ACOV_{i,t})}, \tag{5.8}$$

where the null is $\chi^2(12)$ with a critical value of 21.03 (26.22) at the 5% (1%) level. I also use 12 lags to calculate the Newey-West (1987) variances to account for possible autocorrelation in the average covariances of each industry.

5.3.4 Data

My sample consists of monthly return data of all available stocks from the three major US Exchanges (i.e. the NYSE, AMEX, and NASDAQ) from the CRSP database accessed via the Wharton Research Data Services (WRDS). The sample spans the period January 2006 to December 2011, and covers the entire subprime and the subsequent global financial crises. The entire sample period is segregated into fmy subperiods, as discussed in Chapter 2: pre-crisis, subprime, global and post-crisis subperiods, based on historical events and market performance. The monthly market risk factor is the excess return series of the US value-weighted market index obtained from French's web site, while the monthly returns of the five ABX indices are obtained from Reuters via its platform 3000 Xtra. I correct for the survivorship bias introduced by stock delisting following Shumway (1997), Amihud (2002), and Acharya and Pedersen (2005).[33] To ensure intuitive interpretation of

[33] In particular, whenever the last and delisting returns for the delisting stock are not available, a return of -30% is assigned if the reason for delisting is coded as 500 (reason unavailable), 520 (went to OTC), 551, 573 and 580 (various reasons), 574 (bankruptcy) and 584 (does not meet exchange financial guidelines) in CRSP.

the factor model, and to mitigate the problem of multicollinearity, the excess returns of the ABX indices are orthogonalised (see Section 5.3).

5.3.5 Empirical findings

Interdependence model

First, I report the findings of the interdependence model in which no crisis dummy variables are included. The model is written as:

$$R_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_0'}\mathbf{F_t} + \varepsilon_{i,t}. \tag{5.9}$$

In this interdependence model specification, the factor loadings are not allowed to change over time and, therefore, the fit of this model provides insight as to whether the time-invariant factor loadings are sufficient to capture the variations in the individual stocks. Table 5.1 reports the factor loadings, t-statistics based on robust standard errors clustered by industry SIC, the adjusted R^2 and the diagnostic tests explained in Section 5.3.3.

Firstly, the market betas are all significantly different from zero and are slightly larger than one across the ABX models. Second, the stock returns were considerably correlated with the ABX innovations, suggesting that the ABX indices represent sources of systematic risk. Both the ABX AAA and AA factor loadings are significant and with positive coefficients, albeit small in magnitude. For an average stock, a one percent negative shock to the ABX AAA (AA) index (i.e. a one percent decrease in the ABX innovations) translates into 0.15% (0.03%) lower returns. On the other hand, the ABX A, BBB and BBB- factor loadings are insignificant despite the higher volatilities and downside variations in the ABX indices. The evidence suggests that the ABX AAA and AA factors are to a larger extent relevant to asset valuation than the lower-rated ABX factors. Third, the diagnostic tests of no excess cross-sectional dependence in the residuals are rejected for all five ABX interdependence models, which is suggestive of model mis-specification.

Contagion model

The contagion model allows the factor loadings and the intercepts to change across crisis subperiods by modelling the factors as functions of the crisis dummy variables, as follows:

$$R_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_t'}\mathbf{F_t} + \gamma_{i,0}Subp_t + \eta_{i,0}Global_t + \varepsilon_{i,t}, \tag{5.10}$$

$$\boldsymbol{\beta_t} = \boldsymbol{\beta_0} + \boldsymbol{\xi_0}Subp_t + \boldsymbol{\zeta_0}Global_t. \tag{5.11}$$

As shown in Table 5.2, the market betas are highly significant and larger than those across the ABX models (β_{MKT} are close to 1.20), which is similar to the results of the interdependence model. The ABX AAA, AA and BBB factor loadings are significantly different from zero and are positive. The evidence shows that the US individual stocks are exposed to the variations of the structured finance market before the crisis.

For the crisis dummy variables, my findings are remarkably similar across the ABX models in that the significant γ in the ABX AA, A and BBB- models are negative while the η in all ABX models are significant and positive. This evidence suggests the existence of structural breaks in the relation between stock returns and the risk factors during the sample period. They also suggest that the interdependence model is insufficient in capturing the true data generating process of the stock returns.

Secondly, ξ_{MKT} is highly significant and negative while ζ_{MKT} is insignificant in all ABX models. The findings show that the amount of market systematic risks among individual stocks has become lower during the subprime crisis and remained largely at the pre-crisis level during the global financial crisis. The lower sensitivity of individual stock's to market performance during the subprime crisis is, perhaps, due to the fact that the impact of the troubled structured finance market was not yet fully reflected by the market.

Thirdly, and more importantly, the ξ_{ABX} ($\xi_{ABX} = 0.710$) and ζ_{ABX} ($\zeta_{ABX} = -0.268$) are highly significant in the ABX AAA model. Effectively, the ABX AAA factor loading is significant and close to one ($\beta_{ABX} = 0.310 + 0.710 = 1.020$) during the subprime crisis and zero ($\beta_{ABX} = 0.310 - 0.268 = 0.042$) during the global crisis phase. My results present strong evidence of significantly higher comovement between the US equity and structured finance markets (especially the AAA-rated segment) and they show that the ABX AAA index represented an important source of systematic risk during the subprime crisis. The model fit has been improved in the ABX AAA contagion model over its counterpart in the interdependence model, as evinced by the noticeably smaller average cross-residual covariances (insignificant ICSTAT statistics).

To summarise, my contagion model results suggest strong evidence of contagion from the structured finance market during the subprime crisis, which is consistent with Longstaff (2010) and my empirical analysis in Chapter 4. More importantly, I show that the highest-rated ABX AAA factor is of great relevance to asset pricing and the inclusion of the crisis dummy variables substantially improve the model fit.

5.3.6 Contagion in US industry sectors

In the following sections, I explore to what extent industry sectors are exposed to the ABX innovations using industry subsamples of stocks and similar asset pricing model specifications. My goal is to reveal how industry stocks might be correlated with the ABX innovations and provide implications to investors in the context of investment management with regard to sector performance and risk exposure during the crisis.

Interdependence model

With the same interdependence model as in Equation 5.9, I estimate the asset pricing models using pooled regressions and industry subsamples, and report the factor loadings, robust t-statistics and adjusted R^2 of the five ABX models in Tables 5.3 - 5.7, respectively.

Similar to the results of the full sample models, all market betas are significantly different from zero in all industries and across the ABX models. The market betas for the utilities (SIC=8) and money (SIC=11) stocks are smaller than one, suggesting lower correlation with the market factor than other stocks while the market betas of the durable goods (SIC=2), manufacturing (SIC=3) and energy (SIC=4) stocks all have noticeably higher market systematic risks.

Next, I focus on the ABX factor loadings of the industry models. First, for the ABX AAA model, I find significantly positive ABX factor loadings in the non-durable (SIC=1), durable (SIC=2), manufacturing (SIC=3), utilities (SIC=8), shops (SIC=9), money (SIC=11) and others (SIC=12) industry sectors. In this time-invariant factor interdependence model, the positive factor loadings suggest that these industry stocks were positively associated with the ABX AAA innovations. In the rest of the ABX models, the ABX factor loadings are significant and positive in the non-durable (SIC=1), shops (SIC=9) and money (SIC=11) stocks and negative in the manufacturing (SIC=3) and energy (SIC=4) stocks. Note that the significant ABX factor loadings in the ABX AAA model for all industries are larger than those in the other ABX models, which is consistent with my findings of more significant results in the ABX AAA contagion model, as documented in Section 5.3.5.

Contagion model

I report the results of the industry contagion models of the five ABX models in Tables 5.8 - 5.12, respectively. Panel A reports the factor loadings, robust standard errors and the adjusted R^2 of the contagion models while Panel B reports the sums of factor loadings with statistical significance based on the F-tests on the sums of factor loadings.

In Panel A, the market betas are all significantly positive across the ABX models, which is consistent with the results of the industry interdependence models. Again, utilities (SIC=8) and money (SIC=11) stocks have lower market betas than other stocks. Next, the ABX AAA factor loadings in almost all industries are significant and positive while for the rest of the ABX models, I find significant ABX factor loadings in the non-durable (SIC=1), energy (SIC=4), business equipment (SIC=6), telecom (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10) and money (SIC=11) stocks. I find evidence that the ABX innovations explain the stock returns during the non-crisis period, more prominently in the highest AAA-rated ABX model.

For the loadings on the crisis dummy variables, similar to the full sample contagion models, I document significantly negative γ values in all industry stocks except the manufacturing (SIC=3), energy (SIC=4) and chemicals (SIC=5) stocks. The stock returns during the subprime crisis for most industry stocks were in general lower as the fundamentals and investment sentiment deteriorated. For the global crisis dummy variable, I find significant and positive η values among business equipment (SIC=6), shops (SIC=9), health care (SIC=10), money (SIC=11), and others (SIC=12) stocks and negative η values among the telecommunications (SIC=7) and utilities (SIC=8) stocks. Panel B reports the effective intercepts and factor loadings when the subprime and global crisis dummy variables take on values of unity. Significant and negative intercepts are identified in the models of the non-durable (SIC=1), durable (SIC=2), business equipment (SIC=6), telecommunication (SIC=7), shops (SIC=9), health care (SIC=10), money (SIC=11) and others (SIC=12) stocks in largely all ABX models during the subprime crisis subperiod. On the other hand, during the global crisis, significant and negative intercepts in the utilities (SIC=8) stocks and positive intercepts in the business equipment (SIC=6), shops (SIC=9), health care (SIC=10), money (SIC=11) and other stocks (SIC=12) are found. The evidence shows that stock returns were consistently lower during the subprime crisis and higher during the global crisis compared to the non-crisis period.

Now, I discuss the effects of the crisis on the market and ABX factor loadings in my industry contagion models. At first glance, the factor loadings ξ and ζ are highly significant among most industry sectors across the ABX models. In particular, the significant ξ_{MKT} and ζ_{MKT} values are in general negative across the ABX models (except for the utilities (SIC=8) and money stocks (SIC=11)) in that the market betas were in general lower during the crisis episodes relative to the pre-crisis window. All significant ξ_{ABX} and ζ_{ABX} values in the ABX AAA models are positive and negative, respectively, while the findings in the remaining fmy ABX models are less significant and are in general mixed. In particular, the ABX AAA factor loadings were significant and larger across all industry sectors during the subprime crisis and were lower during the global financial crisis. Again, the evidence lends support to the conjecture that the ABX AAA index is the most relevant in asset valuation among the ABX indices and represents a formidable source of crisis-related risk during the subprime crisis. In Panel B, during the subprime crisis, most industry stocks have larger market risk factors than those during the global crisis, except for the telecommunication (SIC=7), health care (SIC=10) and others (SIC=12) industry stocks. Moreover, the effective ABX risk factors in the ABX AAA model are significantly different from zero in most industries during the subprime crisis and have become insignificant during the global crisis phase.

5.3.7 With instruments of contagion variables

Interdependence model

So far, my empirical evidence suggests significant contagion travelling from the structured finance market to the US equity market during the subprime crisis. To further examine the contagion transmission mechanisms, three contagion variables are included in the pricing model as instruments and are interacted with the factor loadings. I test explicitly whether the changes in factor loadings are associated with the market wide credit and illiquidity risk variables in the US financial system.

The interdependence model with instruments can be written as:

$$R_{i,t} = \alpha_{i,t} + \boldsymbol{\beta}_t' \mathbf{F_t} + \varepsilon_{i,t}, \tag{5.12}$$

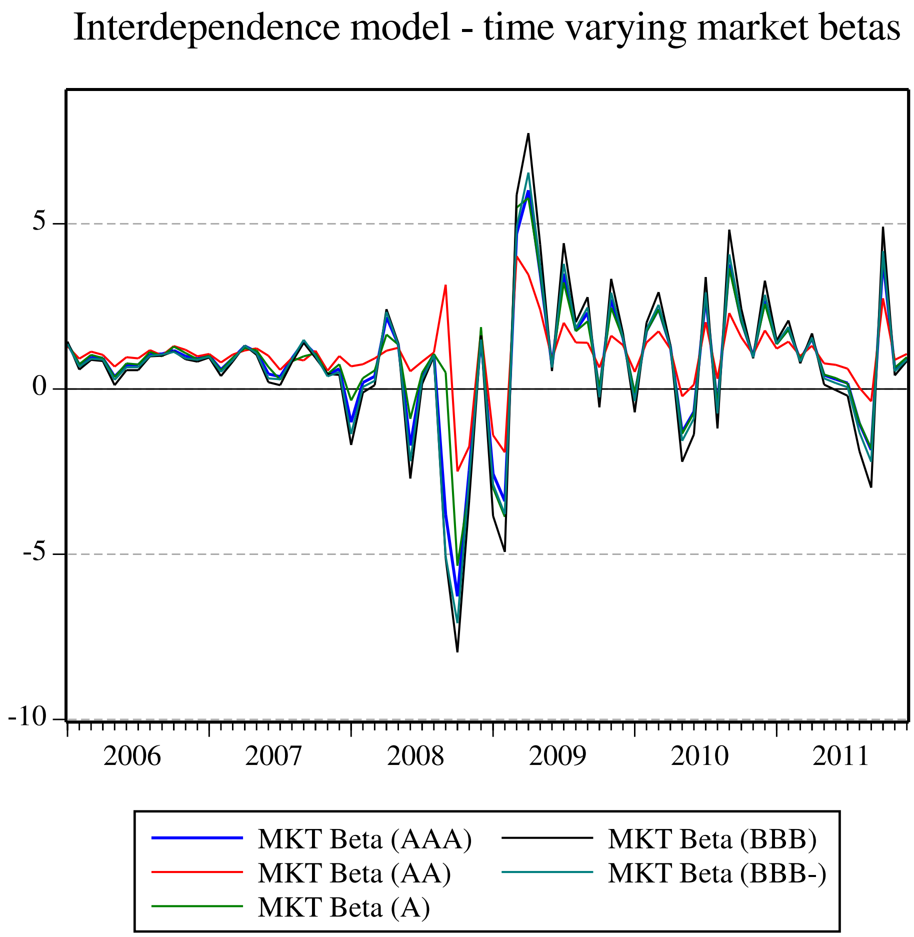
$$\boldsymbol{\beta_t} = \boldsymbol{\beta_0} + \boldsymbol{\phi_1} \mathbf{Z_t}, \tag{5.13}$$

where $\mathbf{Z_t}$ is a 3×1 vector of instruments containing the monthly spreads of the TED, ABCP and Moody's BAA corporate bond yields.

Table 5.13 reports the factor loadings, t-statistics based on robust clustered standard errors, adjusted R^2 and diagnostic tests of cross-sectional dependence. First, I document significant market betas across the ABX models. The market betas are in general smaller than those of the interdependence models without instruments. I find significant and positive ABX AAA and AA factor loadings similar to the findings of the pricing models without instruments. For the contagion variables, I document significant positive relations between ABCP, Moody's BAA spreads and market betas and significant negative relations between TED spreads and market betas. The widening of TED spreads (ABCP and Moody's BAA spreads) are associated with lower (higher) market systematic risk in the US stocks. While for the ABX factor loadings, a higher TED spread (ABCP and Moody's BAA spreads) is associated with higher (lower) ABX factor loadings contemporaneously. The three contagion variables are shown to determine the market betas and the ABX factor loadings, lending support to the contagion transmission via the changes in risk premia and funding illiquidity.

The market betas and the ABX factor loadings of the five ABX models are plotted in Figures 5-1 and 5-2, respectively. First, both series exhibit strong time variation over my sample period. The market betas largely decreased in mid-2007 when the subprime crisis took hold. During the global crisis, the market betas became highly volatile and fell sharply to approximately -8.0 in September 2008 after Lehman Brothers collapsed. The market betas started to rise in late 2008, fell sharply in early 2009 and then rose to as high as 8.0 between March to May 2009. For the rest of the sample period, the market betas remained considerably volatile with occasional peaks (towards the end of 2010) and troughs (in the second half of year 2011). Second, while the ABX factor loadings remained relatively stable in the pre-crisis and the early stage of the subprime crisis, they increased sharply from late-2007 onwards followed by steep declines immediately after the Lehman Brothers' collapse. Both ABX AAA and AA factor loadings rose again from October 2008 onwards, until the

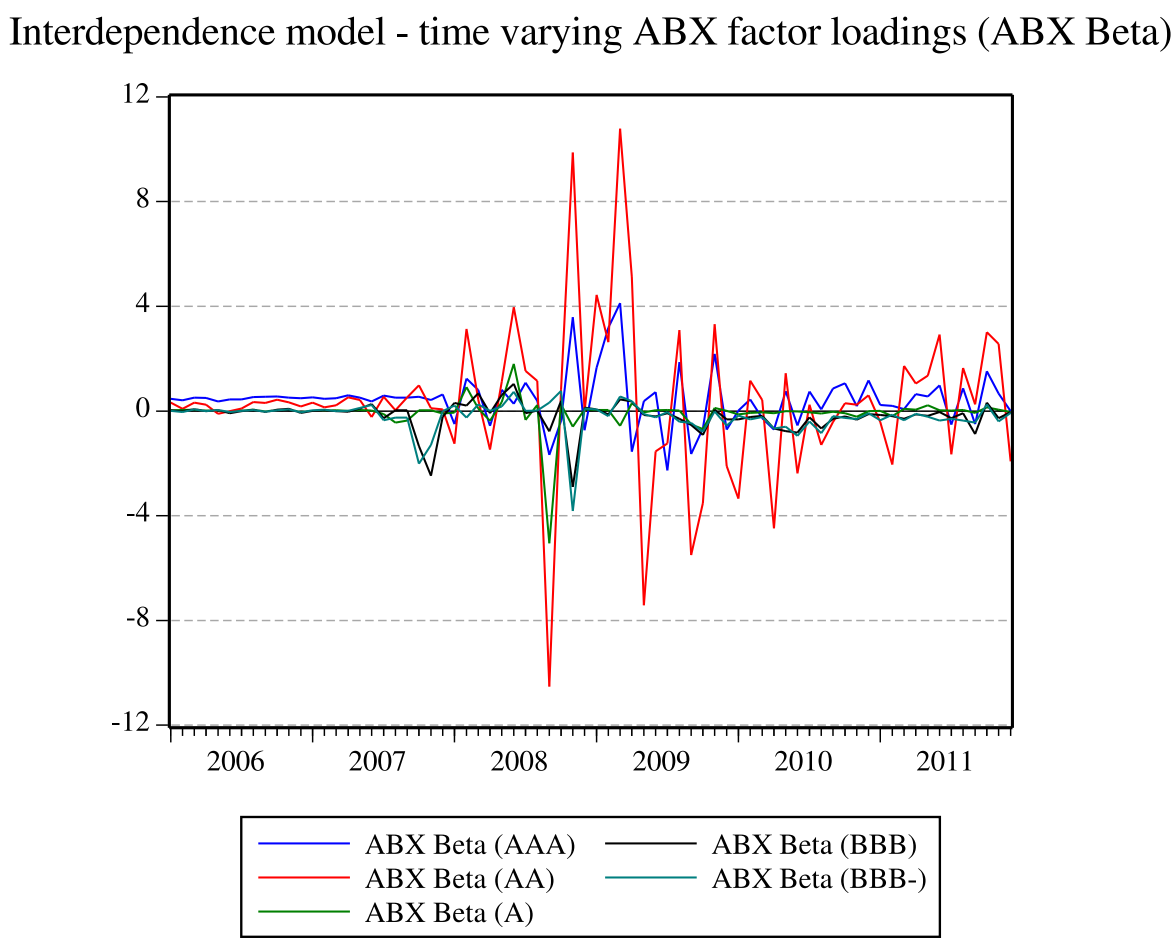
Figure 5-1: Time-varying market beta of the interdependence model with instruments



This figure plots the time-varying market betas from the interdependence model with instruments of the five ABX models over the sample period of January 2006 to December 2011.

end of the global crisis subperiod, and remained volatile for the rest of the sample period. Overall, the market betas and ABX factor loadings backed out from the contagion models with instruments have demonstrated strong time variations while the factor loadings were in general higher and more volatile during the subprime and global crisis subperiods.

Figure 5-2: Time-varying ABX factor loadings of the interdependence model with instruments



This figure plots the time-varying ABX factor loadings (ABX betas) from the interdependence model with instruments of the five ABX models over the sample period of January 2006 to December 2011.

Contagion model

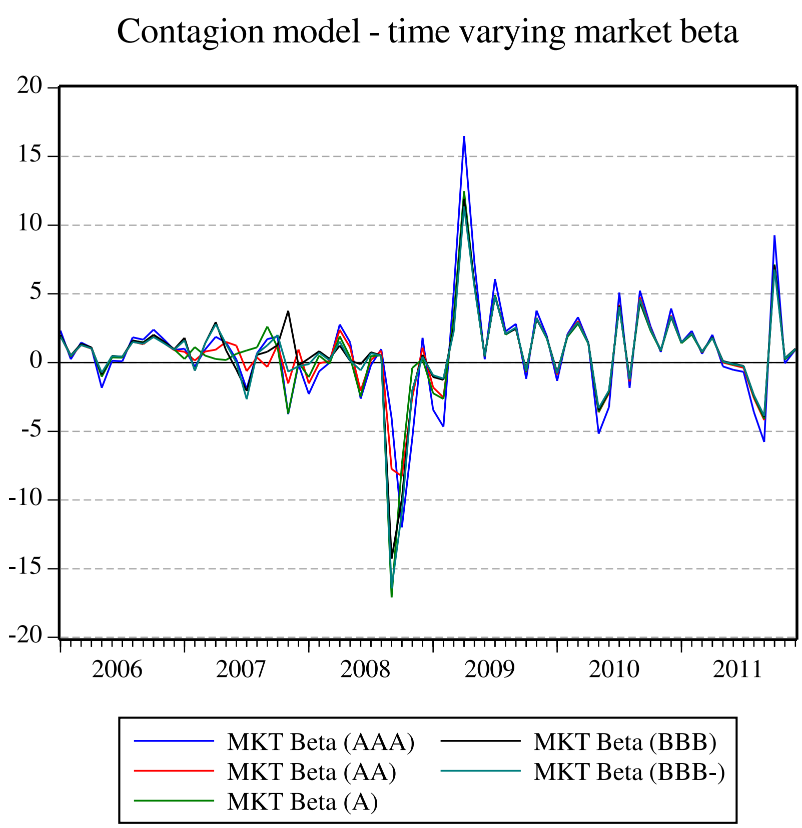
In this section, I further allow the factor loadings to interact with the contagion related instruments and the crisis dummy variables. My full contagion model with instruments is shown in Equations 5.1 to 5.4 with the findings reported in Table 5.14.

Consistent with the findings of the contagion models without instruments, the market betas are all significant across the ABX models despite being smaller in value while the ABX AAA, BBB and BBB- factor loadings are significant and positive. The coefficients on the TED ($\phi_{MKT,TED}$) and Moody's BAA corporate bond yield spreads ($\phi_{MKT,BAA}$) are significant and positive, suggesting that the widening of the TED and Moody's corporate bond yield spreads is associated with higher market betas during the non-crisis period. In addition, I document significant and negative $\xi_{MKT,TED}$ and $\zeta_{MKT,TED}$ values, and positive $\xi_{MKT,BAA}$ and $\zeta_{MKT,BAA}$ values in both the ABX BBB and BBB- models. The positive relation between the changes in corporate bond yield spreads (in TED spreads) and the level of market systematic risk has become stronger (weaker) during the crisis. My results suggest that the individual stock market systematic risks are driven by the level of credit risk and funding illiquidity in the US.

For the ABX factor loadings, significant and negative relations between the ABCP spreads and the ABX factor loadings ($\phi_{ABX,ABCP}$) is documented during the tranquil non-crisis period. The widening of the ABCP spreads is associated with lower ABX factor loadings during the time before and after the crisis. The instruments interacting with the ABX factor loadings and the subprime crisis dummy variables ($\xi_{ABX,TED}, \xi_{ABX,BAA}$ and $\xi_{ABX,ABCP}$) are highly significant and positive in the ABX BBB and BBB- models. The TED, Moody's BAA and ABCP spreads' negative relation with the ABX factor loadings has weakened and even become positive during the subprime and global crisis. In other words, the effects of the contagion variables on the ABX factor loadings have become more positive and when these spreads widened during the crisis the individual stock's exposure to the ABX innovations increased significantly. In addition, I also document significant and positive relations between the TED spreads and the ABX factor loadings, as well as between the corporate bond yield spreads and the ABX factor loadings, particularly during the subprime crisis as evinced by the significant $\xi_{ABX,TED}$ and $\xi_{ABX,BAA}$ values in both the ABX BBB and BBB- models.

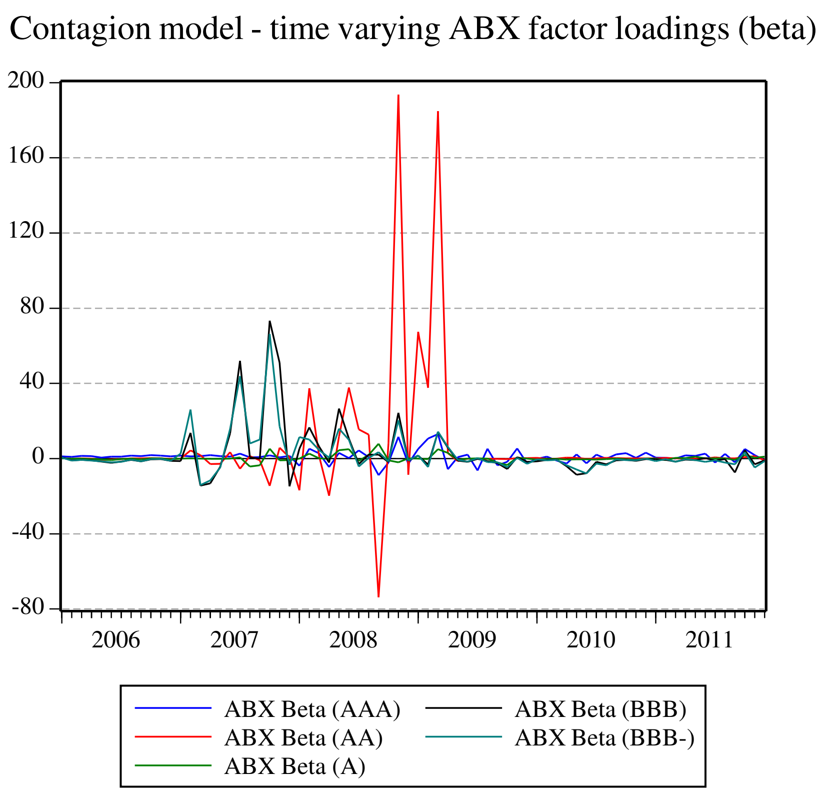
Figures 5-3 and 5-4 plot the time-varying market betas and ABX factor loadings associated with the contagion models with instruments, respectively, based on the scaled variables. The plots of the contagion models are qualitatively similar to those of the interdependence models in that the market betas fell in mid-2007 and became negative when Lehman Brothers collapsed in September and October 2008, followed by occasional positive spikes in mid-2009 and negative dips in mid-2010 and the second half of 2011. The ABX factor loadings were volatile and became unreasonably large during the crisis, which is suggestive of model mis-specification. I observe that the ABX BBB and BBB- factor loadings turned negative in 2007Q1, jumped to as high as 50.0 in mid-2007 and peaked in October 2007. Similar to the findings of the independence model, the ABX factor loadings increased in early and mid-2008 and fell sharply in September and October 2008. The ABX factor loadings increased sharply again in November 2008 (except for the ABX A factor loadings) and remained largely volatile over the remaining sample period.

Figure 5-3: Time-varying market betas of the contagion model with instruments



This figure plots the time-varying market betas of the contagion model with instruments of the five ABX models over the sample period of January 2006 to December 2011.

Figure 5-4: Time-varying ABX factor loadings of the contagion model with instruments



This figure plots the time-varying ABX factor loadings (ABX betas) of the contagion model with instruments of the five ABX models over the sample period of January 2006 to December 2011.

5.3.8 Summary

To my knowledge, this is the first study that examines how individual stocks were exposed to the risks associated with the structured finance market during the recent crisis and it is also the first to explore how the impact of the risk factor related to the ABX indices might have changed over time. Within an asset pricing framework, I document solid evidence of contagion travelling from the US structured finance market to the US equity market, and also to most industry sectors. More importantly, the specification of the contagion model (augmented with the crisis dummy variables) performs better than that of the interdependence model in capturing variation in stock returns.

In the full sample contagion models, I show that the market betas across all the ABX models are significant and are in general smaller during the crisis, especially during the subprime crisis. I document significant increases in the individual stock's exposure to the ABX innovations, particularly to the highest-rated ABX AAA innovations during the subprime crisis, and no significant changes in the ABX factor loadings during the subsequent global crisis. My findings suggest that the highest-rated segment of the structured finance market (referenced by the ABX AAA index) was the most relevant to asset pricing and represented an important source of crisis-related risk in the US equity market, which is consistent with contagion as documented in Longstaff (2010) and in Chapter 4.

In the industry contagion models, the market betas are all significant for all industries and across the ABX models, and have in general become smaller during the crisis. Again, the ABX AAA factor loadings are highly significant across the industry sectors while the findings of the other ABX models are rather mixed. Similar to the results of the full sample contagion models, I document significant increases in the ABX AAA factor loadings in largely all industry sectors during the subprime crisis and comparable loadings in the global crisis to the pre-crisis loadings. Almost all industry stocks were exposed to the shocks from the ABX indices, particularly during the subprime crisis, which is consistent with the conjecture that the crisis effects were reasonably systematic across industries.

I find strong evidence of contagion transmitted via changes in credit and illiquidity risks in that the market betas are driven by the TED spreads and Moody's BAA corporate bond yield spreads, while the ABX factor loadings are explained by the ABCP yield spreads. During the crisis, the positive relation between corporate bond yield spreads and market betas strengthened while the positive relation between the TED spreads and market betas weakened. The evidence suggests that the market wide default risk is relevant in determining the market betas. For the ABX factor loadings, during the subprime crisis, the ABX BBB and BBB- factor loadings increased significantly via the widening of the three yield spreads. During the global crisis, the negative relation between the ABCP yield spreads and the ABX factor loadings weakened and became positive. The evidence in this chapter provides additional empirical support to my conjecture that the increased market linkages between the structured finance and equity markets were closely related to the systematic funding illiquidity, which is consistent with contagion transmission via the funding liquidity channel. The evidence also supports the conclusion of Fender and Scheicher (2009), who argue that the falling ABX prices reflected increasing illiquidity risk and risk aversion during the crisis.

5.4 Do the ABX factors explain the cross-section of expected returns? Evidence based on the daily Fama and French 25 portfolio returns

In the previous sections, I find evidence that the spillovers of shocks from the ABX AAA index impacted the US stock returns in a systematic manner and that the ABX factor was important to asset valuation during the subprime crisis. I will now proceed to explore whether the ABX factors explain the cross-section of expected returns during the crisis. To this end, a multifactor model is formulated with k factors following Chen et al. (1986). The expected cross-sectional return of stock i is assumed to be generated under the following process:

$$\mathrm{E}(R_t^i) = \sum_{j=1}^{k} \beta_j^i \lambda_j, \tag{5.14}$$

where $\mathrm{E}(R_t^i)$ is the expected return of stock i at time t and λ_j is the price of the j^{th} risk factor.

Empirically, the multifactor model can be tested using a two-pass regression framework following Black et al. (1972), in which the first pass is a time-series regression and the second pass is a cross-sectional regression. In the first stage, I obtain estimates of the factor betas on each sorted portfolios using the following time-series regression:

$$R_t^i = a^i + \beta^{i'} F_t + \varepsilon_t^i, \tag{5.15}$$

where R_t^i is the excess return of portfolio i, $\beta^{i'}$ is a $1 \times k$ vector of factor loadings and F_t is a $k \times 1$ vector of factors.

The second stage is then a cross-sectional regression using the portfolios' expected (average) returns as dependent variable:

$$\bar{R}_T^i = \widehat{\beta^{i'}} \lambda + \alpha, \tag{5.16}$$

where $\bar{R}_T$ is the time series average return of the test portfolio i, $\widehat{\beta^{i'}}$ is a $1 \times k$ vector of estimated factor loadings from the time series regression (first stage) used as explanatory variables and λ is a $k \times 1$ vector containing the coefficients of the factor betas.

The pricing errors in this two-pass regression framework are given by the cross-sectional regression residuals α in Equation 5.16, which are the time series average of the residuals in the factor model shown as $\mathrm{E}(\alpha\alpha') = \frac{1}{T}\Sigma$. While the residuals are cross-sectionally correlated, a generalised least squares (GLS) regression should provide more efficient estimates in the second stage regression (Cochrane, 2000, pp. 222).[34] The vector of prices of risks and their variances are estimated as follows:

$$\hat{\lambda} = (\beta'\Sigma^{-1}\beta)^{-1}\beta'\Sigma^{-1}\bar{R}_T, \tag{5.17}$$

$$\sigma^2(\hat{\lambda}) = \frac{1}{T}(\beta'\Sigma^{-1}\beta)^{-1}. \tag{5.18}$$

The estimated pricing errors and their covariance matrix are estimated as follows:

$$\hat{\alpha} = \bar{R}_T - \beta\hat{\lambda}, \tag{5.19}$$

$$cov(\hat{\alpha}) = \frac{1}{T}(\Sigma - \beta(\beta'\Sigma^{-1}\beta)^{-1}\beta'). \tag{5.20}$$

The tests of the pricing errors have a χ^2 distribution with $N - k$ degrees of freedom and are

[34] The GLS regression decomposes the Σ into CC' (by Choleski Decomposition) and is equivalent to ordinary OLS regressions with transformed dependent and explanatory variables by pre-multiplication of C. Intuitively, this transformation allows me to focus on the statistically most informative portfolios with lower residual variances Σ.

expressed as:

$$T\hat{\alpha}'\Sigma^{-1}\hat{\alpha} \sim \chi^2_{N-k}, \tag{5.21}$$

where N and k are the numbers of test assets and asset pricing factors, respectively.

Practically, I use the Fama-French (1993) 25 portfolios sorted on size (market equity) and book-to-market ratios as test assets for the empirical tests of the multifactor model.[35] The portfolios are intersections of five portfolios sorted on market capitalisation (ME) and five portfolios sorted on book-to-market ratios (in quintiles). Given my short sample period, I use daily excess returns of these 25 portfolios to increase the number of time series observations. As for the factors, I include the excess returns of the value-weighted CRSP market index as the market risk factor, the Small-Minus-Big (SMB), High-Minus Low (HML) and the Cahart (1997) Momentum factors (collectively known as the FF-4 factors) in the asset pricing model. In addition, I include an ABX risk factor as a proxy of the risks associated with the structured finance market. In particular, the ABX factor is orthogonalised by regressing the daily excess returns of the ABX indices upon the FF-4 factors using the full sample period. The five series of ABX innovations (residuals of the time series regressions based on the five ABX indices) are then used in the two-pass regression. The ABX innovations can be interpreted intuitively as the shocks in the structured finance market unexplained by the market, size and value premium risk factors.

5.4.1 Empirical findings

Tables 5.15 - 5.20 report the estimates of the prices of risk (λ), the t-statistics and the pricing errors statistics of the models as shown in Equation 5.21, based on the two-pass regressions (the time series and GLS cross-sectional regressions) of the 25 portfolios based on the full sample and the crisis subsamples.

For the results of the full sample models, the market risk (λ_{MKT}) is priced with positive premium and with t-statistics lying between 4.0 and 6.0 across the models. The SMB factor is also priced with positive premium. A higher sensitivity to the return spreads between the small and big firms is associated with a higher expected daily return, which is consistent with Petkova (2006) despite the SMB factor in her study being insignificant. The results in Table 5.15 show that the HML,

[35] The data on the portfolios are obtained from Kenneth R. French web site, retrieved on 8 December 2012 from: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/tw_5_ports.html

Momentum and ABX factors are insignificant in explaining the cross section of portfolio returns. In addition, the null hypotheses of no pricing errors are all significantly rejected at the 1% level in that the pricing models do not hold empirically.

My sample period is relatively short and comprises of six years of data with 1488 daily observations. An important feature of my sample is that there were possible structural changes in the risk-return relationship among the portfolio returns; for example, the returns had become substantially more volatile during the crisis. Empirically, structural breaks have been identified in the market and funding illiquidity measures (Frank et al., 2008), the return volatilities of the S&P 500 composite index (Bouaziz et al., 2012) and the LIBOR-OIS spreads (Olson et al., 2012). To account for the possible structural breaks, I estimate the cross-sectional tests for each crisis subsample and investigate whether the ABX factors explain the cross-section of expected returns during the crisis.

Table 5.16 reports the findings for the pre-crisis subperiod. Similar to the results of the full sample tests, the market risk factors are all systematically priced with positive prices of risk across the model specifications. I document significant value premia (positive λ_{HML}), which is consistent with the findings in Fama and French (1992, 1993). In Models 6, 7 and 8, I find some moderately significant results in the ABX A, BBB and BBB- factors, all with negative risk premia, monotonically decreasing towards the lowest-rated ABX factors. Portfolios with higher ABX factor loadings have lower expected returns.

For the test results of the subprime crisis subsample, the market risk premia are significantly priced with positive λ. Both the SMB and HML factors in all models are priced with negative risk premia while the Momentum factors are cross-sectionally priced with positive risk premia. More importantly for this study, I document significantly negative ABX AAA factor risk premia in Models 4 and 9. In Model 9, a one unit increase in the ABX AAA factor loadings during the subprime crisis amounts to a 0.195% lower daily expected return (t-statistic is -2.947). The null hypothesis of no pricing errors in Model 9 is significantly rejected. In Model 4, after including the FF-3 and Momentum factors, the price of the ABX AAA factor risk remained highly significant with a coefficient of -0.217 and t-statistics of -3.145. Note that the pricing error statistics become smaller and statistically insignificant. The main implication is that the asset pricing model performs significantly better with the inclusion of the ABX AAA factor during this period and that the ABX AAA factor explains the cross-section of expected stock returns when contagion occurred. Together with the previous results documented in Section 5.3, the negative price of risk of the ABX AAA factor is consistent with the findings that individual stocks positively correlated with the ABX innovations had lower returns during the subprime crisis. The empirical evidence confirms my expectation in that the impact of the spillovers of shocks from the ABX indices on the stock returns was reasonably systematic and was specific to this subprime crisis subperiod.

The results for the global crisis subsample are reported in Table 5.18. Significant and negative prices of the market risk and size premia are documented while the price of the momentum premium is marginally significant and positive. Portfolios with higher market betas had lower expected returns when the market index declined during the global crisis. On the other hand, all λ_{ABX} values are insignificant across the model specifications. One possible explanation is that the structured finance market was no longer the source of shocks as the crisis went global. In addition, the informativeness of the ABX indices might have already been reflected in the market index when the ABX indices received more coverage and attention as an important class of risk barometer at the onset of the subprime crisis. To my surprise, all pricing error statistics are insignificant in this period, which is suggestive of good model fit.

As for the post-crisis subperiod, the market risk factors, SMB and Momentum factors are priced with positive λ. I find that the ABX BBB factor is priced in Models 7 and 12 with significant and negative prices, respectively. The test results associated with the other ABX factors are somewhat mixed. The findings are in general consistent with the findings of no significant contagion from the ABX indices to the equity market during the post-crisis subperiod. The null hypotheses of no pricing errors are significantly rejected for all model specifications.

I further examine the cross-sectional risk-return relation using observations from both the subprime and global crisis subperiods to test whether the significant price of ABX AAA risk in the subprime crisis subsample still persists. As shown in Table 5.20, the prices of market risk are all significant and negative identical to the global crisis subsample results while the HML and momentum factors are priced (negative λ_{HML} and positive λ_{MOM} values). The λ_{ABX} associated with all the ABX factors for all model specifications are in general insignificant. The evidence leads me to conclude that the ABX AAA factor was priced only during the subprime crisis subperiod and that the ABX AAA innovations were the most relevant to asset pricing.

To summarise, my full sample tests document little evidence that the ABX factors explain the cross-section of expected returns while the subsample pricing tests present reasonably strong evidence that the ABX AAA factors explain the cross-section of expected returns during the subprime crisis subperiod. In particular, the Carhart (1997) four-factor model augmented with the ABX AAA factor holds, as evinced by the insignificant pricing error statistics.

5.5 The exposure to the ABX innovations - firm-level evidence

In the first part of this chapter, I have shown that the ABX innovations represented an important source of crisis-related risk during the subprime crisis. Now, to formally examine how the individual stock's exposure to the ABX innovation evolved over time and to quantify the time-varying exposure, I create a simple statistic based on stock-level information.

5.5.1 Empirical framework

To capture the individual stock's sensitivity to the ABX innovations over time, I estimate a standard market model, which is augmented with the contemporaneous and lagged ABX index returns (daily), for each of the available individual stocks at the end of each month using all available daily observations in the month. The motivation of the model specification is similar in spirit to the factor model framework that is used in the contagion literature, in that the market risk factor is the common risk factor while the ABX factors represent the idiosyncratic shocks from the US structured finance market. I am aware that nonsynchronous trading of individual stocks and in the ABX indices may create significant bias in the factor loadings. As pointed out by Lo and MacKinlay (1990), small stocks tend to react with delay to market information and, hence, factor loadings computed based on daily contemporaneous returns may not capture the dynamic nature of the factors with respect to the stock returns. Following Dimson (1979) and Lewellen and Nagel (2006), I include the current and lagged market excess returns and ABX index returns in the augmented market model and compute the sums of the market betas and ABX factor loadings on the contemporaneous and lagged variables. In addition, I average the $t-2$ to $t-5$ lags and estimate one coefficient for the average constrained lagged returns to reduce the number of estimated parameters. The first model is written as follows:

$$\begin{aligned} R_t^{(i)} = \quad & \alpha^{(i)} + \beta_{1,t}^{(i)} MKT_t + \beta_{2,t}^{(i)} MKT_{t-1} + \beta_{3,t}^{(i)} (\frac{MKT_{t-2} + MKT_{t-3} + MKT_{t-4} + MKT_{t-5}}{4}) \\ & + \gamma_{1,t}^{(i)} ABX_t + \gamma_{2,t}^{(i)} ABX_{t-1} + \gamma_{3,t}^{(i)} (\frac{ABX_{t-2} + ABX_{t-3} + ABX_{t-4} + ABX_{t-5}}{4}) + \epsilon_t^{(i)}, \end{aligned} \tag{5.22}$$

where $R_t^{(i)}$ refers to the excess return of stock i in day t and MKT_t refers to the excess return of the value-weighted portfolio of the NYSE, AMEX, and NASDAQ stocks from French's web site. ABX_{t-j} refers to the ABX index returns at time $t-j$, and $\epsilon_t^{(i)}$ is an error term with zero mean and is uncorrelated with the right-hand side variables.

The specification of the augmented market model allows me to measure the sensitivities of individual stocks to the past returns of the ABX indices within one trading week. To allow the dependency between the stock returns and the lagged ABX index returns to change over time, I estimate Equation 5.22 using all trading days in each month to obtain monthly estimates of the ABX factor loadings for each US stock from the CRSP database.[36]

Taking into account the fact that the market factor might correlate with the ABX factors during the crisis, I estimate Equation 5.22 using both unorthogonalised (Model 1) and orthogonalised (Model 2) ABX index returns.[37] The orthogonalisation separates the effects of the ABX indices from the market risk factor and allows me to interpret the ABX innovations as shocks of the ABX indices unexplained by the market. Model 2 is written as:

$$\begin{aligned} R_t^{(i)} = \quad & \alpha^{(i)} + \beta_{1,t}^{(i)} MKT_t + \beta_{2,t}^{(i)} MKT_{t-1} + \beta_{3,t}^{(i)} (\frac{MKT_{t-2} + MKT_{t-3} + MKT_{t-4} + MKT_{t-5}}{4}) \\ & + \gamma_{1,t}^{(i)} \epsilon_{ABX,t} + \gamma_{2,t}^{(i)} \epsilon_{ABX,t-1} + \gamma_{3,t}^{(i)} (\frac{\epsilon_{ABX,t-2} + \epsilon_{ABX,t-3} + \epsilon_{ABX,t-4} + \epsilon_{ABX,t-5}}{4}) + \epsilon_t^{(i)}, \end{aligned} \tag{5.23}$$

[36] I screen out any stocks for which 15 observations are not available for the daily time series regressions in any month. After running the augmented market model regressions, I cross-merge the estimated factor loadings with monthly market capitalisation ($MCAP$), monthly returns, book-to-market ratios (BE/ME), and a few firm-specific variables using PERMNO. I then screen out those stocks whose monthly $MCAP$ are negative or not available, following Fama and French (1992).

[37] I orthogonalise the daily excess returns of the ABX indices with regard to the market risk factor by regressing the market risk factor, SMB, HML and Carhart (1997) momentum factors on the daily excess returns of the ABX indices using the full sample (from January 2006 to December 2011) and obtain ABX innovations (regression residuals). I also tried regressing only the market risk factor on the daily excess returns of the ABX indices. However, the ABX innovations are qualitatively similar to those obtained from the four-factor model specification, and are not presented here for the sake of brevity.

where $\epsilon_{ABX,t}$ is the orthogonalised ABX innovations at time t.

In addition, to make my model estimation comparable to the findings of the cross-sectional tests in previous sections, I further estimate a FF-4 model augmented with a contemporaneous ABX risk factor (Model 3) to control for the possible size and value effects on the stock returns as follows:

$$R_t^{(i)} = \alpha^{(i)} + \beta_{MKT,t}^{(i)} MKT_t + \beta_{SMB,t}^{(i)} SMB_t + \beta_{HML,t}^{(i)} HML_t + \beta_{MOM,t}^{(i)} MOM_t + \beta_{ABX,t}\epsilon_{ABX,t} + \epsilon_t^{(i)}, \tag{5.24}$$

where the daily SMB, HML and MOM factors are obtained from French's web site.

After I obtain the monthly estimated factor loadings of the three models, I apply F-tests of joint significance (t-tests in Model 3) (at a threshold significance level of 5%) on the ABX factors with null hypothesis: $h_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, to identify stocks with significant exposure to the ABX index returns (the ABX innovations). I then create simple statistics that gauge the aggregate level of exposure to the ABX indices by computing the proportion of stocks with significant factor loadings to the total number of available individual stocks in my sample for each month. I then examine the time series properties and determinants of the time variation in the aggregate ABX risk exposure measures using a number of contagion variables. I then examine the determinants of the cross-section of individual stocks' exposure to the ABX indices with the use of a number of firm-specific fundamental and market variables.

5.5.2 Data

My sample consists of all available US stocks from the CRSP database during the period January 2006 to December 2011. I obtained the daily and monthly holding period returns, monthly prices, monthly turnover volumes and the number of shares outstanding. The monthly market capitalisation (ME) for each stock is calculated by multiplying monthly prices by the shares outstanding at the end of each month. Following Chordia et al. (2001), liquidity of individual stocks is measured by turnover ratios, calculated as the number of shares traded normalised by the number of shares outstanding. As for the book-to-market (BE/ME) ratios, I follow Fama and French (1992) and use the monthly market capitalisation (size, ME) in June to explain the following 12 months' returns and the book value (BE) at fiscal year t for returns from July of year $t+1$ to June of year $t+2$ to ensure there is sufficient time for the book value information to be made available to the public. I also estimate the idiosyncratic volatilities ($IVol$) for each individual stock with a similar approach to recent studies (see, for example, Ang et al., 2006, 2009; Fu, 2009). I compute the $IVol$ as the standard deviation of the regression residuals of my models in Equation 5.22 - 5.24. I then transform the daily $IVol$ measure into a 30-day equivalent measure by multiplying the volatility measure by the square root of 30 to obtain the 30-day or pseudo monthly $IVol$ measure for each individual stock.[38]

Similar to the empirical analysis in Chapter 4, I omit the daily observations between 1 April and 31 August 2009 because the prices of both the ABX BBB and BBB- indices were stale, causing near-singularity problems in ordinary regressions. Therefore, the post-crisis subperiod for the current analysis starts from 1 September 2009 and lasts until the end of 2011.

5.5.3 Univariate analysis - decile sort portfolios

After the monthly estimates of factor loadings are obtained, I perform univariate portfolio analysis sorted by the ABX factor loadings to address two research objectives: i) to investigate the cross-sectional determinants of individual stocks' exposure to the ABX indices; and, ii) to test whether the ABX factors explain the cross-sectional variations in portfolio returns as a robustness check to Section 5.4. Practically, I sort the stocks into decile portfolios at the end of each month immediately after estimating the models. Stocks are allowed to move across portfolios through time while maintaining the portfolio's relative ABX factor loadings. I report two sets of portfolio sort results based on two sample selection approaches. In the former approach, the sorts are based on the ABX factor loadings on *all available stocks* while the second method sorts *only stocks with significant test statistics (at 5% significance level)* to allow me to focus more closely on those stocks with significant exposure. The equally weighted average characteristics of the deciles portfolios (which includes market capitalisation, turnover ratios, month t returns, month $t+1$ returns, standard deviations, idiosyncratic volatilities, α, market betas, and the ABX factor loadings) are reported, grouped by crisis subperiods.

Tables 5.21 - 5.25 report the equally weighted average characteristics of the deciles portfolios sorted by the sums of ABX factor loadings of Model 1 based on all available stocks and the unorthogonalised ABX AAA, AA, A, BBB and BBB- index returns, respectively. A number of

[38] A similar approach has been adopted by French et al. (1987) and Fu (2009).

points are noteworthy. First, smaller stocks tend to have higher absolute ABX factor loadings across the ABX models. Second, stocks with higher ABX factor loadings have, in general, lower turnover ratios during the subprime and global crisis subperiods. Third, I do not observe any monotonic patterns in the month t and month $t+1$ returns for, largely, all five ABX indices. Fourth, both standard deviations and idiosyncratic volatilities were remarkably higher among portfolios with higher absolute ABX factor loadings in the full sample and the crisis subsamples. Fifth, market betas decrease monotonically towards Portfolio 10 (of the highest ABX factor loadings) across the ABX models and in largely all subperiods. At first glance, the findings of Model 1 do not support the conjecture that the ABX factors explain the cross-section of stock returns during the crisis. In Model 1, the evidence suggests that the ABX factor might have acted as a proxy for higher total volatilities and market risk. In addition, stocks with smaller firm size and lower liquidity were more exposed to the ABX innovations. Next, I report the sorted portfolio results of Model 1 based on stocks with significant factor loadings as shown in Tables 5.26 - 5.30. I find that month t returns monotonically decreased while the ABX AAA and AA factor loadings increased during the subprime crisis. Stocks with positive ABX AAA and AA factor loadings underperformed when the subprime crisis unfolded.

The results of Model 2, based on the orthogonalised ABX factors, are reported in Tables 5.31 - 5.35, respectively. Similar to the results of Model 1, higher standard deviations, idiosyncratic volatilities, lower turnovers and smaller firm size are associated with higher exposure to the ABX innovations. Again, I do not observe any monotonic patterns in the average month t and $t+1$ returns in the full and crisis subsamples. Interestingly, during the subprime crisis subperiod, the market betas increase (decrease) monotonically with the increases in ABX AAA and AA (A, BBB and BBB-) factor loadings in contrast to the decreasing patterns documented in Model 1. The differing monotonic patterns in market betas between Models 1 and 2 may be related to the possible correlation between the market and ABX indices during the subprime crisis. The evidence also suggests that the informativeness of the ABX indices over stock returns differed between the two highest-rated and the three lowest-rated ABX indices as shown by the monotonic patterns in market betas in opposing directions.[39] The findings of Model 2 with only significant stocks are shown in

[39] These findings are also consistent with the descriptive summary of the ABX indices in that the ABX AAA and AA are highly correlated while the three lowest-rated ABX indices are highly correlated with each other, as shown in Table 4.18 of Chapter 4.

Tables 5.36 - 5.40. The portfolio characteristics remain qualitatively similar while the patterns of the market betas are more distinctive.

So far, the multifactor models of Model 1 and Model 2 include both the market risk factor and the ABX risk factor and their lagged terms. In Model 3, I further include the SMB, HML and the momentum factors and report the equally-weighted average portfolio characteristics in Tables 5.41 - 5.45, respectively. Regarding the firm size, turnover ratios, standard deviations and idiosyncratic volatilities, the results of Model 3 are, in general, identical to those of Models 1 and 2. I find a weak and monotonically decreasing pattern in month t returns for the ABX AAA and AA factor loadings during the subprime crisis. Note that the patterns occur largely during the subprime crisis; that is, the spillover of shocks from the ABX indices has impacted on the US equity market in a systematic way. The monotonic patterns largely disappeared in the subsequent subperiods, which is consistent with my results in Section 5.4. The month $t+1$ returns are lowest in Portfolios 1 and 10 for all five ABX indices during the subprime crisis. Although the evidence suggests some return predictability in the ABX factor loadings during the subprime crisis, the relationship between the ABX factor loadings and the one-month ahead returns is not linear. These findings are consistent with my contention that the ABX factor loadings are proxies for return volatilities and, thus, underperformed during the subprime crisis. In addition, the market betas increase monotonically with the ABX AAA, AA and A factor loadings during the subprime crisis while the pattern no longer exist during the global and post-crisis subperiods. The results of Model 3 based on stocks with significant ABX factor loadings are reported in Tables 5.46 - 5.50. Similarly, the month t returns decreased monotonically during the subprime crisis in largely all ABX models (more prominently in the ABX AAA and AA models). I also find monotonically increasing market betas across the portfolios during the subprime crisis for all ABX models except the ABX BBB model. The evidence suggests that, even after controlling for the SMB, HML and the momentum factors, the ABX factors still explain the cross-section of expected returns during the subprime crisis.

Note that the findings based on the unorthogonalised and orthogonalised ABX factors differ substantially, as evinced by the opposing monotonic patterns in the average market betas. Since I focus on the individual stock's exposure to the spillover of shocks from the structured finance market, empirical analyses based on the orthogonalised ABX factors are more intuitive and appropriate in that the orthogonalisation allows me to focus on the variations of the ABX innovations that were not explained by the market. Therefore, for the rest of this chapter, I base my investigation on the orthogonalised ABX factors of Model 2 and Model 3.

5.5.4 The time-varying exposure to the ABX innovations

My empirical results in the previous sections suggest that the US stocks' exposure to the ABX innovations varied strongly over time, with the exposure heightened during the subprime crisis. I am the first to explore how US stock exposure to the spillovers of shocks from the US structured finance market evolved over time.

To gauge the level of exposure to the ABX innovations in each month, I introduce a simple statistic, denoted κ_t, calculated as the proportion of stocks with significant test statistics (F-tests for Model 2 and t-tests for Model 3) (at a 5% significance level) to the total number of available stocks in my sample at the end of each month. The aggregate exposure statistic is expressed as follows:

$$\kappa_{ABX,t} = \frac{N_{sig,t}}{N_{sig,t} + N_{insig,t}}, \tag{5.25}$$

where $N_{sig,t}$ is the number of stocks with significant test statistics in the regressions of Equations 5.23 and 5.24 using observations in month t and $N_{insig,t}$ is the number of stocks with insignificant test statistics.

The intuition is that a higher $\kappa_{ABX,t}$ reflects a higher degree of cross-market linkage between the equity and the structured finance market consistent with contagion. In the following sections, I analyse the exposure series of Models 2 and 3 graphically.

5.5.5 The exposure to the ABX innovations - Model 2

First, looking at the aggregate exposure to the ABX innovations, as shown in Fig. 5-5 (a) to (d), the first observation that emerges is that the exposure series varied strongly over time. For the pre-crisis subperiod, despite a fair amount of time variation, I do not observe a distinct pattern in the $\kappa_{ABX,t}$, which is consistent with my expectation of a relatively tranquil period. During the subprime crisis, I observe remarkably higher levels of exposure to the ABX AAA and AA innovations (close to 70% for the ABX AAA and 50% for the ABX AA model) in February 2007. The high exposure to the ABX innovations occurred in the month during which a number of financial institutions revealed troubles relating to their subprime mortgage businesses[40], following which the ABX indices started to decline sharply. In addition, I observe a moderately high level of exposure in July and October 2007, again coinciding with a number of distress events and bankruptcies among financial institutions[41] and surging funding illiquidity in the US financial system.[42] As the crisis evolved into a global context, the exposure to the ABX innovations heightened in 2008Q1 and 2008Q4 after the Lehman Brothers collapse. During the post-crisis subperiod, I still observe a fair amount of volatility in the exposure series but I find lower correlation among the five ABX exposure series, suggesting that the common factors that drove the stock markets' exposure to the structured finance market might no longer exist.

Next, I analyse and discuss the exposure series that are grouped according to the signs of exposure[43] as shown in Fig. 5-7 (a) to (h). The exposure series to the ABX innovations are qualitatively similar to those without grouping by sign. During the subprime crisis, both the positive and negative exposure series heightened in February 2007. In addition, in July 2007 and 2007Q4, I observe a higher level of positive exposure than negative exposure in that more stocks have comoved positively with the ABX innovations consistent with contagion. During the global crisis subperiod, the exposure to the ABX innovation was most considerable in 2008Q1 and 2008Q4. The maximal exposure to the ABX innovations was attained shortly after the collapse of Lehman Brothers. As for the post-crisis subperiod, I still observe reasonably strong time variations in the stocks' exposure, with spikes in the positive exposure series in August 2011.

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[40]Some of these troubled institutions include various subprime mortgage lenders; for example, Ownit Mortgage Solutions Inc. (in January 2007), Mortgage Lenders Network USA Inc. (in January 2007) (Cox and Glapa, 2009), American Freedom Mortgage Inc. (filed Chapter 7 for liquidation on the 30^{th} January 2007) and ResMae Mortgage Corp. (filed Chapter 11 in February 2007 as the 26^{th} largest subprime mortgage lender). On the 22 February 2007, HSBC announced a surprise increase in bad debt provision for 2006 and fired the head of their subprime mortgage businesses, who was responsible for a loss of $10.5 billion (BBC News). On the 27 February 2007, the Federal Home Loan Mortgage Corporation (Freddie Mac) stated that it would not buy the most risky subprime mortgages and mortgage-related securities (Federal Reserve Bank of St. Louis).

[41]As the subprime crisis substantiated, a number of financial institutions suffered significant write-downs and bankruptcies, as follows: Deutsche Bank ($3.0 billion write-down on bad debts in October 2007), UBS ($3.7 billion write-down in September 2007), Merrill Lynch ($7.9 billion exposure to bad debts in October 2007), Citigroup ($5.9 billion write-down on bad debts), Nomura (closed down subprime mortgage division and suffered $621 million losses) and Bank of China ($9 billion losses in subprime businesses in September 2007), etc.

[42]As shown in Figure 5.7, both the Moody's BAA corporate bond and the ABCP yield spreads started to widen from August 2007 onwards. The heightening threat of insolvency hit the overnight lending market (LIBOR reached 6.75%) and the liquidity in the money market quickly dried up in early September 2007 (BBC News). The European Central Bank also expressed concern about funding illiquidity in the money markets as a result of the troubles in the subprime mortgage market, as reflected by the widening EURIBOR (ECB Timeline of the financial crisis).

[43]The direction of exposure is determined by the signs of the significant ABX factor loadings.

5.5.6 The exposure to the ABX innovations - Model 3

To check the robustness of the above results, I estimate Model 3 of Equation 5.24 for each individual stock and compute the $\kappa_{ABX,t}$ as explained in Section 5.5.4. Note that Model 3 is different from Model 2 in two major ways. First, Model 3 includes only the contemporaneous regressors while Model 2 contains both contemporaneous and lagged regressors. Therefore, F-tests of joint significance are estimated on the contemporaneous and lagged ABX factors in Model 2, while t-tests on the contemporaneous ABX factor are used in Model 3 to compute the exposure series. Second, Model 3 controls for the size, value, and momentum effects, and allows me to focus on the incremental explanatory power of the ABX factors.

Fig. 5-8 (a) to (d) plot the $\kappa_{ABX,t}$ of the five ABX indices in each crisis subperiod, respectively. First, I find that the $\kappa_{ABX,t}$ of Model 3 are in general lower than those of Model 2 throughout the sample period. The observation suggests that the FF-3 factors and momentum factor might have significant explanatory power over the individual stock's returns and, hence, the ABX factor loadings in Model 3 have become less significant. On the other hand, it also suggests the explanatory power in the lagged market and ABX index returns over the individual stocks' returns is not captured. During the subprime crisis, the US stock market experienced substantially higher level of exposure to the ABX innovations in February 2007, consistent with Model 2. In addition, I observe peaks in exposure in February, August and November 2008 during the global crisis. The $\kappa_{ABX,t}$ values sorted by exposure direction, as shown in Fig. 5-9 (a) to (h), are qualitatively similar to those of Model 2, in which a higher level of exposure to the ABX innovations is identified in February 2007, February, August and November 2008.

5.5.7 Discussions

The graphical analysis demonstrates strong time variations in the individual stock's exposure to the ABX innovations throughout my sample period. I find remarkably higher levels of exposure to the ABX innovations in February, August and October 2007, during the subprime crisis, and in February, August and November 2008, during the global crisis. The noticeable increases in the level of ABX exposure during the subprime crisis are consistent with the significant increases in cross-market linkages between the US equity and structured finance markets, as documented by Longstaff (2010) and in Chapter 4. The simple statistics associated with the ABX exposure are robust to an alternative model specification that controls for the size, value and momentum effects and are qualitatively similar between Models 2 and 3.

5.5.8 Granger-causality tests of the $\kappa_{ABX,t}$

In this section, I am interested in the determinants of the time variation in the $\kappa_{ABX,t}$. To this end, I estimate a VAR model on the monthly $\kappa_{ABX,t}$, with a few well-acknowledged contagion variables, and test for Granger-causality. Since my findings of significant contagion are concentrated in the ABX AAA model, I report the results of the $\kappa_{ABX,t}$ for the ABX AAA model only. My VAR(1) model with n endogenous variables is written as:[44]

$$\mathbf{y}_t = \boldsymbol{\alpha_t} + \mathbf{A_1}\mathbf{y_{t-1}} + \boldsymbol{\varepsilon_t}, \tag{5.26}$$

where $\mathbf{y_t}$ is a $n \times 1$ vector of endogenous variables, $\mathbf{A_1}$ is a $n \times n$ matrix of coefficients of the endogenous variables, and $\boldsymbol{\varepsilon_t}$ is a $n \times 1$ vector of errors uncorrelated to the right hand side variables.

A few contagion variables, which are correlated with the heightening credit risk levels, and market and funding illiquidity in the US financial system, are included in the VAR model. These variables include (level data) the TED spreads, ABCP spreads, Moody's BAA - 10 Year constant maturity yield spreads (BAA), LIBOR-OIS spreads[45], the average market illiquidity ($AILLIQ$) following Amihud (2002), and the monthly value-weighted average idiosyncratic volatilities ($VWIVol$).[46]

Granger-causality test results

The F-statistics and the corresponding p-values (in squared brackets) associated with the Granger-causality tests are reported in Table 5.53.

First, I find that $\kappa_{ABX,t}$ is Granger-caused by the lagged average market illiquidity, *LIBOR-OIS* spreads and average idiosyncratic volatilities. The coefficients on the $AILLIQ$ and *LIBOR-OIS* spreads are negative while the coefficient on $VWIVol$ is positive. Increases in the average idiosyncratic risks translated into higher one-month ahead stocks' exposure to the ABX innovations.

[44] The first-order lag structure is found to best fit the data as shown by the minimum Schwarz Information Criterion (SIC).

[45] The LIBOR-OIS spread is the yield differential between the LIBOR and the overnight indexed swap rate.

[46] The summary statistics and correlation matrix of the monthly contagion variables are reported in Tables 5.51 and 5.52, respectively. For a detailed description of the contagion variables, please refer to Appendix A.1.

To my surprise, higher market and funding illiquidity in the last month is associated with lower ABX exposure.

Second, the average market illiquidity is driven by the $ABCP$ and $LIBOR\text{-}OIS$ spreads with positive relations and by the TED spreads with a negative relation. The findings are consistent with Brunnermeier and Pedersen (2009) in that market illiquidity was positively related to funding illiquidity.

Third, the $LIBOR\text{-}OIS$, TED, and $ABCP$ spreads were relatively more exogenous to the contagion variables and were in general not explained by the endogenous variables. The Moody's BAA corporate bond yield spreads were predicted by the $ABCP$, $LIBOR\text{-}OIS$ (positive relation) and TED spreads (negative relation), respectively. The VAR model results suggest that the heightening market wide default risks were related to the exogenous shocks to funding liquidity in the previous month. In addition, the average idiosyncratic volatilities were driven positively by the $ABCP$, $LIBOR\text{-}OIS$ spreads and the $AILLIQ$. Higher market wide average firm-specific risks were related significantly to past increases in the market and funding illiquidity and insolvency risks.

5.6 Determinants of individual stock's exposure to the ABX innovations

In the following sections, I investigate the cross-sectional determinants of an individual stock's significant exposure to the ABX innovations using a diverse set of firm-specific fundamental variables. The significance of the stock's ABX exposure is determined by the t-statistics of the ABX factor in Equation 5.24 (Model 3) at a 5% significance level.[47] I obtained the firm-specific fundamental variables from Compustat and merge the accounting data with the asset-pricing factor loadings using CUSIP.[48]

[47] Although my previous analysis shows that the lagged ABX factors of Model 2 might explain in part stock returns, the complex lag structure inevitably introduces noise in the findings. In addition, the absence of the FF-3 factors and the Carhart (1997) momentum factor may be inappropriate. To make the findings comparable to previous asset pricing tests and control for the pricing anomalous effects, the empirical analysis in the following sections are based on Model 3's specification.

[48] CUSIP is a unique identifier for a financial security in North America for the purposes of facilitating clearing and settlement of trades.

5.6.1 Asset pricing factors and dependent variables

The asset pricing factor loadings are obtained by estimating the augmented four-factor model of Equation 5.24 using all daily observations in each crisis subperiod. Two categorical variables, SIG, whose value is 1 if the stock has a significant t-statistic ($p <= 0.05$) and zero otherwise, and $SIGN$, whose value is 1 if the stock has a significant t-statistic ($p <= 0.05$) and a positive ABX factor loading ($\beta_{ABX} > 0$), 2 if the stock with a significant t-statistic ($p <= 0.05$) has a negative ABX factor loading ($\beta_{ABX} < 0$), and zero otherwise, are included. A set of logistic and multinomial logistic regressions using SIG and $SIGN$ as dependent variables are estimated to identify the significant determinants. I also estimate multivariate regressions using the ABX factor loadings (β_{ABX}) as dependent variables to test the relation between the exposure to the ABX innovation and the fundamental characteristics at a firm level. To mitigate the problematic effects caused by outliers, I winsorise each independent variable at a 90% level (5% at each tail) to reduce cross-sectional variations.[49]

5.6.2 Firm-specific variables

Since there is little theoretical explanation as to which firm-specific characteristics may explain the cross-section of individual stock's exposure to the ABX innovations, my investigation is of an exploratory nature. In addition, because the evidence presented in the previous sections suggests that the ABX factor loadings might have been a proxy for the increasing total and idiosyncratic volatilities, my investigation is centered on a diverse set of fundamental variables that are empirically important in explaining the individual stock's return volatilities.

Firm-specific variables are computed from the balance sheet, income statement and cash flow statement data items from the Compustat database of annual updates. I use Datadate in the Compustat as the basis of data inclusion and assume that the fundamental financial information are made available to the public within four months. For instance, if I estimate the model in December of year t, I include data from firms with fiscal ending dates within the period September of year $t-1$ to August of year t. Regardless of whether the subperiod is longer or shorter than one

[49] I experimented with other levels of winsorisation, first with 0.5% at each tail, 1% at each tail and then 5% at each tail. The levels of winsorisation have had little effect on my findings. I also checked the outcome of the winsorisation using summary statistics and box plots, and find that the winsorisation at 5% gives a more reasonable cross-sectional dispersion.

year, the same approach is followed.

Profitability and growth variables

Pástor and Veronesi (2003) find that increasing uncertainty in a firm's profitability explains the increases in the stock's average idiosyncratic volatilities. Rajgopal and Venkatachalam (2011) find that deteriorating earning qualities are associated with higher idiosyncratic volatilities. In a broad sense, individual firm's profitability and earnings may have a considerable negative impact on stock return volatilities. Since the ABX factor might have represented a portion of idiosyncratic volatilities, I expect that lower profitability and earnings are related to higher exposure to the ABX innovations. To measure a firm's profitability and growth rates, I include the earning-yield ($Earn\_yield$), annual percentage changes in sales ($Sales\_growth$) and the annual changes in earnings before interests, taxes, depreciation and amortisation (EBITDA), which are normalised by total assets ($EBITDA\_growth$). In addition, I include the amount of capital expenditure as a fraction of total assets ($CAPX\_AT$) as a measure of growth orientation.

Leverage variables

Schwert (1989) finds that, when firms issue more debt relative to their original capital structure (i.e. increases in aggregate financial leverage), the return volatilities of the market portfolio increase. Christie (1982) finds that stock return variances are positively associated with both financial leverage and interest rates. One common explanation is that the declines in stock prices lead to a firm's higher leverage and, in turn, results in a firm's higher equity and stock return volatilities. I expect that firms with higher amounts of total debt have higher return volatilities and are more subject to the spillovers of shocks from the structured finance market. For the leverage measures ($Leverage$), I divide the total debts by total assets.[50]

Balance sheet liquidity variables

Titman et al. (2004) find that increases in a firm's investment result in lower subsequent stock returns. Richardson (2006) argues that the lower future stock returns are related to the overinvestments concentrated in firms with the highest level of free cash flow. Taken together, a better

[50] The total debts are calculated by adding preferred stock to total liability less any convertible debt and deferred tax liabilities if available.

liquidity position (more free cash flow) translates into lower future returns. On the other hand, Irvine and Pontiff (2008) find that the idiosyncratic volatilities in fundamental cash flows have increased substantially and are correlated positively with the increases in a stock's idiosyncratic volatilities over time. In addition, firms with less free balance sheet liquidity may rely more on debt financing and have higher equity volatilities and return volatilities. In that sense, I expect a negative relation between a firm's cash flow liquidity position and exposure to the ABX innovations. I measure an individual firm's balance sheet liquidity position by computing the total amount of free cash flow normalised by total assets (FCF_AT) in which the free cash flows are calculated by subtracting the total capital expenditures ($CAPX$) from the total operating cash flows (OCF).

Other variables

I include the dividend yields (Div_yield) of individual firms and a $BIG4$ dummy variable in the analysis.[51] Pástor and Veronesi (2003) have documented empirical evidence that firms with no dividends have higher return volatilities, which is consistent with their theoretical prediction. I expect firms with lower dividend yields to have higher exposure to the crisis-related shocks. In addition, the $BIG4$ dummy variable is a proxy for better earning quality since firms audited by the BIG4 auditors should have more reliable and accurate information, and are expected to be negatively related to the ABX exposure.

5.6.3 MCAP, BE/ME, turnover, risks, returns, and other variables

The time-series average log market capitalisation (LN_MCAP), log book-to-market ratios (LN_BE/ME) and log turnover ratios (LN_TURN) over the crisis subperiods are included. A few risk measures, including the standard deviations ($Stdev$, of the daily returns in each crisis subperiod) and idiosyncratic volatilities ($IVol$, see Section 5.5.2) are included while the time series average (over each crisis subperiod) excess monthly returns of the individual stocks are also included.

5.6.4 Empirical results

Tables 5.54 to 5.58 report the results of the logistic, multinomial logistic and multivariate cross-sectional regressions of the ABX AAA, AA, A, BBB and BBB- indices, respectively. The estimated

[51] The $BIG4$ dummy variable is 1 when the individual firm has been audited with a BIG4 accounting firm during the data year, and 0 otherwise.

coefficients, t-statistics based on robust standard errors clustered by the 12-industry SIC, the number of observations, Pseudo R^2 (for logistic regressions), and adjusted R^2 are reported grouped by crisis subperiods. In each table, Panel A reports the findings of the logistic regressions, Panels B and C report the findings of the multinomial logistic regressions based on the model $SIGN = 1$ (positive ABX exposure) and $SIGN = 2$ (negative ABX exposure) respectively, and Panel D reports the findings of the multivariate regressions using β_{ABX} as dependent variables.

The ABX AAA index

Given the findings of significant increases in ABX AAA factor loadings during the subprime crisis, I focus my attention on reporting and discussing the results of the ABX AAA models.

First, the findings of the logistic regressions are qualitatively similar across the ABX indices. In Table 5.54, my results (Panel A) show that higher standard deviations and lower idiosyncratic volatilities are associated with higher probabilities of having significant ABX factor loadings in all crisis subperiods. In addition, stocks with lower market betas are more likely to have significant ABX factor loadings during the global crisis subperiod.

Next, I split the samples into two groups according to the signs of the ABX factor loadings, as defined by the $SIGN$ variable, and report the multinomial logistic regression results in Panel B and C. First, the significant findings in the standard deviations and idiosyncratic volatilities in Panel A were largely dominated by the model of negative ABX exposure ($SIGN = 2$ of Panel C). In Panel B, higher idiosyncratic volatilities and lower standard deviations are associated with higher probabilities of having a significant positive exposure to the ABX AAA innovations. Note that the coefficient signs of the standard deviations and idiosyncratic volatilities have reversed in the global crisis subperiod in both models, suggesting changes in the determinants of risk exposure. Higher (lower) market betas are associated with higher likelihood of observing significant positive (negative) ABX exposure in all subperiods except the global crisis subperiod, which is consistent with my decile portfolio sort results (in Table 5.41). In addition, I find evidence that value stocks are more likely to be exposed to the ABX innovations during the subprime crisis, as evinced by the significant and positive coefficients of the book-to-market ratios in Panel B.

For the multivariate regression results reported in Panel D, stocks with lower standard deviations and higher idiosyncratic volatilities are associated with higher ABX factor loadings in the subprime crisis subperiod. Again, the coefficient signs of the standard deviations and idiosyncratic volatilities reversed in the global crisis subperiod. I document significant and positive relationships between the market betas (β_{MKT}) and the ABX factor loadings (β_{ABX}) only during the subprime crisis subperiod. I also find that higher log turnover and book-to-market ratios are associated with higher ABX factor loadings in the subprime crisis subperiod. On the other hand, I find weak evidence of explanatory power in the firm-specific fundamental variables over individual stocks' ABX factor loadings.

The other ABX indices

Consistent with the fact that both ABX AAA and AA indices were correlated, the results of the ABX AA models are qualitatively similar to those of the AAA model with the same coefficient signs in most variables. With regard to the other ABX models, the findings are different in a few major ways. First, I find significant and positive (negative) relations between the standard deviations (idiosyncratic volatilities) and ABX factor loadings in the subprime crisis subsample, as shown in Panel D of Tables 5.56 and 5.58. In addition, the market betas and the ABX factor loadings are negatively related as opposed to the positive relation documented in the AAA and AA models. Again, I find little evidence of explanatory power in the firm-specific variables over the ABX factor loadings.

5.6.5 Robustness tests - fixed effects models

In Section 5.6.4, I performed cross-sectional regressions at the end of each crisis subperiod using variables that are contemporaneous in relation to one another. To check the robustness of the findings, and to account for possible firm and time fixed effects, the time series cross-sectional (TSCS) analysis is employed. I organise the data within a panel structure with six years (annual data at the end of December) and individual stocks as cross-sectional units (identified by PERMNO). The variables used are constructed in the same manner as in the previous sections. The time series averages (of, for example, the monthly excess returns, turnover ratios, book-to-market ratios, etc.) are computed over a year instead of over each crisis subperiod. The firm-specific fundamental variables are assumed to be made public to investors within four months, similar to the previous section.[52]

[52] Any duplicate observations of a firm within the same year (e.g. from September 2005 to August 2006 as in year 2006) are corrected so that the most recent announcement has been retained. I find 16 duplications of observations

The dependent variables of the fixed effects models are the five ABX factor loadings from Model 3. All panel regressions are subject to the Hausman tests and all are significant. Hence, the fixed effects models are appropriate and generate consistent estimates.

The results of the fixed effects models are reported in Table 5.59. Most of the findings are qualitatively similar to those documented in the previous sections (in Panel D of Tables 5.54 to 5.58). The signs on the standard deviations, idiosyncratic volatilities and market beta are the same, although the statistical significance is lower towards the lowest-rated ABX models. I find that lower average monthly excess returns are associated with higher ABX factor loadings across the ABX models. Firm size is also positively related to the ABX factor loadings in the ABX AAA, AA and BBB- models. In addition, higher dividend yields are associated with higher ABX A factor loadings while lower earnings are related to higher ABX BBB factor loadings. Again, I find little evidence that the fundamental variables explain the ABX factor loadings.

Discussions and implications

The main implication of my analysis is that return volatilities have played an important role in explaining the magnitude and likelihood of individual stock's exposure to the ABX factor throughout my sample period. In other words, the ABX factor acted as a proxy for return volatilities and was correlated positively with the individual stock's idiosyncratic risks, particularly during the subprime crisis. In addition, stocks with higher market systematic risks had a higher correlation with the ABX innovations. In addition, the evidence suggests that individual stock's exposure to the ABX innovations were primarily driven by the stock-market elements rather than the firm-specific fundamental characteristics. This is perhaps consistent with the view that contagion is the sudden shock transmission across markets that is unexplained by fundamentals. The weak explanatory power in the firm-specific variables lends support to my contention that the spillovers of shocks from the ABX indices impacted the US stock market in a systematic manner. Overall, this chapter presents reasonably strong evidence that the ABX index family represented an important type of risk barometers and reflected the heightened market illiquidity risks and the investors' risk aversion in the US financial system (Fender and Scheicher, 2009).

when constructing the panel data, which are mostly due to changes in the fiscal year date.

5.7 Conclusions

This chapter makes a number of important contributions to the existing empirical literature. First, I contribute to the contagion literature and provide strong evidence of contagion travelling from the US structured finance market to the US equity market, which is consistent with Longstaff (2010) and the findings documented in Chapter 4. I differentiate this present study from other contagion studies by utilising firm-level information from the major US Exchanges and using an asset pricing framework to quantify an individual stock's exposure to the shock components of the ABX indices, which are unexplained by the market.

Second, I test, within a formal cross-sectional asset pricing framework, whether the ABX innovations explain the cross-section of expected returns. More precisely, I use a two-pass regression procedure and demonstrate how the inclusion of the ABX AAA factor significantly improves the pricing model performance during the time when contagion was present. The evidence shows that the Carhart (1997) four-factor model augmented with the orthogonalised ABX AAA factor only holds and yields insignificant pricing error statistics during the subprime crisis subperiod. The main implication is that the impact of shocks from the structured finance market on individual stocks was considerably systematic and that the phenomenon of significant increases in cross-market linkages as documented in the contagion literature has profound implications for asset pricing. Amongst the ABX index family, I demonstrate that the ABX AAA index was the most relevant in asset pricing and represented an important source of systematic risk during the crisis.

Third, I propose simple and innovative statistics (monthly) that gauge the degree of an individual stock's exposure to the ABX innovations over time. I analyse graphically and find remarkably higher levels of exposure to the ABX innovations in February, July and October 2007 and in February, July and November 2008. Within a VAR model framework, the Granger-causality analysis shows that the value-weighted idiosyncratic volatilities predicted the level of ABX exposure. The evidence suggests strong linkages between market wide average idiosyncratic volatilities, market and funding illiquidity, and the individual stock's exposure to the ABX innovations, further lending support to the argument that the changes in risk premia and illiquidity provided the channel of contagion transmission.

Lastly, I investigate the determinants of an individual stock's exposure to the ABX innovations using logistic, multinomial logistic and multivariate cross-sectional regressions. The findings show that higher idiosyncratic volatilities and lower standard deviations are associated with higher (and also higher likelihood of having significant) ABX factor loadings, more prominently in the ABX AAA and AA models. I also find positive relations between the market betas and the ABX factor loadings. Nonetheless, I find little evidence that the firm-specific fundamental variables explain the individual stock's exposure to the ABX innovations.

Table 5.1: Interdependence model

This table reports the coefficients, robust t-statistics clustered by industry SIC, the number of observations, adjusted R^2 and the diagnostic tests associated with the following model:

$$R_{i,t} \quad = \quad \alpha_{i,t} + \boldsymbol{\beta_0'}\mathbf{F_t} + \varepsilon_{i,t}.$$

Under this specification, the factor loadings reflect the average level of interdependence between the average stock, the market index and the ABX innovations over the full sample, respectively. This specification is referred to as the interdependence model as the crisis dummy variables are not included and the factor loadings are not allowed to change over time. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX factor. The EXTEST is distributed as $\chi^2(1)$ with a critical value of 3.84 (6.63) at the 5% (1%) level while the ICSTAT is distributed as $\chi^2(12)$ with a critical value of 21.03 (26.22) at the 5% (1%) level. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Interdependence model										
ABX	AAA		AA		A		BBB		BBB-	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
β_{MKT}	1.139***	[11.345]	1.139***	[11.292]	1.138***	[11.247]	1.138***	[11.227]	1.138***	[11.245]
β_{ABX}	0.151***	[2.944]	0.029**	[2.105]	0.008	[0.619]	0.021	[1.410]	0.015	[1.087]
α_0	0.003	[0.032]	0.002	[0.018]	0.002	[0.018]	0.007	[0.067]	0.005	[0.052]
N	443,188		443,188		443,188		443,188		443,188	
Adj. R^2	0.125		0.125		0.125		0.125		0.125	
EXTEST	8.556***		8.069***		8.415***		8.523***		8.521***	
ICSTAT	107.978***		8.583		8.887		9.031		8.999	

Table 5.2: Contagion model

This table reports the coefficients, robust t-statistics clustered by industry SIC, the number of observations, adjusted R^2 and the diagnostic tests associated with the following model:

$$\begin{aligned} R_{i,t} &= \alpha_{i,t} + \boldsymbol{\beta_t'}\mathbf{F_t} + \gamma_{i,0}Subp_t + \eta_{i,0}Global_t + \varepsilon_{i,t}, \\ \boldsymbol{\beta_t} &= \boldsymbol{\beta_0} + \boldsymbol{\xi_0}Subp_t + \boldsymbol{\zeta_0}Global_t. \end{aligned}$$

Under this specification, γ and η measure the degree of contagion unrelated to the factors. Any significant loadings suggest that the interdependence model is insufficient in capturing the variations of the US stock returns during the crisis. In addition, I model the factor loadings as functions of both the subprime and global crisis dummy variables and thus allow shift changes in the factor loadings during the crisis. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX factor. The EXTEST is distributed as $\chi^2(1)$ with a critical value of 3.84 (6.63) at the 5% (1%) level while the ICSTAT is distributed as $\chi^2(12)$ with a critical value of 21.03 (26.22) at the 5% (1%) level. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively.

Panel A: Contagion model

ABX	AAA		AA		A		BBB		BBB-	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
β_{MKT}	1.209***	[9.263]	1.212***	[9.260]	1.205***	[8.861]	1.265***	[8.352]	1.224***	[8.511]
β_{ABX}	0.310***	[9.859]	0.068***	[4.004]	0.017	[1.061]	0.102***	[2.806]	0.046	[1.400]
γ	−0.172	[−0.691]	−0.787**	[−2.573]	−0.901**	[−2.867]	−0.285	[−0.703]	−0.783**	[−2.259]
η	0.485**	[2.619]	0.407**	[2.597]	0.527**	[2.623]	1.162***	[3.841]	0.786**	[2.597]
ξ_{MKT}	−0.185***	[−3.086]	−0.222**	[−2.247]	−0.226***	[−4.052]	−0.329***	[−4.943]	−0.235***	[−4.031]
ζ_{MKT}	−0.089	[−1.625]	−0.095	[−1.647]	−0.081	[−1.311]	−0.131	[−1.660]	−0.093	[−1.387]
ξ_{ABX}	0.710***	[4.561]	−0.035	[−0.317]	−0.03	[−0.684]	−0.083*	[−1.711]	−0.057	[−1.151]
ζ_{ABX}	−0.268**	[−2.718]	−0.07	[−1.569]	0.003	[0.086]	−0.068	[−1.275]	−0.015	[−0.322]
α_0	−0.116	[−1.058]	−0.099	[−0.743]	−0.009	[−0.056]	−0.491*	[−1.825]	−0.181	[−0.751]
N	443,188		443,188		443,188		443,188		443,188	
Adj. R^2	0.127		0.126		0.126		0.126		0.126	
EXTEST	8.662***		8.106***		8.716***		8.643***		8.783***	
ICSTAT	8.680		8.384		8.811		8.728		8.871	

Panel B: Interacted factor loadings with the crisis dummy variables

	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
$\alpha_0 + \gamma$	−0.288	[0.192]	−0.886***	[0.002]	−0.910***	[0.001]	−0.776***	[0.002]	−0.964***	[0.000]
$\alpha_0 + \eta$	0.369**	[0.013]	0.308**	[0.036]	0.518***	[0.010]	0.671***	[0.005]	0.605**	[0.010]
$\beta_{MKT} + \xi_{MKT}$	1.024***	[0.000]	0.990***	[0.000]	0.979***	[0.000]	0.936***	[0.000]	0.989***	[0.000]
$\beta_{MKT} + \zeta_{MKT}$	1.12***	[0.000]	1.117***	[0.000]	1.124***	[0.000]	1.134***	[0.000]	1.131***	[0.000]
$\beta_{ABX} + \xi_{ABX}$	1.020***	[0.000]	0.033	[0.755]	−0.013	[0.669]	0.019	[0.192]	−0.011	[0.579]
$\beta_{ABX} + \zeta_{ABX}$	0.042	[0.617]	−0.002	[0.963]	0.020	[0.384]	0.034	[0.129]	0.031*	[0.086]

Table 5.3: Interdependence model - industry subsamples (ABX AAA)

This table reports the coefficients, Newey-West (1987) robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample interdependence model:

$$R_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_0'}\mathbf{F_t} + \varepsilon_{i,t}.$$

The industry subsamples are based on the 12-industry classification codes obtained from French's web site. Under this specification, the factor loadings reflect the level of interdependence between the average stock, the market index and the ABX AAA innovations over the full sample, respectively, for each industry subsample of stocks. This specification is referred to as the interdependence model as the crisis dummy variables are not included in the model and the factor loadings are not allowed to change over time. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX AAA factor. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10), money finance (SIC=11), and other (SIC=12).

Interdependence model												
ABX AAA												
Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.136***	1.617***	1.454***	1.502***	1.334***	1.282***	1.300***	0.705***	1.287***	1.149***	0.862***	1.239***
t-stat	(40.409)	(35.419)	(68.517)	(39.610)	(31.925)	(85.434)	(40.386)	(32.353)	(54.887)	(44.515)	(109.849)	(83.312)
β_{ABX}	0.366***	0.237***	0.130***	0.134	0.115	0.009	−0.071	0.085**	0.256***	0.024	0.270***	0.051*
t-stat	(7.107)	(2.680)	(2.971)	(1.457)	(1.552)	(0.318)	(−1.063)	(2.151)	(6.384)	(0.474)	(18.422)	(1.857)
α_0	0.109	−0.279	0.318***	0.431***	0.441**	0.148**	0.217	0.343***	0.287***	0.080	−0.276***	−0.166**
t-stat	(0.964)	(−1.483)	(3.643)	(2.934)	(2.371)	(2.130)	(1.500)	(3.929)	(3.100)	(0.701)	(−8.943)	(−2.503)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.139	0.208	0.197	0.140	0.155	0.132	0.138	0.146	0.143	0.067	0.134	0.134

Table 5.4: Interdependence model - industry subsamples (ABX AA)

This table reports the coefficients, Newey-West (1987) robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample interdependence model:

$$R_{i,t} = \alpha_{i,t} + \boldsymbol{\beta}_{\mathbf{0}}'\mathbf{F_t} + \varepsilon_{i,t}.$$

The industry subsample is based on the 12-industry classification codes obtained from French's web site. Under this specification, the factor loadings reflect the level of interdependence between the average stock, the market index and the ABX AA innovations over the full sample, respectively, for each industry subsample of stocks. This specification is referred to as the interdependence model as the crisis dummy variables are not included in the model and the factor loadings are not allowed to change over time. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX AA factor. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10), money finance (SIC=11), and other (SIC=12).

Interdependence model												
ABX AA												
Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.135***	1.618***	1.454***	1.502***	1.335***	1.282***	1.299***	0.705***	1.287***	1.149***	0.860***	1.239***
t-stat	(40.247)	(35.307)	(68.461)	(39.621)	(31.875)	(85.414)	(40.281)	(32.343)	(54.749)	(44.526)	(109.310)	(83.456)
β_{ABX}	0.083***	0.020	−0.015	0.058	−0.001	−0.007	−0.003	0.031**	−0.001	0.016	0.066***	0.018**
t-stat	(5.364)	(0.668)	(−0.948)	(1.689)	(−0.056)	(−0.782)	(−0.141)	(2.542)	(−0.107)	(0.841)	(13.252)	(2.022)
α_0	0.106	−0.284	0.314***	0.433***	0.438**	0.147**	0.219	0.343***	0.281***	0.080	−0.278***	−0.165**
t-stat	(0.935)	(−1.512)	(3.595)	(2.953)	(2.351)	(2.120)	(1.514)	(3.928)	(3.026)	(0.705)	(−8.978)	(−2.489)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.136	0.207	0.197	0.141	0.155	0.132	0.138	0.146	0.141	0.067	0.132	0.134

Table 5.5: Interdependence model - industry subsamples (ABX A)

This table reports the coefficients, Newey-West (1987) robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample interdependence model:

$$R_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_0'}\mathbf{F_t} + \varepsilon_{i,t}.$$

The industry subsample is based on the 12-industry classification codes obtained from French's web site. Under this specification, the factor loadings reflect the level of interdependence between the average stock, the market index and the ABX A innovations over the full sample, respectively, for each industry subsample of stocks. This specification is referred to as the interdependence model because the crisis dummy variables are excluded from the model and the factor loadings are not allowed to change over time. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX A factor. Superscripts ***, ** and * denote statistical significance at 1%, 5% and 10% level, respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10), money finance (SIC=11), and other (SIC=12).

Interdependence model												
ABX A												
Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.134***	1.617***	1.454***	1.504***	1.335***	1.282***	1.299***	0.705***	1.287***	1.149***	0.858***	1.239***
t-stat	(40.227)	(35.296)	(68.395)	(39.832)	(31.865)	(85.362)	(40.281)	(32.357)	(54.646)	(44.483)	(108.905)	(83.486)
β_{ABX}	0.053***	0.019	−0.029***	−0.106***	−0.014	−0.012**	0.014	−0.008	0.021**	−0.015	0.044***	−0.001
t-stat	(5.414)	(1.133)	(−3.339)	(−5.757)	(−0.895)	(−2.082)	(1.103)	(−0.930)	(2.585)	(−1.440)	(15.426)	(−0.238)
α_0	0.107	−0.283	0.313***	0.416***	0.436**	0.146**	0.222	0.343***	0.282***	0.075	−0.268***	−0.166**
t-stat	(0.950)	(−1.506)	(3.576)	(2.853)	(2.340)	(2.099)	(1.529)	(3.920)	(3.049)	(0.664)	(−8.680)	(−2.502)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.136	0.207	0.197	0.144	0.155	0.132	0.138	0.146	0.141	0.067	0.132	0.134

Table 5.6: Interdependence model - industry subsamples (ABX BBB)

This table reports the coefficients, Newey-West (1987) robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample interdependence model:

$$R_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_0'}\mathbf{F_t} + \varepsilon_{i,t}$$

The industry subsample is based on the 12-industry classification codes obtained from French's web site. Under this specification, the factor loadings reflect the level of interdependence between the average stock, the market index and the ABX BBB innovations over the full sample, respectively, for each industry subsample of stocks. This specification is referred to as the interdependence model because the crisis dummy variables are not included in the model and the factor loadings are not allowed to change over time. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX BBB factor. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10), money finance (SIC=11), and other (SIC=12).

Interdependence model												
ABX BBB												
Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.134***	1.617***	1.454***	1.504***	1.335***	1.282***	1.298***	0.705***	1.285***	1.148***	0.857***	1.239***
t-stat	(40.232)	(35.304)	(68.359)	(39.768)	(31.846)	(85.370)	(40.285)	(32.358)	(54.662)	(44.451)	(108.878)	(83.464)
β_{ABX}	0.071***	0.018	−0.020**	−0.118***	0.001	0.005	0.032**	−0.004	0.055***	0.018*	0.055***	−0.009
t-stat	(6.597)	(1.115)	(−2.330)	(−7.159)	(0.079)	(0.776)	(2.204)	(−0.373)	(6.673)	(1.710)	(19.748)	(−1.537)
α_0	0.114	−0.281	0.312***	0.408***	0.438**	0.149**	0.231	0.343***	0.294**	0.087	−0.252***	−0.165**
t-stat	(1.008)	(−1.497)	(3.571)	(2.801)	(2.351)	(2.150)	(1.599)	(3.921)	(3.188)	(0.774)	(−8.150)	(−2.484)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.136	0.207	0.197	0.144	0.155	0.132	0.138	0.146	0.142	0.067	0.133	0.134

Table 5.7: Interdependence model - industry subsamples (ABX BBB-)

This table reports the coefficients, Newey-West (1987) robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample interdependence model:

$$R_{i,t} = \alpha_{i,t} + \boldsymbol{\beta_0'}\mathbf{F_t} + \varepsilon_{i,t}$$

The industry subsample is based on the 12-industry classification codes obtained from French's web site. Under this specification, the factor loadings reflect the level of interdependence between the average stock, the market index and the ABX BBB- innovations over the full sample, respectively, for each industry subsample of stocks. This specification is referred to as the interdependence model because the crisis dummy variables are not included in the model and the factor loadings are not allowed to change over time. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX BBB factor. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), healthcare (SIC=10), money finance (SIC=11), and other (SIC=12).

Interdependence model												
ABX BBB-												
Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.134***	1.618***	1.454***	1.504***	1.335***	1.282***	1.298***	0.705***	1.285***	1.148***	0.858***	1.239***
t-stat	(40.225)	(35.309)	(68.355)	(39.774)	(31.842)	(85.367)	(40.274)	(32.354)	(54.646)	(44.448)	(108.931)	(83.472)
β_{ABX}	0.072***	0.011	−0.019**	−0.121***	−0.003	0.004	0.031*	−0.002	0.051***	0.013	0.047***	−0.021**
t-stat	(6.399)	(0.601)	(−2.064)	(−6.726)	(−0.157)	(0.581)	(1.937)	(−0.163)	(5.755)	(1.085)	(15.034)	(−3.144)
α_0	0.115	−0.283	0.311***	0.408**	0.437**	0.149**	0.232	0.343***	0.295***	0.085	−0.256***	−0.164**
t-stat	(1.016)	(−1.506)	(3.570)	(2.804)	(2.345)	(2.148)	(1.600)	(3.922)	(3.195)	(0.753)	(−8.273)	(−2.462)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.136	0.207	0.197	0.144	0.155	0.132	0.138	0.146	0.142	0.067	0.132	0.134

Table 5.8: Contagion model - industry subsample (ABX AAA)

This table reports the coefficients, robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample contagion model:

$$\begin{aligned} R_{i,t} &= \alpha_{i,t} + \boldsymbol{\beta_t'}\mathbf{F_t} + \gamma_{i,0}Subp_t + \eta_{i,0}Global_t + \varepsilon_{i,t}, \\ \boldsymbol{\beta_t} &= \boldsymbol{\beta_0} + \boldsymbol{\xi_0}Subp_t + \boldsymbol{\zeta_0}Global_t. \end{aligned}$$

Under this specification, γ and η measure the degree of contagion unrelated to the factors and that any significant loadings suggest that the interdependence model is insufficient in capturing the variations of stock returns in individual *industry sectors*. In addition, I model the factor loadings as functions of both the subprime and global crisis dummy variables and thus allow shift changes in the factor loadings during the crisis. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX AAA innovations. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10), money finance (SIC=11), and other (SIC=12).

Panel A: Contagion Model												
ABX AAA												
Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.224***	1.730***	1.551***	1.652***	1.507***	1.396***	1.326***	0.648***	1.387***	1.287***	0.832***	1.357***
t-stat	(30.305)	(26.286)	(56.825)	(45.337)	(25.726)	(66.486)	(31.264)	(24.756)	(36.256)	(34.784)	(75.914)	(67.385)
β_{ABX}	0.594***	0.674***	0.322***	0.548***	0.248**	0.297***	0.035	0.165***	0.476***	0.225***	0.249***	0.309***
t-stat	(6.806)	(4.586)	(5.930)	(7.672)	(2.263)	(6.631)	(0.333)	(3.413)	(7.357)	(3.328)	(11.607)	(7.871)
γ	0.150	0.317	1.046***	1.007**	1.356**	0.307	−0.465	−0.586**	−0.990***	−0.731**	−0.716***	0.241
t-stat	(0.484)	(0.683)	(4.304)	(3.252)	(2.495)	(1.514)	(−1.216)	(−2.101)	(−3.879)	(−2.399)	(−10.580)	(1.241)
η	−0.462	−0.024	0.518	1.501*	−0.116	0.411*	−1.577***	−0.839***	1.173***	1.231***	0.174	1.069***
t-stat	(−1.220)	(−0.038)	(1.461)	(1.931)	(−0.204)	(1.810)	(−3.398)	(−2.972)	(3.818)	(3.149)	(1.639)	(4.741)
ξ_{MKT}	−0.210**	−0.437**	−0.490***	−0.329***	−0.560***	−0.354***	−0.002	−0.002	−0.314***	−0.141	−0.013	−0.042
t-stat	(−2.415)	(−3.043)	(−6.897)	(−4.098)	(−4.208)	(−6.840)	(−0.018)	(−0.035)	(−3.942)	(−1.644)	(−0.670)	(−0.765)
ζ_{MKT}	−0.184***	−0.178	−0.112**	−0.189	−0.296***	−0.163***	−0.144*	0.072	−0.088	−0.187***	0.083***	−0.182***
t-stat	(−2.810)	(−1.629)	(−2.011)	(−1.603)	(−3.164)	(−4.778)	(−1.955)	(1.489)	(−1.629)	(−3.013)	(4.616)	(−5.245)
ξ_{ABX}	1.353***	1.142**	1.033***	−0.498	1.724***	0.736***	0.970**	−0.483	1.234***	0.238	0.961***	−0.000
t-stat	(3.584)	(2.055)	(3.611)	(−1.365)	(2.960)	(3.071)	(2.042)	(−1.461)	(4.092)	(0.571)	(11.923)	(−0.002)
ζ_{ABX}	−0.429***	−0.748***	−0.311***	−0.609***	−0.245	−0.477***	−0.264*	−0.174**	−0.376***	−0.303**	0.002	−0.387***
t-stat	(−3.916)	(−4.101)	(−3.854)	(−4.174)	(−1.627)	(−8.174)	(−1.892)	(−2.262)	(−4.509)	(−3.148)	(0.065)	(−6.996)
α_0	0.085	−0.509**	−0.013	−0.427***	0.123	−0.142	0.587***	0.598***	0.220**	−0.256*	0.015	−0.674***
t-stat	(0.638)	(−2.272)	(−0.122)	(−3.001)	(0.502)	(−1.585)	(2.965)	(5.995)	(2.039)	(−1.938)	(0.389)	(−8.593)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.142	0.213	0.199	0.143	0.158	0.135	0.139	0.148	0.148	0.069	0.136	0.136
Panel B: Interacted factor loadings												
$\alpha_0+\gamma$	0.235	−0.192	1.033***	0.580**	1.479***	0.165	0.122	0.012	−0.770***	−0.987***	−0.701***	−0.433**
$\alpha_0+\eta$	−0.377	−0.533	0.505	1.074	0.007	0.269	−0.990**	−0.241	1.393***	0.975***	0.189*	0.395*
$\beta_{MKT}+\xi_{MKT}$	1.014***	1.293***	1.061***	1.323***	0.947***	1.042***	1.324***	0.646***	1.073***	1.146***	0.819***	1.315***
$\beta_{MKT}+\zeta_{MKT}$	1.040***	1.552***	1.439***	1.463***	1.211***	1.233***	1.182***	0.720***	1.299***	1.100***	0.915***	1.175***
$\beta_{ABX}+\xi_{ABX}$	1.947***	1.816***	1.355***	0.050	1.972***	1.033***	1.005**	−0.318	1.710***	0.463	1.210***	0.309
$\beta_{ABX}+\zeta_{ABX}$	0.165**	−0.074	0.011	−0.061	0.003	−0.180***	−0.229**	−0.009	0.100*	−0.078	0.251***	−0.078**

Table 5.9: Contagion model - industry subsample (ABX AA)

This table reports the coefficients, robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample contagion model:

$$
\begin{aligned}
R_{i,t} &= \alpha_{i,t} + \boldsymbol{\beta_t'}\mathbf{F_t} + \gamma_{i,0}Subp_t + \eta_{i,0}Global_t + \varepsilon_{i,t}, \\
\boldsymbol{\beta_t} &= \boldsymbol{\beta_0} + \boldsymbol{\xi_0}Subp_t + \boldsymbol{\zeta_0}Global_t.
\end{aligned}
$$

Under this specification, γ and η measure the degree of contagion unrelated to the factors and that any significant loadings suggest that the interdependence model is insufficient in capturing the variations of stock returns in individual *industry sectors*. In addition, I model the factor loadings as functions of both the subprime and global crisis dummy variables and thus allow shift changes in the factor loadings during the crisis. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX AA innovations. Superscripts ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10), money finance (SIC=11), and other (SIC=12).

Panel A: Contagion Model												
ABX AA												
Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.215***	1.711***	1.535***	1.694***	1.499***	1.402***	1.331***	0.658***	1.361***	1.317***	0.834***	1.361***
t-stat	(31.153)	(26.781)	(57.721)	(47.076)	(26.294)	(67.763)	(32.061)	(25.751)	(38.144)	(33.735)	(78.277)	(69.746)
β_{ABX}	0.068***	0.022	−0.012	0.274***	0.005	0.071***	0.024	0.074***	−0.036*	0.153***	0.051***	0.097***
t-stat	(3.243)	(0.575)	(−0.769)	(12.006)	(0.171)	(5.850)	(0.831)	(5.437)	(−1.923)	(5.617)	(7.740)	(8.595)
γ	−1.154***	−1.069***	0.043	1.284***	0.094	−0.319**	−1.024***	−0.342*	−2.336***	−0.758***	−1.421***	0.054
t-stat	(−4.584)	(−2.713)	(0.219)	(5.196)	(0.225)	(−1.979)	(−3.218)	(−1.689)	(−11.276)	(−3.139)	(−24.668)	(0.347)
η	−0.258	−0.237	0.171	0.945	−0.431	0.110	−1.745***	−1.078***	1.084***	0.996***	0.363***	0.974***
t-stat	(−0.662)	(−0.390)	(0.539)	(1.571)	(−0.736)	(0.480)	(−3.650)	(−3.493)	(3.486)	(2.698)	(3.380)	(4.190)
ξ_{MKT}	−0.175*	−0.425***	−0.536***	−0.482***	−0.512***	−0.519***	−0.105	−0.098	−0.326***	−0.204**	0.059***	−0.206***
t-stat	(−1.860)	(−2.790)	(−7.065)	(−5.428)	(−3.563)	(−9.071)	(−0.934)	(−1.294)	(−3.908)	(−2.190)	(2.728)	(−3.442)
ζ_{MKT}	−0.162**	−0.153	−0.102*	−0.265**	−0.295***	−0.179***	−0.153**	0.049	−0.053	−0.234***	0.082***	−0.190***
t-stat	(−2.502)	(−1.439)	(−1.900)	(−2.383)	(−3.224)	(−5.272)	(−2.088)	(1.015)	(−1.015)	(−3.761)	(4.610)	(−5.538)
ξ_{ABX}	0.175*	0.145	0.023	−0.490***	0.269*	−0.287***	−0.121	−0.278***	0.129	−0.175	0.216***	−0.388***
t-stat	(1.756)	(0.960)	(0.327)	(−5.212)	(1.899)	(−4.507)	(−0.909)	(−3.625)	(1.656)	(−1.461)	(9.888)	(−6.318)
ζ_{ABX}	0.022	−0.018	−0.006	−0.417***	−0.033	−0.152***	−0.100**	−0.123***	0.095***	−0.243***	0.029***	−0.131***
t-stat	(0.667)	(−0.304)	(−0.196)	(−6.304)	(−0.654)	(−7.927)	(−2.174)	(−4.486)	(3.379)	(−6.134)	(2.804)	(−6.966)
α_0	0.268*	−0.174	0.198*	−0.758***	0.253	−0.145	0.548***	0.520***	0.572***	−0.505***	0.034	−0.705***
t-stat	(1.956)	(−0.770)	(1.918)	(−5.409)	(1.046)	(−1.636)	(2.776)	(5.113)	(5.095)	(−4.001)	(0.903)	(−8.858)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.138	0.208	0.198	0.150	0.157	0.135	0.139	0.151	0.145	0.071	0.135	0.137
Panel B: Interacted factor loadings												
$\alpha_0 + \gamma$	−0.886***	−1.243***	0.241	0.526***	0.347	−0.464***	−0.476*	0.178	−1.764***	−1.263***	−1.387***	−0.651***
$\alpha_0 + \eta$	0.010	−0.411	0.369	0.187	−0.178	−0.035	−1.197***	−0.558*	1.656***	0.491	0.397***	0.269
$\beta_{MKT} + \xi_{MKT}$	1.040***	1.286***	0.999***	1.212***	0.987***	0.883***	1.226***	0.56***	1.035***	1.113***	0.893***	1.155***
$\beta_{MKT} + \zeta_{MKT}$	1.053***	1.558***	1.433***	1.429***	1.204***	1.223***	1.178***	0.707***	1.308***	1.083***	0.916***	1.171***
$\beta_{ABX} + \xi_{ABX}$	0.243**	0.167	0.011	−0.216**	0.274**	−0.216***	−0.097	−0.204***	0.093	−0.022	0.267***	−0.291***
$\beta_{ABX} + \zeta_{ABX}$	0.090***	0.004	−0.018	−0.143**	−0.028	−0.081***	−0.076**	−0.049**	0.059***	−0.090***	0.080***	−0.034**

Table 5.10: Contagion model - industry subsample (ABX A)

This table reports the coefficients, robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample contagion model:

$$\begin{aligned} R_{i,t} &= \alpha_{i,t} + \boldsymbol{\beta_t'}\mathbf{F_t} + \gamma_{i,0}Subp_t + \eta_{i,0}Global_t + \varepsilon_{i,t}, \\ \boldsymbol{\beta_t} &= \boldsymbol{\beta_0} + \boldsymbol{\xi_0}Subp_t + \boldsymbol{\zeta_0}Global_t. \end{aligned}$$

Under this specification, γ and η measure the degree of contagion unrelated to the factors and that any significant loadings suggest that the interdependence model is insufficient in capturing the variations of stock returns in individual *industry sectors*. In addition, I model the factor loadings as functions of both the subprime and global crisis dummy variables and thus allow shift changes in the factor loadings during the crisis. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX A innovations. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10), money finance (SIC=11), and other (SIC=12).

Panel A: Contagion Model												
ABX A												
Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.212***	1.713***	1.533***	1.713***	1.492***	1.412***	1.339***	0.643***	1.352***	1.274***	0.814***	1.372***
t-stat	(31.769)	(27.422)	(58.588)	(47.358)	(26.408)	(67.870)	(31.947)	(25.253)	(39.349)	(33.471)	(77.818)	(69.752)
β_{ABX}	0.025	0.014	−0.009	0.159***	−0.012	0.050***	0.027	0.005	−0.034**	−0.011	−0.017***	0.063***
t-stat	(1.472)	(0.457)	(−0.723)	(8.261)	(−0.376)	(4.560)	(1.109)	(0.357)	(−2.179)	(−0.623)	(−3.172)	(6.500)
γ	−1.199***	−1.070**	−0.008	1.190***	0.073	−0.388**	−1.044***	−0.575***	−2.427***	−1.207***	−1.551***	−0.035
t-stat	(−4.616)	(−2.591)	(−0.039)	(4.640)	(0.168)	(−2.346)	(−3.289)	(−2.734)	(−11.174)	(−4.912)	(−26.187)	(−0.219)
η	−0.180	0.035	−0.066	−0.663	−0.557	0.573**	−1.180**	−1.246***	1.476***	1.274***	0.382***	1.361***
t-stat	(−0.449)	(0.051)	(−0.181)	(−0.856)	(−0.878)	(2.328)	(−2.387)	(−3.883)	(4.386)	(3.085)	(3.212)	(5.567)
ξ_{MKT}	−0.303***	−0.513***	−0.529***	−0.365***	−0.659***	−0.386***	−0.042	0.044	−0.356***	−0.143	−0.076***	−0.034
t-stat	(−3.547)	(−3.668)	(−7.649)	(−4.565)	(−5.018)	(−7.500)	(−0.410)	(0.653)	(−4.683)	(−1.605)	(−3.973)	(−0.635)
ζ_{MKT}	−0.156**	−0.146	−0.108*	−0.339***	−0.290***	−0.171***	−0.141	0.065	−0.030	−0.165**	0.107***	−0.187***
t-stat	(−2.431)	(−1.348)	(−1.941)	(−2.832)	(−3.170)	(−5.030)	(−1.917)	(1.353)	(−0.573)	(−2.616)	(5.988)	(−5.438)
ξ_{ABX}	−0.001	−0.007	−0.018	−0.230***	0.055	−0.134***	−0.081**	−0.066***	0.018	−0.006	0.072***	−0.158***
t-stat	(−0.040)	(−0.157)	(−0.835)	(−7.858)	(1.193)	(−7.074)	(−2.019)	(−3.028)	(0.722)	(−0.180)	(9.893)	(−8.945)
ζ_{ABX}	0.049**	0.015	−0.026	−0.417***	−0.013	−0.061***	−0.026	−0.039**	0.119***	0.023	0.088***	−0.050***
t-stat	(2.149)	(0.391)	(−1.479)	(−13.640)	(−0.346)	(−4.339)	(−0.834)	(−1.983)	(6.014)	(1.010)	(12.631)	(−3.774)
α_0	0.326**	−0.179	0.206*	−0.752***	0.313	−0.183*	0.493**	0.678***	0.628***	−0.080	0.222***	−0.734***
t-stat	(2.183)	(−0.713)	(1.896)	(−4.861)	(1.214)	(−1.941)	(2.497)	(5.933)	(4.986)	(−0.577)	(5.500)	(−8.734)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.137	0.208	0.198	0.154	0.157	0.134	0.139	0.149	0.146	0.069	0.135	0.136
Panel B: Interacted factor loadings												
$\alpha_0+\gamma$	−0.873***	−1.249***	0.198	0.438**	0.386	−0.571***	−0.551**	0.103	−1.799***	−1.287***	−1.329***	−0.769***
$\alpha_0+\eta$	0.146	−0.144	0.140	−1.415*	−0.244	0.390*	−0.687	−0.568*	2.104***	1.194***	0.604***	0.627***
$\beta_{MKT}+\xi_{MKT}$	0.909***	1.200***	1.004***	1.348***	0.833***	1.026***	1.297***	0.687***	0.996***	1.131***	0.738***	1.338***
$\beta_{MKT}+\zeta_{MKT}$	1.056***	1.567***	1.425***	1.374***	1.202***	1.241***	1.198***	0.708***	1.322***	1.109***	0.921***	1.185***
$\beta_{ABX}+\xi_{ABX}$	0.024	0.007	−0.027	−0.071***	0.043	−0.084***	−0.054*	−0.061***	−0.016	−0.017	0.055***	−0.095***
$\beta_{ABX}+\zeta_{ABX}$	0.074***	0.029	−0.035***	−0.258***	−0.025	−0.011	0.001	−0.034**	0.085***	0.012	0.071***	0.013***

Table 5.11: Contagion model - industry subsample (ABX BBB)

This table reports the coefficients, robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample contagion model:

$$
\begin{aligned}
R_{i,t} &= \alpha_{i,t} + \boldsymbol{\beta_t'}\mathbf{F_t} + \gamma_{i,0}Subp_t + \eta_{i,0}Global_t + \varepsilon_{i,t}, \\
\boldsymbol{\beta_t} &= \boldsymbol{\beta_0} + \boldsymbol{\xi_0}Subp_t + \boldsymbol{\zeta_0}Global_t.
\end{aligned}
$$

Under this specification, γ and η measure the degree of contagion unrelated to the factors and that any significant loadings suggest that the interdependence model is insufficient in capturing the variations of stock returns in individual *industry sectors*. In addition, I model the factor loadings as functions of both the subprime and global crisis dummy variables and thus allow shift changes in the factor loadings during the crisis. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX BBB innovations. Superscripts ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10), money finance (SIC=11), and other (SIC=12).

Panel A: Contagion model												
ABX BBB												
Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.289***	1.766***	1.591***	1.796***	1.500***	1.534***	1.438***	0.652***	1.375***	1.393***	0.830***	1.446***
t-stat	(28.601)	(22.917)	(50.698)	(40.949)	(22.104)	(60.124)	(26.800)	(21.056)	(36.264)	(30.786)	(62.911)	(58.779)
β_{ABX}	0.134***	0.089	0.080***	0.245***	0.004	0.222***	0.168***	0.016	0.010	0.168***	0.012	0.158***
t-stat	(3.447)	(1.264)	(2.827)	(6.205)	(0.070)	(9.411)	(3.225)	(0.577)	(0.283)	(4.607)	(0.881)	(6.946)
γ	−0.140	−0.358	0.733***	2.088***	0.628	0.648***	−0.158	−0.597**	−2.004***	−0.207	−1.239***	0.478**
t-stat	(−0.410)	(−0.647)	(2.868)	(6.032)	(1.093)	(2.979)	(−0.379)	(−2.172)	(−6.967)	(−0.655)	(−14.011)	(2.305)
η	0.567	0.304	0.433	0.123	−0.269	1.892***	−0.340	−1.257***	2.094***	2.666***	0.617***	1.966***
t-stat	(1.208)	(0.375)	(1.013)	(0.136)	(−0.360)	(6.540)	(−0.578)	(−3.446)	(5.241)	(5.504)	(4.351)	(6.955)
ξ_{MKT}	−0.532***	−0.665***	−0.679***	−0.510***	−0.842***	−0.514***	−0.165	0.075	−0.458***	−0.274**	−0.161***	−0.061
t-stat	(−5.293)	(−4.085)	(−8.842)	(−5.294)	(−5.401)	(−8.263)	(−1.299)	(0.975)	(−5.368)	(−2.467)	(−7.028)	(−0.958)
ζ_{MKT}	−0.221**	−0.203*	−0.167***	−0.440***	−0.291***	−0.279***	−0.238***	0.049	−0.026	−0.263***	0.104***	−0.260***
t-stat	(−3.204)	(−1.717)	(−2.826)	(−3.509)	(−2.920)	(−7.447)	(−2.901)	(0.960)	(−0.483)	(−3.818)	(5.256)	(−6.897)
ξ_{ABX}	−0.055	−0.040	−0.041	−0.228***	0.088	−0.236***	−0.167***	−0.048	0.025	−0.165***	0.033**	−0.199***
t-stat	(−1.238)	(−0.514)	(−1.270)	(−5.108)	(1.304)	(−8.628)	(−2.811)	(−1.466)	(0.659)	(−3.681)	(2.341)	(−7.553)
ζ_{ABX}	−0.052	−0.077	−0.110***	−0.480***	−0.007	−0.201***	−0.163***	−0.056*	0.110***	−0.115***	0.065***	−0.146***
t-stat	(−1.212)	(−1.017)	(−3.541)	(−10.609)	(−0.106)	(−7.836)	(−2.815)	(−1.698)	(3.034)	(−2.873)	(4.576)	(−5.825)
α_0	−0.297	−0.605	−0.260	−1.437***	0.243	−1.173***	−0.307	0.607***	0.436**	−1.039***	0.091	−1.347***
t-stat	(−1.227)	(−1.434)	(−1.473)	(−5.708)	(0.585)	(−7.570)	(−0.979)	(3.241)	(2.033)	(−4.672)	(1.231)	(−9.520)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.138	0.208	0.198	0.149	0.158	0.134	0.139	0.148	0.147	0.069	0.135	0.136
Panel B: Interacted factor loadings												
$\alpha_0 + \gamma$	−0.437*	−0.963***	0.473**	0.651***	0.871**	−0.525***	−0.465*	0.010	−1.568***	−1.246***	−1.148***	−0.869***
$\alpha_0 + \eta$	0.270	−0.301	0.173	−1.314	−0.026	0.719***	−0.647	−0.650**	2.530***	1.627***	0.708***	0.619**
$\beta_{MKT} + \xi_{MKT}$	0.757***	1.101***	0.912***	1.286***	0.658***	1.020***	1.273***	0.727***	0.917***	1.119***	0.669***	1.385***
$\beta_{MKT} + \zeta_{MKT}$	1.068***	1.563***	1.424***	1.356***	1.209***	1.255***	1.200***	0.701***	1.349***	1.130***	0.934***	1.186***
$\beta_{ABX} + \xi_{ABX}$	0.079***	0.049	0.039	0.017	0.092***	−0.014	0.001	−0.032*	0.035**	0.003	0.045***	−0.041***
$\beta_{ABX} + \zeta_{ABX}$	0.082***	0.012	−0.030**	−0.235***	−0.003	0.021**	0.005	−0.040**	0.120***	0.053***	0.077***	0.012

Table 5.12: Contagion model - industry subsample (ABX BBB-)

This table reports the coefficients, robust t-statistics, the number of observations and adjusted R^2 associated with the following industry subsample contagion model:

$$\begin{aligned} R_{i,t} &= \alpha_{i,t} + \boldsymbol{\beta_t}'\mathbf{F_t} + \gamma_{i,0}Subp_t + \eta_{i,0}Global_t + \varepsilon_{i,t}, \\ \boldsymbol{\beta_t} &= \boldsymbol{\beta_0} + \boldsymbol{\xi_0}Subp_t + \boldsymbol{\zeta_0}Global_t. \end{aligned}$$

Under this specification, γ and η measure the degree of contagion unrelated to the factors and that any significant loadings suggest that the interdependence model is insufficient in capturing the variations of stock returns in individual *industry sectors*. In addition, I model the factor loadings as functions of both the subprime and global crisis dummy variables and thus allow shift changes in the factor loadings during the crisis. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX BBB- index innovations. Superscripts ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively. The industry classification is as follows: consumer non-durable (SIC=1), consumer durable (SIC=2), manufacturing (SIC=3), energy (SIC=4), chemicals (SIC=5), business equipment (SIC=6), telecommunication (SIC=7), utilities (SIC=8), shops (SIC=9), health care (SIC=10), money finance (SIC=11), and other (SIC=12).

Panel A: Contagion model												
ABX BBB- Industry	1	2	3	4	5	6	7	8	9	10	11	12
β_{MKT}	1.218***	1.684***	1.570***	1.786***	1.493***	1.484***	1.415***	0.716***	1.277***	1.305***	0.811***	1.388***
t-stat	(29.830)	(23.180)	(52.557)	(42.796)	(22.813)	(60.907)	(27.244)	(24.173)	(38.100)	(31.203)	(63.451)	(58.848)
β_{ABX}	0.033	−0.038	0.056	0.267***	−0.008	0.170***	0.153**	0.129***	−0.158***	0.043	−0.019	0.084***
t-stat	(0.722)	(−0.439)	(1.660)	(5.725)	(−0.116)	(6.250)	(2.465)	(3.990)	(−3.715)	(0.998)	(−1.223)	(3.124)
γ	−0.875**	−1.317**	0.352	2.043***	0.273	−0.093	−0.474	−0.097	−3.071***	−1.040***	−1.473***	−0.197
t-stat	(−2.390)	(−2.140)	(1.268)	(5.503)	(0.442)	(−0.405)	(−1.050)	(−0.337)	(−9.537)	(−3.012)	(−15.024)	(−0.887)
η	0.055	−0.400	0.447	0.445	−0.313	1.781***	−0.397	−0.654*	1.088**	1.925***	0.148	1.528***
t-stat	(0.116)	(−0.484)	(1.054)	(0.511)	(−0.408)	(6.135)	(−0.669)	(−1.772)	(2.637)	(3.974)	(1.024)	(5.337)
ξ_{MKT}	−0.354***	−0.484***	−0.576***	−0.463***	−0.692***	−0.396***	−0.102	−0.001	−0.291***	−0.157	−0.087***	0.005
t-stat	(−3.837)	(−3.155)	(−7.821)	(−5.313)	(−4.790)	(−6.981)	(−0.872)	(−0.020)	(−3.632)	(−1.578)	(−4.042)	(0.089)
ζ_{MKT}	−0.150**	−0.122	−0.139**	−0.416***	−0.282***	−0.222***	−0.213**	−0.014	0.063	−0.178***	0.107***	−0.203***
t-stat	(−2.273)	(−1.061)	(−2.407)	(−3.381)	(−2.896)	(−6.055)	(−2.641)	(−0.278)	(1.230)	(−2.702)	(5.496)	(−5.508)
ξ_{ABX}	0.009	0.041	−0.057	−0.269***	0.046	−0.242***	−0.182**	−0.169***	0.159***	−0.061	0.047***	−0.156***
t-stat	(0.190)	(0.446)	(−1.562)	(−5.320)	(0.590)	(−8.052)	(−2.678)	(−4.730)	(3.519)	(−1.236)	(2.914)	(−5.258)
ζ_{ABX}	0.066	0.051	−0.074**	−0.510***	0.008	−0.123***	−0.142**	−0.174***	0.281***	0.012	0.074***	−0.073**
t-stat	(1.348)	(0.554)	(−2.023)	(−9.682)	(0.099)	(−4.208)	(−2.079)	(−4.618)	(6.231)	(0.259)	(4.422)	(−2.489)
α_0	0.258	0.079	−0.122	−1.507***	0.309	−0.858***	−0.195	0.015	1.310***	−0.351	0.252***	−0.930***
t-stat	(0.962)	(0.162)	(−0.612)	(−5.338)	(0.659)	(−5.148)	(−0.568)	(0.073)	(5.201)	(−1.403)	(2.987)	(−5.882)
N	17,824	7,840	30,579	17,686	7,687	60,887	13,871	10,908	31,356	38,940	141,520	63,805
Adj. R^2	0.138	0.208	0.198	0.148	0.157	0.135	0.139	0.149	0.147	0.069	0.134	0.136
Panel B: Interacted factor loadings												
$\alpha_0 + \gamma$	−0.617**	−1.238***	0.230	0.536**	0.582	−0.951***	−0.669**	−0.082	−1.761***	−1.391***	−1.221***	−1.127***
$\alpha_0 + \eta$	0.313	−0.321	0.325	−1.062	−0.004	0.923***	−0.592	−0.639**	2.398***	1.574***	0.400***	0.598**
$\beta_{MKT} + \xi_{MKT}$	0.864***	1.200***	0.994***	1.323***	0.801***	1.088***	1.313***	0.715***	0.986***	1.148***	0.724***	1.393***
$\beta_{MKT} + \zeta_{MKT}$	1.068***	1.562***	1.431***	1.370***	1.211***	1.262***	1.202***	0.702***	1.340***	1.127***	0.918***	1.185***
$\beta_{ABX} + \xi_{ABX}$	0.042**	0.003	−0.001	−0.002	0.038	−0.072***	−0.029	−0.040***	0.001	−0.018	0.028***	−0.072***
$\beta_{ABX} + \zeta_{ABX}$	0.099***	0.013	−0.018	−0.243***	0.000	0.047***	0.011	−0.045**	0.123***	0.055***	0.055***	0.011

Table 5.13: Interdependence model - with instruments

This table reports the coefficients, robust t-statistics clustered by industry SIC, number of observations, adjusted R^2 and diagnostic tests associated with the following interdependence model with instruments ($\mathbf{Z_t}$):

$$\begin{aligned} R_{i,t} &= \alpha_{i,t} + \boldsymbol{\beta}_t'\mathbf{F_t} + \varepsilon_{i,t}, \\ \boldsymbol{\beta_t} &= \boldsymbol{\beta_0} + \boldsymbol{\phi_1}\mathbf{Z_t}. \end{aligned}$$

Under this specification, the factor loadings reflect the level of interdependence between the average stock, the market index and the ABX innovations over the full sample, respectively. This specification is referred to as the interdependence model as the crisis dummy variables are not included in the model and the factor loadings are modelled as linear functions of the contagion variables. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX factor. The EXTEST is distributed as $\chi^2(1)$ with a critical value of 3.84 (6.63) at the 5% (1%) level while the ICSTAT is distributed as $\chi^2(12)$ with a critical value of 21.03 (26.22) at the 5% (1%) level. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively.

Interdependence model										
ABX	AAA		AA		A		BBB		BBB-	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
β_{MKT}	0.805***	(5.564)	0.966***	(7.238)	0.817***	(5.164)	0.672***	(3.905)	0.746***	(4.601)
β_{ABX}	0.467**	(2.616)	0.318***	(6.063)	0.031	(0.812)	0.023	(0.686)	0.008	(0.233)
$\phi_{MKT,TED}$	−0.219***	(−3.722)	0.114**	(2.386)	−0.054	(−0.980)	−0.346***	(−6.482)	−0.282***	(−5.002)
$\phi_{MKT,ABCP}$	0.143**	(2.342)	−0.154***	(−3.127)	−0.043	(−0.944)	0.211***	(4.483)	0.196**	(2.705)
$\phi_{MKT,BAA}$	0.107***	(4.096)	0.049**	(2.317)	0.104***	(3.937)	0.151***	(4.372)	0.120***	(3.832)
$\phi_{ABX,TED}$	0.368*	(1.868)	0.262***	(3.795)	0.078**	(2.096)	0.183***	(7.848)	0.190***	(7.601)
$\phi_{ABX,ABCP}$	−0.204	(−1.427)	−0.207***	(−5.296)	−0.083***	(−4.047)	−0.104***	(−4.038)	−0.088**	(−2.593)
$\phi_{ABX,BAA}$	−0.126**	(−2.159)	−0.093***	(−4.696)	−0.005	(−0.366)	−0.030***	(−7.446)	−0.033***	(−6.609)
α_0	0.101	(1.041)	−0.021	(−0.199)	0.109	(1.043)	0.269*	(1.930)	0.297	(1.808)
N	443,188		443,188		443,188		443,188		443,188	
Adj. R^2	0.126		0.127		0.126		0.127		0.127	
EXTEST	9.785***		9.266***		9.414***		10.730***		10.829	
ICSTAT	117.897***		111.989***		112.490***		129.506***		130.040***	

Table 5.14: Contagion model - with instruments

This table reports the coefficients, robust t-statistics clustered by industry SIC, number of observations, adjusted R^2 and diagnostic tests associated with the contagion model with instruments ($\mathbf{Z_t}$):

$$\begin{aligned} R_{i,t} &= \alpha_{i,t} + \boldsymbol{\beta_t'}\mathbf{F_t} + \gamma_{i,0}Subp_t + \eta_{i,0}Global_t + \varepsilon_{i,t}, \\ \boldsymbol{\beta_t} &= \boldsymbol{\beta_0} + \boldsymbol{\phi_1}\mathbf{Z_t} + \boldsymbol{\xi_t}Subp_t + \boldsymbol{\zeta_t}Global_t, \\ \boldsymbol{\xi_t} &= \boldsymbol{\xi_0} + \boldsymbol{\xi_1}\mathbf{Z_t}, \\ \boldsymbol{\zeta_t} &= \boldsymbol{\zeta_0} + \boldsymbol{\zeta_1}\mathbf{Z_t}. \end{aligned}$$

First, under this specification, γ and η measure the degree of contagion unrelated to the factors. Any significant loadings suggest that the interdependence model is insufficient in capturing the variations of the US stock returns. Second, I model the factor loadings as functions of the contagion variable instruments ($\mathbf{Z_t}$), and the subprime and global crisis dummy variables and thus allow changes in the factor loadings over time. In addition, the ξ and ζ terms are conditional on the contagion instruments so that shift changes in the impacts of the contagion instruments on the factor loadings are allowed during the crisis. The 2×1 vector of factors ($\mathbf{F_t}$) entails the excess returns of the value-weighted market index and the orthogonalised ABX factor. The EXTEST is distributed as $\chi^2(1)$ with a critical value of 3.84 (6.63) at the 5% (1%) level while the ICSTAT is distributed as $\chi^2(12)$ with a critical value of 21.03 (26.22) at the 5% (1%) level. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Contagion model ABX		AAA		AA		A		BBB		BBB-	
		Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
β_{MKT}		0.484**	(2.612)	0.621***	(4.040)	0.630***	(3.781)	0.696***	(3.637)	0.668***	(3.700)
β_{ABX}		1.177*	(1.947)	0.101	(0.798)	0.138	(0.932)	0.645***	(4.765)	0.574***	(4.316)
$\phi_{MKT,TED}$		0.853**	(2.646)	0.440**	(2.070)	0.542***	(3.849)	0.528***	(3.665)	0.366**	(2.331)
$\phi_{MKT,ABCP}$		0.052	(0.226)	−0.028	(−0.126)	0.068	(0.249)	−0.031	(−0.119)	0.030	(0.113)
$\phi_{MKT,BAA}$		0.129	(1.215)	0.128***	(3.647)	0.106***	(2.756)	0.113***	(2.930)	0.122***	(3.201)
$\xi_{MKT,TED}$	Subp	−1.017*	(−1.866)	0.451	(0.587)	−0.454	(−1.141)	−2.882***	(−3.476)	−1.774***	(−3.731)
$\xi_{MKT,ABCP}$	Subp	−0.279	(−0.956)	−0.866	(−1.401)	0.186	(0.614)	0.798**	(2.296)	0.144	(0.376)
$\xi_{MKT,BAA}$	Subp	1.042*	(1.927)	−0.043	(−0.048)	0.511	(0.608)	1.604**	(2.435)	1.815**	(2.524)
$\zeta_{MKT,TED}$	Global	−0.557	(−0.741)	−0.627	(−0.755)	−1.824***	(−3.375)	−1.218***	(−3.833)	−1.101***	(−6.246)
$\zeta_{MKT,ABCP}$	Global	−0.209	(−0.421)	0.255	(0.457)	0.971**	(1.974)	0.736**	(2.258)	0.746***	(2.828)
$\zeta_{MKT,BAA}$	Global	−0.140	(−0.670)	−0.051	(−0.218)	0.285	(1.678)	0.208*	(1.732)	0.195*	(1.926)
$\phi_{ABX,TED}$		−0.267	(−0.228)	−0.332	(−1.198)	0.062	(0.554)	−0.192	(−1.362)	−0.112	(−0.768)
$\phi_{ABX,ABCP}$		0.420	(1.190)	−0.223**	(−2.358)	−0.395***	(−6.285)	−0.581***	(−4.876)	−0.651***	(−4.453)
$\phi_{ABX,BAA}$		−0.346	(−1.074)	0.045	(0.634)	−0.001	(−0.019)	−0.100*	(−1.888)	−0.096*	(−1.858)
$\xi_{ABX,TED}$	Subp	2.105	(1.106)	1.166	(0.964)	0.032	(0.083)	0.408**	(2.132)	0.039	(0.185)
$\xi_{ABX,ABCP}$	Subp	−0.194	(−0.157)	−1.026	(−1.518)	0.060	(0.208)	0.324***	(3.248)	0.744***	(5.090)
$\xi_{ABX,BAA}$	Subp	−1.500	(−0.439)	−1.005	(−1.008)	0.032	(0.050)	0.807***	(4.575)	0.657***	(4.845)
$\zeta_{ABX,TED}$	Global	1.441	(1.085)	0.763**	(2.095)	0.132	(0.576)	0.249	(0.885)	0.243	(1.029)
$\zeta_{ABX,ABCP}$	Global	−1.124***	(−2.708)	0.041	(0.453)	0.401***	(6.857)	0.741***	(4.789)	0.784***	(3.653)
$\zeta_{ABX,BAA}$	Global	0.101	(0.281)	−0.143*	(−1.753)	−0.017	(−0.185)	0.086	(0.822)	0.065	(0.748)
ξ_{MKT}	Subp	−1.347	(−1.566)	−0.032	(−0.023)	−1.336	(−1.065)	−1.371	(−1.868)	−1.958**	(−2.015)
ζ_{MKT}	Global	0.355	(0.753)	−0.026	(−0.041)	−0.992**	(−2.287)	−1.169***	(−4.072)	−1.155**	(−2.630)
ξ_{ABX}	Subp	1.226	(0.242)	2.088	(1.344)	0.015	(0.012)	−2.057***	(−4.968)	−1.679***	(−9.272)
ζ_{ABX}	Global	−0.908	(−1.419)	−0.029	(−0.240)	−0.274	(−1.609)	−0.809***	(−5.130)	−0.751***	(−5.158)
γ	Subp	−0.061	(−0.196)	0.006	(0.013)	0.255	(0.355)	0.256	(0.689)	−0.192	(−0.461)
η	Global	0.152	(0.703)	0.223	(0.838)	0.753**	(2.560)	1.390***	(3.938)	1.109***	(3.304)
α_0		−0.013	(−0.112)	−0.134	(−1.120)	−0.125	(−0.875)	−0.821***	(−3.828)	−0.544**	(−2.792)
N		443,188		443,188		443,188		443,188		443,188	
Adj. R^2		0.131		0.132		0.131		0.132		0.132	
EXTEST		12.567***		12.202***		11.707***		11.663***		11.861***	
ICSTAT		170.969***		160.695***		140.288***		145.298***		139.890***	

Table 5.15: Cross-sectional regressions (generalised least squares) of the 25 Fama-French (1993) size and book-to-market portfolios (full sample)

In a multifactor model framework, I study the Fama-French (1993) three-factor (FF-3), the Cahart (1997) momentum factor and the five ABX risk factors and test explicitly if the factors are priced using the 25 Fama-French (1993) size and book-to-market sorted portfolios. I adopt a two-pass regression approach in which each portfolio is regressed against the factor to obtain 25 coefficient estimates in the first stage (time series regression with daily data), and then a cross-sectional regression (the generalised least squares (GLS) approach) is estimated using the cross-section of expected portfolio returns and the coefficient estimates to obtain the price of risk (λ). The table reports the λ and t-statistics of the various model specifications of the second stage GLS regressions over the full sample period. In addition, the test statistics associated with the pricing errors are also reported. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Full sample										
Model	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ^{ABX}_{AAA}	λ^{ABX}_{AA}	λ^{ABX}_{A}	λ^{ABX}_{BBB}	λ^{ABX}_{BBB-}	Pricing Errors
1	0.023***									43.467***
t-stat	(5.764)									
2	0.023***	0.014***	0.005							42.883***
t-stat	(5.635)	(3.143)	(0.831)							
3	0.026***	0.015***	0.006	0.030						42.361***
t-stat	(4.481)	(3.194)	(0.933)	(0.662)						
4	0.025***	0.014***	0.007	0.014	−0.096					41.551***
t-stat	(4.159)	(3.131)	(0.992)	(0.291)	(−0.916)					
5	0.025***	0.014***	0.007	0.024		−0.152				41.964***
t-stat	(4.382)	(3.141)	(0.969)	(0.529)		(−0.642)				
6	0.026***	0.015***	0.007	0.026			−0.095			42.296***
t-stat	(4.400)	(3.155)	(0.966)	(0.558)			(−0.258)			
7	0.025***	0.015***	0.007	0.023				−0.158		42.178***
t-stat	(4.224)	(3.177)	(1.005)	(0.476)				(−0.432)		
8	0.027***	0.015***	0.005	0.047					0.294	41.682***
t-stat	(4.543)	(3.286)	(0.708)	(0.946)					(0.831)	
9	0.023***				−0.109					42.300***
t-stat	(5.764)				(−1.102)					
10	0.023***					−0.177				42.912***
t-stat	(5.765)					(−0.759)				
11	0.023***						−0.150			43.292***
t-stat	(5.776)						(−0.422)			
12	0.023***							−0.210		43.112***
t-stat	(5.703)							(−0.602)		
13	0.023***								0.168	43.210***
t-stat	(5.766)								(0.511)	

Table 5.16: Cross-sectional regressions (generalised least squares) of the 25 Fama-French (1993) size and book-to-market portfolios (pre-crisis subperiod)

In a multifactor model framework, I study the Fama-French (1993) three-factor (FF-3), the Cahart (1997) momentum factor and the five ABX risk factors and test explicitly if the factors are priced using the 25 Fama-French (1993) size and book-to-market sorted portfolios. I adopt a two-pass regression approach in which each portfolio is regressed against the factor to obtain 25 coefficient estimates in the first stage (time series regression with daily data), and then a cross-sectional regression (the generalised least squares (GLS) approach) is estimated using the cross-section of expected portfolio returns and the coefficient estimates to obtain the price of risk (λ). The table reports the λ and t-statistics of the various model specifications of the second stage GLS regressions over the pre-crisis subperiod. In addition, the test statistics associated with the pricing errors are also reported. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Pre-crisis subperiod										
Model	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ^{ABX}_{AAA}	λ^{ABX}_{AA}	λ^{ABX}_{A}	λ^{ABX}_{BBB}	λ^{ABX}_{BBB-}	Pricing Errors
1	0.034***									44.629***
t-stat	(6.947)									
2	0.034***	0.010*	0.043***							36.911**
t-stat	(6.769)	(1.720)	(6.382)							
3	0.034***	0.010	0.043***	0.038						36.770**
t-stat	(6.600)	(1.523)	(6.334)	(1.289)						
4	0.033***	0.009	0.042***	0.033	0.002					36.338**
t-stat	(6.071)	(1.358)	(6.082)	(1.073)	(0.499)					
5	0.035***	0.009	0.044***	0.034		−0.010				36.535**
t-stat	(6.226)	(1.305)	(6.315)	(1.143)		(−1.184)				
6	0.036***	0.009	0.043***	0.042			−0.012**			34.839**
t-stat	(6.744)	(1.410)	(6.354)	(1.414)			(−2.252)			
7	0.033***	0.011	0.044***	0.027				−0.037*		32.288**
t-stat	(6.250)	(1.685)	(6.444)	(0.924)				(−1.945)		
8	0.033***	0.012*	0.044***	0.025					−0.060**	31.211*
t-stat	(6.322)	(1.861)	(6.457)	(0.829)					(−2.289)	
9	0.035***				0.003					42.367***
t-stat	(7.051)				(1.208)					
10	0.034***					−0.005				44.600***
t-stat	(6.786)					(−1.330)				
11	0.034***						−0.010**			42.757***
t-stat	(6.952)						(−2.256)			
12	0.034***							0.004		44.574***
t-stat	(6.925)							(0.281)		
13	0.034***								0.002	44.594***
t-stat	(6.908)								(0.107)	

Table 5.17: Cross-sectional regressions (generalised least squares) of the 25 Fama-French (1993) size and book-to-market portfolios (subprime crisis subperiod)

In a multifactor model framework, I study the Fama-French (1993) three-factor (FF-3), the Cahart (1997) momentum factor and the five ABX risk factors and test explicitly if the factors are priced using the 25 Fama-French (1993) size and book-to-market sorted portfolios. I adopt a two-pass regression approach in which each portfolio is regressed against the factor to obtain 25 coefficient estimates in the first stage (time series regression with daily data), and then a cross-sectional regression (the generalised least squares (GLS) approach) is estimated using the cross-section of expected portfolio returns and the coefficient estimates to obtain the price of risk (λ). The table reports the λ and t-statistics of the various model specifications of the second stage GLS regressions over the subprime crisis subperiod. In addition, the test statistics associateid with the pricing errors are also reported. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Subprime crisis subperiod										
Model	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ^{ABX}_{AAA}	λ^{ABX}_{AA}	λ^{ABX}_{A}	λ^{ABX}_{BBB}	λ^{ABX}_{BBB-}	Pricing Errors
1	0.017***									49.173***
t-stat	(3.079)									
2	0.018***	−0.043***	−0.052***							36.960**
t-stat	(3.267)	(−6.837)	(−7.973)							
3	0.019***	−0.042***	−0.051***	0.073*						36.541**
t-stat	(3.328)	(−6.747)	(−7.702)	(1.857)						
4	0.021***	−0.038***	−0.048***	0.091***	−0.217***					27.770
t-stat	(3.757)	(−5.945)	(−7.222)	(2.295)	(−3.145)					
5	0.021***	−0.042***	−0.050***	0.073*		−0.216				34.202**
t-stat	(3.615)	(−6.653)	(−7.468)	(1.867)		(−1.622)				
6	0.021***	−0.043***	−0.051***	0.073*			−0.403			35.163**
t-stat	(3.529)	(−6.730)	(−7.732)	(1.880)			(−1.253)			
7	0.021***	−0.042***	−0.051***	0.073*				−0.438		35.561**
t-stat	(3.465)	(−6.764)	(−7.556)	(1.869)				(−1.060)		
8	0.019***	−0.042***	−0.051***	0.074*					−0.059	36.478**
t-stat	(3.302)	(−6.707)	(−7.499)	(1.874)					(−0.144)	
9	0.020***				−0.195***					41.709***
t-stat	(3.555)				(−2.947)					
10	0.019***					−0.194				47.407***
t-stat	(3.332)					(−1.461)				
11	0.019***						−0.328			48.242***
t-stat	(3.223)						(−1.037)			
12	0.019***							−0.461		48.049***
t-stat	(3.251)							(−1.123)		
13	0.016***								0.183	48.996***
t-stat	(2.939)								(0.459)	

Table 5.18: Cross-sectional regressions (generalised least squares) of the 25 Fama-French (1993) size and book-to-market portfolios (global crisis subperiod)

In a multifactor model framework, I study the Fama-French (1993) three-factor (FF-3), the Cahart (1997) momentum factor and the five ABX risk factors and test explicitly if the factors are priced using the 25 Fama-French (1993) size and book-to-market sorted portfolios. Practically, I adopt a two-pass regression approach in which each portfolio is regressed against the factor to obtain 25 coefficient estimates in the first stage (time series regression with daily data), and then a cross-sectional regression (the generalised least squares (GLS) approach) is estimated using the cross-section of expected portfolio returns and the coefficient estimates to obtain the price of risk (λ). The table reports the λ and t-statistics of the various model specifications of the second stage GLS regressions over the global crisis subperiod. In addition, the test statistics associated with the pricing errors are also reported. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Global crisis subperiod										
Model	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ^{ABX}_{AAA}	λ^{ABX}_{AA}	λ^{ABX}_{A}	λ^{ABX}_{BBB}	λ^{ABX}_{BBB-}	Pricing Errors
1	-0.123^{***}									25.674
t-stat	(-9.881)									
2	-0.124^{***}	0.046^{***}	-0.025							25.097
t-stat	(-9.895)	(3.027)	(-1.047)							
3	-0.104^{***}	0.041^{**}	-0.009	0.232^{**}						23.385
t-stat	(-5.305)	(2.656)	(-0.335)	(1.980)						
4	-0.105^{***}	0.042^{**}	-0.008	0.223^{*}	-0.118					23.167
t-stat	(-5.324)	(2.687)	(-0.320)	(1.882)	(-0.471)					
5	-0.103^{***}	0.042^{**}	-0.006	0.234^{*}		-0.274				23.073
t-stat	(-5.223)	(2.686)	(-0.238)	(1.996)		(-0.553)				
6	-0.105^{***}	0.041^{**}	-0.009	0.232^{*}			0.005			23.383
t-stat	(-5.267)	(2.598)	(-0.336)	(1.970)			(0.007)			
7	-0.105^{***}	0.041^{**}	-0.009	0.229^{*}				0.067		23.371
t-stat	(-5.234)	(2.654)	(-0.349)	(1.923)				(0.121)		
8	-0.107^{***}	0.042^{**}	-0.012	0.224^{*}					0.445	22.862
t-stat	(-5.346)	(2.698)	(-0.460)	(1.906)					(0.761)	
9	-0.123^{***}				-0.134					25.418
t-stat	(-9.881)				(-0.541)					
10	-0.123^{***}					-0.181				25.549
t-stat	(-9.864)					(-0.369)				
11	-0.124^{***}						0.143			25.633
t-stat	(-9.654)						(0.206)			
12	-0.124^{***}							0.227		25.515
t-stat	(-9.872)							(0.419)		
13	-0.125^{***}								0.542	24.786
t-stat	(-9.920)								(0.970)	

Table 5.19: Cross-sectional regressions (generalised least squares) of the 25 Fama-French (1993) size and book-to-market portfolios (post-crisis subperiod)

In a multifactor model framework, I study the Fama-French (1993) three-factor (FF-3), the Cahart (1997) momentum factor and the five ABX risk factors and test explicitly if the factors are priced using the 25 Fama-French (1993) size and book-to-market sorted portfolios. I adopt a two-pass regression approach in which each portfolio is regressed against the factor to obtain 25 coefficient estimates in the first stage (time series regression with daily data), and then a cross-sectional regression (the generalised least squares (GLS) approach) is estimated using the cross-section of expected portfolio returns and the coefficient estimates to obtain the price of risk (λ). The table reports the λ and t-statistics of the various model specifications of the second stage GLS regressions over the post-crisis subperiod. In addition, the test statistics associated with the pricing errors are also reported. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Post-crisis subperiod										
Model	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ_{AAA}^{ABX}	λ_{AA}^{ABX}	λ_{A}^{ABX}	λ_{BBB}^{ABX}	λ_{BBB-}^{ABX}	Pricing Errors
1	0.059***									47.115***
t-stat	(14.772)									
2	0.059***	0.019***	−0.007							46.222***
t-stat	(14.559)	(3.731)	(−1.284)							
3	0.060***	0.021***	−0.008	0.082**						43.896***
t-stat	(14.494)	(4.009)	(−1.322)	(2.094)						
4	0.060***	0.021***	−0.008	0.082**	−0.007					43.890***
t-stat	(14.489)	(4.008)	(−1.308)	(2.094)	(−0.078)					
5	0.061***	0.021***	−0.008	0.082**		0.051				43.868***
t-stat	(14.471)	(4.012)	(−1.290)	(2.097)		(0.165)				
6	0.060***	0.021***	−0.008	0.083**			−0.119			43.704***
t-stat	(14.033)	(3.960)	(−1.389)	(2.116)			(−0.405)			
7	0.059***	0.020***	−0.008	0.044				−0.774***		35.630**
t-stat	(13.904)	(3.774)	(−1.296)	(1.060)				(−2.962)		
8	0.060***	0.023***	−0.010	0.090**					0.380	41.895***
t-stat	(14.260)	(4.234)	(−1.672)	(2.277)					(1.465)	
9	0.059***				−0.011					47.105***
t-stat	(14.766)				(−0.126)					
10	0.059***					−0.010				47.114***
t-stat	(14.744)					(−0.033)				
11	0.059***						−0.010			47.113***
t-stat	(14.224)						(−0.034)			
12	0.058***							−0.837***		36.298**
t-stat	(14.527)							(−3.383)		
13	0.058***								0.409	44.392***
t-stat	(14.455)								(1.663)	

Table 5.20: Cross-sectional regressions (generalised least squares) of the 25 Fama-French (1993) size and book-to-market portfolios (subprime + global crisis subperiods)

In a multifactor model framework, I study the Fama-French (1993) three-factor (FF-3), the Cahart (1997) momentum factor and the five ABX risk factors and test explicitly if the factors are priced using the 25 Fama-French (1993) size and book-to-market sorted portfolios. Practically, I adopt a two-pass regression approach in which each portfolio is regressed against the factor to obtain 25 coefficient estimates in the first stage (time series regression with daily data), and then a cross-sectional regression (the generalised least squares (GLS) approach) is estimated using the cross-section of expected portfolio returns and the coefficient estimates to obtain the price of risk (λ). The table reports the λ and t-statistics of the various model specifications of the second stage GLS regressions over the subprime and global crisis subperiods. In addition, the test statistics associated with the pricing errors are also reported. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Subprime + Global crisis subperiods										
Model	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ_{AAA}^{ABX}	λ_{AA}^{ABX}	λ_{A}^{ABX}	λ_{BBB}^{ABX}	λ_{BBB-}^{ABX}	Pricing Errors
1	-0.062^{***}									40.197^{**}
t-stat	(-7.930)									
2	-0.062^{***}	0.014	-0.041^{***}							39.473^{**}
t-stat	(-7.913)	(1.500)	(-2.903)							
3	-0.042^{***}	0.010	-0.028^{*}	0.238^{***}						35.561^{**}
t-stat	(-3.226)	(1.048)	(-1.819)	(2.884)						
4	-0.042^{***}	0.010	-0.028^{*}	0.239^{***}	0.005					35.560^{**}
t-stat	(-3.132)	(1.035)	(-1.813)	(2.740)	(0.031)					
5	-0.042^{***}	0.010	-0.028^{*}	0.239^{***}		0.041				35.553^{**}
t-stat	(-3.221)	(1.043)	(-1.819)	(2.863)		(0.122)				
6	-0.042^{***}	0.010	-0.028^{*}	0.236^{***}			-0.143			35.530^{**}
t-stat	(-3.219)	(1.061)	(-1.728)	(2.842)			(-0.231)			
7	-0.042^{***}	0.010	-0.028^{*}	0.238^{***}				-0.045		35.556^{**}
t-stat	(-3.217)	(1.051)	(-1.780)	(2.880)				(-0.077)		
8	-0.042^{***}	0.009	-0.031^{*}	0.246^{***}					0.561	34.704^{**}
t-stat	(-3.257)	(0.999)	(-1.957)	(2.963)					(0.944)	
9	-0.062^{***}				-0.075					40.009^{**}
t-stat	(-7.930)				(-0.455)					
10	-0.062^{***}					0.011				40.196^{**}
t-stat	(-7.921)					(0.034)				
11	-0.061^{***}						-0.390			39.779^{**}
t-stat	(-7.391)						(-0.661)			
12	-0.062^{***}							-0.081		40.179^{**}
t-stat	(-7.858)							(-0.140)		
13	-0.063^{***}								0.417	39.692^{**}
t-stat	(-7.961)								(0.717)	

Table 5.21: Decile portfolios sorted by ABX AAA factor loadings (Model 1 using unorthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *unorthogonalized* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3}\beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3}\gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX AAA index.

ABX AAA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,172,637	1,328,452	1,478,530	1,326,684	1,011,718
2	2,677,012	2,888,933	2,914,949	2,397,921	2,797,302
3	3,448,176	3,847,746	3,635,659	2,772,545	3,727,678
4	3,323,210	3,364,426	3,836,093	2,645,978	3,499,561
5	3,140,813	3,398,082	3,534,250	2,634,810	3,209,142
6	3,175,955	3,320,140	3,591,396	2,770,040	3,279,954
7	3,414,452	3,158,787	4,350,498	2,888,631	3,498,673
8	3,153,435	3,065,314	3,849,403	2,677,599	3,259,054
9	2,423,820	2,627,505	2,657,343	2,342,748	2,406,900
10	1,076,864	1,388,836	1,164,774	1,088,878	1,019,046

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.27	0.39	-1.49	-1.97	0.58
2	0.42	0.68	-1.07	-2.12	1.10
3	0.33	0.77	-1.10	-2.27	1.11
4	0.40	0.66	-0.64	-1.95	1.00
5	0.31	0.68	-0.74	-1.88	0.95
6	0.18	0.78	-0.76	-2.21	0.74
7	0.13	0.83	-1.14	-2.13	0.66
8	0.18	0.97	-1.33	-2.04	0.66
9	0.16	0.83	-1.40	-2.51	0.71
10	-0.05	0.27	-1.80	-2.03	-0.04

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.35	0.29	-0.08	-0.06	0.66
2	0.08	0.08	-0.09	-0.05	0.19
3	0.04	0.04	-0.06	-0.01	0.10
4	0.03	0.01	-0.05	0.03	0.06
5	0.02	-0.01	-0.02	0.06	0.02
6	0.00	-0.02	-0.02	0.06	-0.01
7	-0.02	-0.05	-0.03	0.10	-0.05
8	-0.04	-0.09	-0.03	0.16	-0.11
9	-0.09	-0.17	-0.03	0.23	-0.22
10	-0.11	-0.29	0.09	0.64	-0.49

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.66	2.24	2.41	2.79	2.89
2	2.85	1.68	2.06	3.08	3.52
3	2.84	1.55	2.08	3.17	3.38
4	3.13	1.69	2.38	3.44	3.74
5	3.33	1.61	2.77	4.07	3.52
6	3.24	1.50	2.53	4.16	3.61
7	3.01	1.48	2.51	3.50	3.32
8	2.82	1.55	2.63	3.19	3.17
9	2.63	1.67	2.01	3.00	2.93
10	2.88	2.29	2.57	3.15	3.15

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.08	3.72	3.91	7.48	4.45
2	3.15	2.26	2.46	4.73	2.75
3	2.60	1.84	2.03	3.95	2.27
4	2.23	1.58	1.71	3.47	1.94
5	1.99	1.36	1.54	3.22	1.69
6	2.02	1.38	1.55	3.27	1.73
7	2.29	1.55	1.78	3.65	1.98
8	2.65	1.91	2.07	4.14	2.28
9	3.22	2.34	2.50	4.89	2.77
10	5.16	3.78	4.00	7.75	4.43

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	2.45	1.02	2.67	3.39	2.33
2	1.59	1.12	1.70	1.94	1.48
3	1.25	0.94	1.28	1.49	1.22
4	1.03	0.93	1.04	1.20	0.98
5	0.86	0.87	0.81	0.99	0.81
6	0.81	0.86	0.77	0.86	0.77
7	0.80	0.95	0.77	0.79	0.73
8	0.77	1.20	0.64	0.68	0.68
9	0.71	1.43	0.56	0.51	0.57
10	0.32	2.04	0.02	-0.32	0.07

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.41	1.43	0.17	-3.70	1.65
2	-0.01	0.55	-0.75	-3.74	0.43
3	-0.08	0.46	-0.71	-3.64	0.51
4	0.02	0.54	-0.74	-3.19	0.74
5	0.04	0.48	-0.35	-3.03	0.68
6	-0.03	0.42	-0.64	-3.67	0.93
7	-0.14	0.17	-0.82	-3.99	0.91
8	-0.20	0.36	-0.93	-4.29	0.87
9	-0.27	-0.16	-1.05	-4.22	0.67
10	1.54	1.08	-0.21	-3.72	2.30

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.76	2.90	2.95	5.37	3.27
2	2.19	1.73	1.80	3.19	1.83
3	1.73	1.40	1.46	2.57	1.43
4	1.45	1.19	1.20	2.20	1.17
5	1.25	1.01	1.05	1.99	0.98
6	1.28	1.04	1.05	2.01	1.02
7	1.50	1.17	1.24	2.32	1.21
8	1.79	1.46	1.47	2.71	1.45
9	2.25	1.79	1.83	3.34	1.86
10	3.84	2.92	3.03	5.69	3.24

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-142.97	-774.63	-95.92	-7.66	-12.20
2	-55.15	-297.58	-38.49	-3.13	-4.46
3	-29.99	-160.99	-21.76	-1.74	-2.40
4	-14.80	-78.79	-11.31	-0.88	-1.17
5	-4.01	-20.46	-3.93	-0.22	-0.30
6	5.63	32.34	2.03	0.39	0.46
7	17.05	95.19	8.89	1.09	1.36
8	33.18	183.93	18.70	2.02	2.62
9	59.93	330.90	35.13	3.46	4.75
10	150.98	823.67	96.44	8.35	12.59

Table 5.22: Decile portfolios sorted by ABX AA factor loadings (Model 1 using unorthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *unorthogonalized* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3}\beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3}\gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX AA index.

ABX AA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,137,188	1,295,402	1,408,675	1,193,800	1,019,763
2	2,668,295	3,121,909	3,021,968	2,241,342	2,685,153
3	3,398,695	3,393,549	3,763,562	2,970,391	3,572,511
4	3,547,502	3,787,067	4,245,750	2,849,311	3,597,606
5	3,161,214	3,098,740	3,502,100	2,767,313	3,370,199
6	3,202,588	3,372,286	3,614,640	3,027,180	3,189,201
7	3,367,185	3,342,550	3,860,842	2,877,660	3,566,034
8	3,108,096	3,215,458	3,632,063	2,618,158	3,191,036
9	2,398,987	2,610,203	2,830,360	2,002,060	2,505,082
10	1,027,604	1,159,349	1,139,449	1,003,051	1,032,760

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.27	0.26	-1.77	-1.72	0.53
2	0.27	0.56	-1.45	-2.14	0.93
3	0.21	0.64	-0.86	-2.41	0.93
4	0.25	0.68	-0.64	-2.22	0.83
5	0.26	0.76	-0.87	-1.95	0.85
6	0.28	0.79	-0.86	-1.96	0.91
7	0.19	0.78	-1.03	-2.34	0.82
8	0.19	1.04	-1.27	-2.54	0.87
9	0.23	0.77	-1.36	-2.12	0.69
10	0.19	0.58	-1.36	-1.73	0.13

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.04	0.31	-0.37	-0.72	0.53
2	-0.02	0.08	-0.18	-0.31	0.16
3	-0.02	0.05	-0.12	-0.18	0.09
4	-0.01	0.02	-0.07	-0.09	0.05
5	0.00	0.00	-0.05	0.00	0.02
6	0.01	-0.03	-0.02	0.08	0.00
7	0.02	-0.05	0.01	0.18	-0.03
8	0.03	-0.09	0.03	0.31	-0.08
9	0.04	-0.17	0.09	0.49	-0.17
10	0.23	-0.31	0.38	1.31	-0.32

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.72	2.23	2.47	2.68	3.06
2	2.70	1.68	1.90	3.13	3.03
3	2.93	1.53	2.03	3.11	3.69
4	3.14	1.52	2.62	3.89	3.46
5	3.37	1.59	2.53	4.19	3.81
6	3.27	1.59	2.72	3.88	3.69
7	3.04	1.54	2.41	3.94	3.27
8	2.87	1.56	2.67	3.34	3.17
9	2.60	1.72	2.06	2.75	2.97
10	2.76	2.32	2.55	2.68	3.10

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.08	3.72	3.92	7.53	4.46
2	3.13	2.22	2.43	4.73	2.76
3	2.59	1.81	2.03	3.99	2.27
4	2.24	1.55	1.71	3.50	1.95
5	1.98	1.36	1.53	3.17	1.71
6	2.02	1.39	1.55	3.28	1.70
7	2.29	1.57	1.79	3.66	1.94
8	2.67	1.88	2.12	4.16	2.27
9	3.22	2.37	2.48	4.88	2.77
10	5.17	3.87	4.00	7.66	4.46

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	2.88	2.61	3.09	3.37	2.41
2	1.70	1.61	1.71	1.94	1.53
3	1.30	1.19	1.35	1.45	1.20
4	1.05	1.01	1.05	1.15	1.00
5	0.88	0.87	0.88	0.98	0.82
6	0.79	0.82	0.78	0.91	0.72
7	0.76	0.81	0.75	0.84	0.71
8	0.70	0.83	0.68	0.75	0.65
9	0.56	0.89	0.50	0.44	0.57
10	-0.13	0.33	-0.25	-0.32	0.02

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.29	0.88	0.23	-3.85	1.76
2	-0.06	0.14	-0.71	-4.03	0.63
3	-0.06	0.33	-0.89	-3.68	0.72
4	-0.08	0.55	-0.70	-3.50	0.66
5	-0.08	0.38	-0.74	-3.30	0.72
6	0.00	0.42	-0.65	-3.27	0.77
7	-0.04	0.36	-0.62	-3.56	0.85
8	-0.09	0.45	-0.91	-3.88	0.75
9	-0.25	0.38	-0.96	-4.40	0.58
10	1.65	1.48	-0.06	-3.73	2.28

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.78	2.92	2.94	5.48	3.27
2	2.17	1.69	1.78	3.19	1.84
3	1.74	1.37	1.46	2.60	1.44
4	1.45	1.17	1.20	2.22	1.18
5	1.24	1.00	1.04	1.94	1.00
6	1.27	1.04	1.05	2.00	0.99
7	1.49	1.18	1.25	2.32	1.19
8	1.79	1.43	1.51	2.72	1.44
9	2.25	1.80	1.81	3.32	1.86
10	3.85	3.01	3.02	5.59	3.27

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-47.77	-239.11	-50.37	-2.75	-3.76
2	-18.26	-92.09	-18.66	-1.08	-1.41
3	-10.01	-50.64	-10.07	-0.60	-0.77
4	-5.09	-25.90	-5.03	-0.30	-0.39
5	-1.59	-8.24	-1.45	-0.08	-0.11
6	1.54	7.57	1.70	0.13	0.12
7	5.26	26.46	5.40	0.37	0.39
8	10.49	53.20	10.40	0.69	0.78
9	19.18	97.84	18.57	1.21	1.43
10	49.31	251.34	47.73	2.96	3.83

Table 5.23: Decile portfolios sorted by ABX A factor loadings (Model 1 using unorthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *unorthogonalized* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3}\beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3}\gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX A index.

ABX A Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,110,714	1,395,215	1,396,923	1,224,069	925,131
2	2,531,914	2,893,014	2,902,620	2,363,428	2,413,678
3	3,292,835	3,251,317	4,062,675	2,820,937	3,282,228
4	3,378,972	3,409,900	3,773,595	3,181,535	3,399,573
5	3,288,339	3,541,488	3,366,087	2,993,522	3,453,324
6	3,164,633	3,081,826	3,486,597	2,764,551	3,343,468
7	3,303,129	3,400,288	4,281,180	2,703,080	3,352,566
8	3,200,454	3,195,333	3,610,004	2,479,959	3,569,077
9	2,563,606	2,643,570	2,995,033	1,914,893	2,812,226
10	1,179,787	1,573,689	1,143,734	1,098,503	1,176,303

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.24	-0.14	-1.68	-1.20	0.32
2	0.27	0.38	-1.09	-1.89	0.81
3	0.26	0.65	-0.88	-2.49	0.93
4	0.37	0.75	-0.78	-2.06	1.03
5	0.26	0.67	-0.75	-2.09	0.89
6	0.16	0.70	-0.83	-2.27	0.78
7	0.17	0.95	-1.19	-2.54	0.88
8	0.27	1.05	-1.06	-2.09	0.80
9	0.31	0.94	-1.40	-2.10	0.84
10	0.01	0.93	-1.85	-2.37	0.21

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	-0.24	0.30	-0.44	-1.31	0.23
2	-0.12	0.09	-0.21	-0.52	0.05
3	-0.07	0.04	-0.14	-0.27	0.01
4	-0.03	0.01	-0.08	-0.12	0.01
5	0.00	-0.01	-0.04	0.01	0.01
6	0.03	-0.03	-0.01	0.13	0.01
7	0.06	-0.06	0.03	0.26	-0.01
8	0.09	-0.10	0.07	0.46	-0.03
9	0.15	-0.15	0.14	0.75	-0.07
10	0.54	-0.25	0.53	2.11	-0.10

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.85	2.30	2.37	3.06	3.26
2	2.56	1.74	2.02	2.99	2.75
3	2.95	1.51	2.03	3.84	3.31
4	3.09	1.52	2.34	3.85	3.49
5	3.38	1.52	2.89	4.28	3.71
6	3.16	1.54	2.45	3.76	3.63
7	3.09	1.45	2.47	3.39	3.68
8	2.76	1.57	2.19	2.95	3.16
9	2.67	1.72	1.97	2.96	3.11
10	2.88	2.41	3.23	2.51	3.14

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.10	3.80	3.91	7.39	4.52
2	3.17	2.34	2.45	4.70	2.83
3	2.61	1.88	2.02	3.96	2.31
4	2.25	1.58	1.69	3.49	2.00
5	1.99	1.37	1.54	3.08	1.77
6	2.01	1.37	1.55	3.32	1.68
7	2.27	1.54	1.80	3.65	1.90
8	2.63	1.83	2.07	4.16	2.20
9	3.18	2.28	2.49	4.90	2.71
10	5.18	3.76	4.03	7.91	4.38

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	2.20	1.85	2.92	3.24	1.44
2	1.49	1.43	1.77	1.89	1.17
3	1.20	1.17	1.34	1.42	1.04
4	1.00	0.97	1.03	1.13	0.93
5	0.84	0.79	0.87	0.92	0.81
6	0.77	0.79	0.72	0.81	0.75
7	0.76	0.79	0.60	0.71	0.81
8	0.75	0.86	0.47	0.58	0.86
9	0.69	0.92	0.20	0.31	0.93
10	0.33	0.76	-0.78	-0.55	0.98

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.13	1.03	-0.15	-4.11	2.01
2	-0.04	0.57	-0.78	-3.80	0.69
3	-0.12	0.58	-0.92	-3.40	0.49
4	-0.07	0.31	-0.68	-3.33	0.65
5	0.00	0.30	-0.52	-3.17	0.77
6	-0.08	0.28	-0.76	-3.55	0.83
7	-0.09	0.08	-0.72	-3.64	0.82
8	-0.12	0.09	-0.79	-4.05	0.77
9	-0.13	0.31	-0.89	-4.56	0.69
10	1.79	1.80	0.14	-3.59	2.01

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.79	2.95	2.93	5.36	3.33
2	2.21	1.79	1.79	3.17	1.92
3	1.77	1.43	1.45	2.59	1.49
4	1.46	1.19	1.19	2.18	1.23
5	1.25	1.02	1.06	1.88	1.04
6	1.27	1.02	1.05	2.04	0.99
7	1.48	1.16	1.26	2.33	1.15
8	1.77	1.39	1.48	2.74	1.41
9	2.22	1.74	1.81	3.34	1.82
10	3.87	2.92	3.06	5.82	3.22

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-29.66	-161.46	-8.15	-2.55	-4.82
2	-11.49	-62.74	-3.20	-0.97	-1.86
3	-6.32	-34.49	-1.82	-0.51	-1.04
4	-3.13	-16.91	-0.98	-0.23	-0.54
5	-0.86	-4.51	-0.37	-0.02	-0.20
6	1.01	5.72	0.14	0.18	0.09
7	3.20	17.76	0.70	0.42	0.41
8	6.28	34.66	1.49	0.74	0.85
9	11.26	61.81	2.76	1.26	1.62
10	28.91	156.88	7.49	3.14	4.56

Table 5.24: Decile portfolios sorted by ABX BBB factor loadings (Model 1 using unorthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *unorthogonalized* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3}\beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3}\gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX BBB index.

ABX BBB Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,053,296	1,204,632	1,191,640	1,032,135	1,002,579
2	2,551,902	2,882,671	2,831,357	2,134,054	2,631,806
3	3,297,047	3,715,134	3,307,913	2,814,043	3,508,099
4	3,437,202	3,324,867	3,827,774	2,861,480	3,665,441
5	3,319,374	3,411,491	3,615,320	3,001,634	3,338,887
6	3,195,027	3,389,318	3,435,074	2,746,283	3,311,962
7	3,494,787	3,399,035	4,259,559	2,961,761	3,579,689
8	3,259,371	3,165,559	4,204,585	2,642,384	3,283,942
9	2,476,485	2,585,077	3,074,271	2,224,207	2,424,959
10	1,100,205	1,295,960	1,272,243	1,130,359	979,687

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	-0.11	0.24	-1.85	-2.00	0.23
2	0.29	0.63	-0.96	-1.70	0.81
3	0.25	0.75	-0.85	-1.97	0.88
4	0.23	0.57	-0.75	-2.15	0.94
5	0.14	0.84	-0.75	-2.46	0.92
6	0.15	0.87	-0.95	-2.10	0.86
7	0.10	0.76	-1.08	-2.12	0.80
8	0.14	0.91	-1.20	-2.12	0.87
9	0.24	0.90	-1.40	-2.17	0.97
10	-0.22	0.41	-1.71	-2.33	0.21

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	-0.19	0.09	-0.71	-1.39	0.46
2	-0.11	-0.02	-0.34	-0.52	0.13
3	-0.06	-0.02	-0.21	-0.28	0.09
4	-0.02	-0.02	-0.12	-0.09	0.04
5	0.00	-0.02	-0.06	0.02	0.01
6	0.03	-0.03	0.01	0.15	-0.01
7	0.05	-0.05	0.06	0.31	-0.05
8	0.08	-0.07	0.13	0.50	-0.10
9	0.13	-0.10	0.26	0.84	-0.20
10	0.46	-0.14	0.78	2.31	-0.39

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.67	2.35	2.49	2.61	2.93
2	2.49	1.66	2.07	2.67	2.87
3	2.77	1.59	2.14	3.18	3.21
4	2.90	1.46	2.22	3.87	3.17
5	3.35	1.63	2.58	4.34	3.69
6	3.38	1.56	2.61	3.90	3.93
7	3.05	1.51	2.39	3.63	3.54
8	2.98	1.56	2.07	3.04	3.86
9	2.73	1.69	2.28	3.03	3.13
10	2.93	2.25	3.11	3.30	2.93

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.02	3.77	3.99	7.39	4.40
2	3.08	2.27	2.49	4.64	2.68
3	2.54	1.83	2.07	3.94	2.19
4	2.23	1.58	1.76	3.52	1.91
5	1.99	1.35	1.55	3.24	1.71
6	2.00	1.38	1.54	3.23	1.73
7	2.26	1.56	1.73	3.61	1.99
8	2.63	1.89	2.03	4.09	2.33
9	3.21	2.34	2.43	4.97	2.83
10	5.14	3.78	3.96	7.92	4.51

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	1.63	2.14	2.76	2.13	0.74
2	1.27	1.65	1.68	1.50	0.86
3	1.06	1.22	1.35	1.23	0.79
4	0.93	0.99	1.04	1.05	0.79
5	0.83	0.83	0.87	0.88	0.76
6	0.78	0.82	0.69	0.81	0.78
7	0.84	0.88	0.64	0.84	0.89
8	0.92	0.91	0.57	0.83	1.08
9	0.97	0.87	0.38	0.77	1.29
10	1.08	0.99	-0.48	0.59	1.86

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.49	0.71	-0.58	-5.23	1.95
2	-0.48	0.18	-0.95	-4.61	0.67
3	-0.33	0.20	-0.97	-3.93	0.95
4	-0.23	0.36	-0.85	-3.24	0.79
5	-0.24	0.42	-0.57	-3.21	0.70
6	-0.14	0.34	-0.53	-3.14	0.80
7	-0.17	0.37	-0.59	-3.36	0.85
8	-0.25	0.42	-0.71	-3.50	0.66
9	-0.37	0.48	-0.65	-3.99	0.39
10	1.35	1.86	0.37	-2.99	1.95

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.74	2.94	3.02	5.39	3.26
2	2.16	1.74	1.84	3.17	1.81
3	1.71	1.38	1.49	2.58	1.40
4	1.45	1.19	1.24	2.22	1.17
5	1.25	1.00	1.07	1.99	0.99
6	1.26	1.03	1.04	1.99	1.01
7	1.46	1.18	1.21	2.27	1.21
8	1.77	1.44	1.45	2.68	1.49
9	2.25	1.80	1.77	3.41	1.91
10	3.84	2.96	3.03	5.82	3.30

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-12.51	-43.58	-3.46	-5.30	-6.84
2	-4.70	-16.46	-1.35	-2.07	-2.50
3	-2.57	-8.91	-0.78	-1.19	-1.36
4	-1.31	-4.45	-0.42	-0.64	-0.69
5	-0.40	-1.21	-0.17	-0.22	-0.21
6	0.41	1.65	0.04	0.16	0.21
7	1.34	4.95	0.27	0.58	0.74
8	2.66	9.64	0.59	1.16	1.48
9	4.86	17.44	1.12	2.08	2.75
10	12.77	44.63	3.02	5.42	7.40

Table 5.25: Decile portfolios sorted by ABX BBB- factor loadings (Model 1 using unorthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *unorthogonalized* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX BBB- index.

ABX BBB- Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,064,036	1,314,092	1,238,273	974,483	1,039,315
2	2,495,896	2,820,283	2,924,595	2,192,801	2,516,722
3	3,193,409	3,543,922	3,164,182	2,722,233	3,474,522
4	3,389,545	3,507,506	3,801,656	3,098,803	3,458,653
5	3,251,797	3,527,703	3,427,306	2,833,222	3,363,744
6	3,251,570	3,536,515	3,622,046	2,834,987	3,342,364
7	3,429,610	3,109,158	4,199,045	3,008,527	3,555,442
8	3,315,605	3,084,866	4,362,002	2,830,666	3,289,500
9	2,514,436	2,757,422	2,925,427	2,101,360	2,560,787
10	1,102,317	1,191,864	1,349,252	950,656	1,110,321

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.20	0.25	-2.05	-1.72	0.52
2	0.43	0.73	-1.05	-2.08	1.06
3	0.49	0.82	-0.75	-1.97	1.12
4	0.35	0.95	-0.74	-2.16	0.98
5	0.39	0.74	-0.75	-1.96	1.09
6	0.22	0.91	-0.92	-2.19	0.89
7	0.16	0.75	-0.91	-2.10	0.71
8	0.12	0.55	-1.18	-1.90	0.60
9	0.05	0.74	-1.51	-2.60	0.56
10	-0.09	0.42	-1.64	-2.47	-0.05

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	-0.27	0.24	-0.90	-1.70	0.37
2	-0.15	0.05	-0.41	-0.68	0.08
3	-0.08	0.01	-0.24	-0.35	0.05
4	-0.03	0.00	-0.14	-0.12	0.02
5	0.00	-0.01	-0.06	0.00	0.02
6	0.03	-0.03	0.01	0.17	-0.01
7	0.06	-0.05	0.08	0.33	-0.03
8	0.11	-0.09	0.17	0.57	-0.07
9	0.18	-0.15	0.34	0.96	-0.13
10	0.58	-0.22	0.98	2.56	-0.22

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.81	2.27	2.48	2.65	3.32
2	2.58	1.65	2.16	2.69	2.99
3	2.71	1.53	2.05	2.96	3.18
4	3.10	1.57	2.65	3.79	3.47
5	3.24	1.51	2.43	4.11	3.62
6	3.39	1.60	2.44	4.25	3.81
7	2.98	1.56	2.31	3.52	3.50
8	2.92	1.56	2.06	3.49	3.28
9	2.63	1.75	2.24	3.22	2.72
10	3.04	2.27	3.14	2.92	3.34

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.09	3.77	3.98	7.39	4.49
2	3.15	2.27	2.51	4.66	2.77
3	2.59	1.86	2.06	3.91	2.26
4	2.25	1.55	1.77	3.50	1.94
5	2.01	1.37	1.55	3.21	1.72
6	2.00	1.36	1.52	3.27	1.70
7	2.27	1.57	1.74	3.64	1.95
8	2.64	1.89	2.04	4.14	2.26
9	3.20	2.36	2.44	4.93	2.75
10	5.19	3.74	3.96	7.91	4.45

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	1.75	1.87	2.79	2.10	1.15
2	1.31	1.47	1.72	1.44	1.03
3	1.10	1.22	1.35	1.16	0.93
4	0.96	0.94	1.09	1.02	0.88
5	0.84	0.80	0.87	0.89	0.79
6	0.78	0.75	0.70	0.84	0.77
7	0.81	0.77	0.64	0.86	0.84
8	0.86	0.83	0.59	0.83	0.94
9	0.91	0.92	0.43	0.79	1.07
10	0.81	0.74	-0.51	0.53	1.31

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.51	0.97	-0.91	-5.70	1.51
2	-0.42	0.32	-1.01	-4.93	0.42
3	-0.20	0.36	-0.93	-3.86	0.66
4	-0.03	0.32	-0.87	-3.34	0.81
5	0.01	0.47	-0.63	-3.32	0.86
6	0.07	0.40	-0.58	-3.13	0.81
7	-0.05	0.34	-0.64	-3.39	0.69
8	0.04	0.19	-0.55	-3.48	0.75
9	0.17	0.32	-0.55	-3.65	0.73
10	2.18	1.66	0.66	-2.42	2.46

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.80	2.95	3.01	5.40	3.31
2	2.20	1.74	1.85	3.18	1.86
3	1.75	1.41	1.49	2.56	1.44
4	1.46	1.17	1.24	2.21	1.17
5	1.27	1.02	1.06	1.97	1.00
6	1.25	1.01	1.03	2.00	0.99
7	1.47	1.18	1.21	2.28	1.19
8	1.77	1.44	1.45	2.70	1.44
9	2.23	1.81	1.78	3.35	1.84
10	3.87	2.91	3.03	5.81	3.26

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-11.16	-27.71	-2.46	-5.19	-6.20
2	-4.25	-10.55	-0.97	-2.03	-2.29
3	-2.36	-5.82	-0.54	-1.15	-1.24
4	-1.23	-2.94	-0.29	-0.59	-0.63
5	-0.39	-0.78	-0.10	-0.15	-0.20
6	0.32	1.11	0.05	0.25	0.18
7	1.14	3.24	0.22	0.70	0.63
8	2.30	6.22	0.47	1.32	1.26
9	4.24	11.23	0.87	2.30	2.32
10	11.30	28.16	2.32	5.68	6.35

Table 5.26: Decile portfolios sorted by ABX AAA factor loadings (Model 1 using unorthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. In this table, the decile portfolios contain only stocks with significant F-statistics of null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX indices. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX AAA index.

ABX AAA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,195,143	1,272,329	1,745,164	1,221,072	1,052,411
2	3,015,418	3,507,217	3,525,666	2,702,900	3,040,009
3	4,001,300	4,478,603	4,450,820	2,951,743	4,129,366
4	3,709,593	3,653,359	4,990,284	3,028,221	3,532,393
5	3,025,819	3,829,842	3,900,195	2,180,224	2,810,759
6	3,164,097	2,916,230	4,343,525	2,531,080	3,288,669
7	3,450,277	3,956,515	4,775,793	2,755,374	3,187,230
8	3,517,623	3,678,404	4,481,043	2,981,030	3,277,974
9	2,622,567	2,991,673	3,056,291	2,585,275	2,442,493
10	1,047,296	1,465,315	864,082	1,179,994	1,013,218

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.67	0.52	-1.41	-0.82	0.64
2	0.51	0.42	-0.96	-2.29	1.47
3	0.35	1.08	-1.15	-2.22	1.10
4	0.48	0.77	-0.60	-1.71	1.02
5	0.26	0.72	-0.78	-2.02	0.97
6	0.11	0.63	-0.86	-2.70	0.76
7	0.07	1.40	-1.02	-2.44	0.51
8	0.01	0.97	-1.70	-2.23	0.70
9	0.11	0.92	-1.49	-2.63	0.63
10	-0.16	0.40	-2.45	-2.25	-0.17

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.36	0.27	-0.05	-0.15	0.74
2	0.12	0.10	-0.04	-0.04	0.26
3	0.06	0.04	-0.04	-0.03	0.16
4	0.04	0.00	-0.03	0.05	0.07
5	0.03	-0.02	-0.03	0.09	0.04
6	0.00	-0.03	-0.05	0.10	-0.01
7	-0.02	-0.08	-0.02	0.15	-0.07
8	-0.08	-0.14	-0.05	0.17	-0.16
9	-0.13	-0.20	-0.07	0.27	-0.28
10	-0.25	-0.38	-0.03	0.61	-0.67

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.76	2.24	2.48	3.01	3.02
2	2.75	1.62	2.06	3.32	3.22
3	2.72	1.66	2.19	2.98	3.12
4	3.06	1.56	2.51	3.52	3.58
5	3.35	2.05	2.73	3.87	3.59
6	3.92	1.54	3.32	5.86	4.04
7	3.36	1.74	4.92	3.36	3.14
8	2.69	1.65	2.13	3.59	2.92
9	2.88	1.69	2.01	3.35	3.54
10	3.00	2.17	2.50	4.19	2.99

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.59	3.38	3.55	6.88	4.01
2	2.92	2.11	2.26	4.49	2.49
3	2.42	1.75	1.89	3.74	2.07
4	2.08	1.46	1.62	3.26	1.79
5	1.91	1.31	1.49	3.11	1.59
6	1.96	1.35	1.55	3.14	1.66
7	2.15	1.47	1.71	3.41	1.81
8	2.47	1.78	1.96	3.77	2.13
9	3.00	2.23	2.36	4.46	2.56
10	4.72	3.52	3.70	7.02	4.07

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	2.66	1.10	2.90	3.94	2.44
2	1.73	1.16	1.72	2.27	1.62
3	1.35	1.05	1.31	1.74	1.26
4	1.08	0.86	1.07	1.34	1.04
5	0.90	0.77	0.83	1.15	0.83
6	0.81	0.87	0.72	0.98	0.73
7	0.72	0.98	0.56	0.85	0.63
8	0.71	1.29	0.55	0.69	0.57
9	0.60	1.59	0.29	0.43	0.44
10	0.18	2.21	-0.26	-0.35	-0.06

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.26	0.59	0.83	-2.38	0.66
2	0.23	0.78	-0.24	-3.16	0.25
3	0.10	0.29	-0.38	-3.02	0.48
4	0.12	-0.10	-0.48	-2.24	0.61
5	0.00	0.03	-0.47	-3.14	0.76
6	0.03	0.24	-0.90	-3.55	1.08
7	0.02	0.05	-0.80	-3.71	1.01
8	-0.32	0.06	-1.00	-4.11	0.79
9	-0.25	0.10	-1.28	-4.71	0.81
10	1.11	1.22	-1.14	-4.32	1.82

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	2.97	2.40	2.35	4.28	2.53
2	1.74	1.44	1.45	2.58	1.40
3	1.39	1.18	1.19	2.08	1.10
4	1.15	0.98	0.97	1.75	0.90
5	1.03	0.86	0.88	1.65	0.77
6	1.06	0.91	0.89	1.62	0.82
7	1.19	0.99	1.03	1.81	0.93
8	1.44	1.22	1.22	2.09	1.16
9	1.81	1.51	1.52	2.59	1.47
10	3.07	2.46	2.49	4.47	2.57

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-164.90	-886.13	-115.58	-9.38	-14.50
2	-68.94	-370.05	-48.80	-4.31	-5.80
3	-39.00	-207.65	-29.10	-2.56	-3.24
4	-19.52	-102.78	-15.59	-1.43	-1.57
5	-4.62	-22.60	-5.17	-0.50	-0.33
6	8.75	50.17	3.28	0.41	0.81
7	24.40	135.52	13.08	1.45	2.12
8	44.79	247.50	25.20	2.67	3.86
9	76.73	420.00	47.24	4.47	6.48
10	174.92	944.53	118.00	10.01	15.44

Table 5.27: Decile portfolios sorted by ABX AA factor loadings (Model 1 using unorthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. In this table, the decile portfolios contain only stocks with significant F-statistics of null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX index. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3}\beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3}\gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX AA index.

ABX AA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,163,614	1,369,855	1,389,684	1,132,865	1,099,090
2	2,987,837	3,667,661	2,821,565	2,623,657	3,123,816
3	4,114,292	3,918,542	4,699,677	3,130,555	4,521,518
4	3,767,968	3,837,531	4,975,303	2,926,966	3,692,850
5	3,073,229	3,215,295	4,074,405	2,634,431	3,029,132
6	3,233,959	3,401,264	3,737,754	2,585,689	3,468,979
7	3,662,827	3,735,980	4,895,037	2,756,292	3,585,057
8	3,389,073	4,117,790	3,877,832	2,942,618	3,321,344
9	2,656,262	2,837,330	2,890,901	2,343,379	2,827,588
10	1,020,168	1,239,308	981,359	1,156,758	987,955

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.47	-0.14	-2.22	-1.05	0.81
2	0.26	-0.14	-1.21	-1.59	0.68
3	0.43	0.95	-0.77	-1.99	1.01
4	0.16	1.14	-0.57	-3.21	0.94
5	0.43	0.91	-0.56	-1.80	0.90
6	0.33	1.04	-0.74	-2.20	0.91
7	0.21	0.91	-1.14	-2.16	0.99
8	0.24	1.60	-0.95	-3.11	0.95
9	0.39	0.65	-1.38	-0.80	0.47
10	0.10	0.93	-1.04	-1.95	-0.06

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	-0.03	0.30	-0.44	-0.91	0.54
2	-0.03	0.10	-0.20	-0.41	0.21
3	-0.02	0.08	-0.14	-0.22	0.12
4	0.01	0.06	-0.08	-0.09	0.09
5	0.02	0.00	-0.05	0.05	0.04
6	0.01	-0.05	-0.01	0.13	-0.01
7	0.02	-0.08	0.01	0.27	-0.06
8	0.04	-0.13	0.04	0.43	-0.10
9	0.05	-0.24	0.12	0.66	-0.21
10	0.18	-0.41	0.31	1.49	-0.45

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.72	1.99	2.47	2.84	3.05
2	2.88	1.86	2.21	2.63	3.61
3	2.76	1.46	1.85	3.25	3.19
4	3.43	1.67	3.16	4.73	3.43
5	3.37	1.69	2.71	4.27	3.56
6	3.26	1.59	2.62	4.16	3.51
7	2.87	1.61	2.36	3.38	3.20
8	2.76	1.75	2.06	3.36	3.08
9	2.53	1.99	2.05	2.63	2.81
10	2.82	2.08	2.30	2.38	3.65

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.58	3.27	3.67	6.75	4.07
2	2.90	2.01	2.34	4.39	2.53
3	2.40	1.70	1.93	3.68	2.10
4	2.08	1.48	1.58	3.24	1.79
5	1.94	1.32	1.44	3.19	1.65
6	1.98	1.36	1.50	3.24	1.63
7	2.16	1.46	1.70	3.43	1.84
8	2.50	1.83	1.98	3.89	2.13
9	3.04	2.26	2.33	4.61	2.60
10	4.76	3.50	3.68	7.08	4.14

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	3.17	2.83	3.44	3.78	2.64
2	1.88	1.75	1.87	2.26	1.66
3	1.42	1.26	1.48	1.63	1.30
4	1.09	0.96	1.06	1.24	1.06
5	0.93	0.80	0.98	1.09	0.87
6	0.82	0.86	0.74	1.03	0.74
7	0.70	0.77	0.73	0.70	0.67
8	0.61	0.97	0.61	0.58	0.54
9	0.42	0.89	0.47	0.24	0.37
10	-0.23	0.34	-0.12	-0.55	-0.16

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.61	0.37	1.03	-3.62	0.02
2	-0.08	-0.08	-0.19	-3.73	0.41
3	0.05	0.30	-0.43	-3.02	0.45
4	0.26	0.58	-0.66	-2.74	1.07
5	0.19	0.30	-0.61	-2.80	1.03
6	-0.05	-0.14	-0.56	-3.64	1.05
7	0.05	0.12	-0.85	-3.22	1.03
8	-0.06	0.31	-1.08	-3.85	1.12
9	-0.02	-0.14	-0.78	-4.19	1.02
10	1.59	1.48	-0.96	-4.02	2.53

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	2.97	2.28	2.44	4.23	2.60
2	1.73	1.35	1.52	2.53	1.44
3	1.38	1.11	1.22	2.04	1.14
4	1.15	0.97	0.98	1.73	0.92
5	1.04	0.85	0.84	1.67	0.82
6	1.08	0.88	0.89	1.70	0.82
7	1.20	0.96	1.03	1.83	0.96
8	1.45	1.21	1.26	2.18	1.16
9	1.84	1.51	1.51	2.69	1.50
10	3.09	2.38	2.49	4.53	2.61

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-56.16	-278.40	-61.49	-3.26	-4.47
2	-23.73	-118.07	-25.63	-1.42	-1.85
3	-13.66	-68.03	-14.73	-0.82	-1.06
4	-7.14	-35.42	-7.84	-0.43	-0.56
5	-2.09	-9.83	-2.77	-0.10	-0.18
6	2.48	13.09	1.90	0.23	0.17
7	7.59	38.78	7.09	0.58	0.57
8	14.61	74.51	14.04	1.01	1.08
9	25.39	129.72	24.30	1.63	1.91
10	58.80	300.49	56.02	3.59	4.63

Table 5.28: Decile portfolios sorted by ABX A factor loadings (Model 1 using unorthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. In this table, the decile portfolios contain only stocks with significant F-statistics with null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX index. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX A index.

ABX A Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,034,553	1,360,223	1,441,661	1,009,661	861,180
2	2,894,463	3,774,925	3,527,655	2,866,185	2,535,276
3	3,735,095	4,035,260	4,329,654	3,123,274	3,529,313
4	3,487,338	3,065,748	4,752,886	2,736,092	3,562,034
5	3,327,233	3,330,005	3,850,490	3,216,265	3,307,765
6	3,291,188	3,268,197	3,526,074	2,725,777	3,725,651
7	3,608,434	3,903,451	5,336,758	2,785,181	3,415,158
8	3,690,145	4,314,155	3,875,068	2,361,833	4,151,675
9	2,891,947	3,647,622	3,416,527	1,920,821	2,988,005
10	1,361,962	1,837,343	1,210,460	1,607,604	1,198,479

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.18	-0.58	-1.52	-1.93	0.54
2	0.25	0.08	-1.16	-1.56	0.84
3	0.30	0.35	-0.86	-2.18	1.22
4	0.57	1.26	-0.54	-2.11	1.23
5	0.42	0.57	-0.44	-1.58	1.08
6	0.40	0.84	-0.63	-1.65	0.92
7	0.42	1.32	-0.83	-1.91	1.10
8	0.03	0.84	-1.10	-2.39	0.67
9	0.18	1.35	-1.38	-2.40	0.76
10	-0.23	0.95	-1.68	-2.74	-0.10

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	-0.36	0.32	-0.45	-1.63	0.11
2	-0.18	0.13	-0.20	-0.76	0.04
3	-0.11	0.05	-0.14	-0.38	0.01
4	-0.04	0.04	-0.08	-0.16	0.01
5	0.01	0.01	-0.03	0.02	0.01
6	0.05	-0.02	0.00	0.20	0.00
7	0.08	-0.06	0.04	0.34	-0.01
8	0.13	-0.11	0.08	0.59	-0.02
9	0.21	-0.16	0.17	0.97	-0.08
10	0.55	-0.31	0.48	2.27	-0.10

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	3.00	2.16	2.16	4.74	2.90
2	2.62	1.79	2.00	3.18	2.83
3	2.80	1.68	2.03	3.72	3.03
4	3.08	1.46	2.52	4.27	3.11
5	3.39	1.83	3.27	4.68	3.40
6	3.37	1.59	3.58	3.69	3.80
7	3.43	1.55	2.50	4.93	3.55
8	2.90	1.56	2.26	3.83	2.88
9	2.72	1.80	1.98	2.94	2.89
10	2.80	2.25	2.62	2.64	3.22

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.68	3.47	3.72	6.74	4.18
2	2.97	2.17	2.27	4.43	2.65
3	2.44	1.77	1.89	3.65	2.20
4	2.14	1.54	1.65	3.26	1.87
5	1.95	1.29	1.49	3.14	1.69
6	1.96	1.31	1.54	3.24	1.62
7	2.13	1.44	1.64	3.46	1.78
8	2.48	1.72	2.00	3.94	2.06
9	2.97	2.11	2.32	4.55	2.56
10	4.68	3.46	3.70	7.13	4.06

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	2.37	1.89	3.23	3.71	1.52
2	1.56	1.44	1.86	2.17	1.17
3	1.28	1.30	1.45	1.52	1.11
4	0.99	0.93	1.07	1.13	0.91
5	0.84	0.83	0.81	0.94	0.81
6	0.74	0.75	0.66	0.77	0.73
7	0.65	0.75	0.48	0.53	0.72
8	0.59	0.79	0.26	0.27	0.76
9	0.48	0.73	-0.13	0.01	0.77
10	0.03	0.64	-1.23	-1.12	0.77

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.14	1.09	1.46	-3.24	1.14
2	-0.21	0.74	-0.19	-4.28	0.29
3	-0.06	0.62	-0.80	-2.46	0.24
4	0.06	0.62	-0.56	-2.73	0.60
5	0.11	0.47	-0.47	-2.65	0.71
6	-0.02	0.45	-0.98	-3.28	0.79
7	-0.02	0.20	-1.02	-3.66	1.08
8	0.15	0.11	-0.77	-3.52	1.16
9	0.21	0.47	-0.90	-3.78	0.89
10	1.19	2.48	-1.31	-4.73	2.16

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.04	2.43	2.47	4.22	2.67
2	1.80	1.46	1.46	2.59	1.54
3	1.42	1.19	1.16	2.05	1.21
4	1.20	1.03	0.99	1.75	0.99
5	1.05	0.83	0.88	1.62	0.86
6	1.06	0.85	0.90	1.69	0.82
7	1.19	0.95	0.98	1.88	0.95
8	1.44	1.15	1.24	2.24	1.14
9	1.79	1.42	1.49	2.63	1.49
10	3.06	2.39	2.49	4.54	2.60

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-35.01	-188.28	-11.06	-3.01	-5.93
2	-15.41	-83.57	-4.81	-1.24	-2.55
3	-9.11	-49.33	-3.02	-0.68	-1.50
4	-4.95	-26.67	-1.82	-0.32	-0.83
5	-1.63	-8.47	-0.85	-0.02	-0.32
6	1.11	6.24	-0.02	0.28	0.13
7	4.19	23.05	0.81	0.61	0.60
8	8.09	44.18	1.86	1.02	1.24
9	13.91	75.58	3.47	1.65	2.22
10	33.99	184.17	8.85	3.76	5.66

Table 5.29: Decile portfolios sorted by ABX BBB factor loadings (Model 1 using unorthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. In this table, the decile portfolios contain only stocks with significant F-statistics of null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX index. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX BBB index.

ABX BBB Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,067,959	1,184,708	1,367,940	1,007,195	981,104
2	2,659,777	3,379,147	2,754,971	2,228,427	2,697,553
3	4,012,233	5,170,010	4,295,984	3,194,767	4,056,156
4	3,506,241	3,789,470	3,677,680	2,905,421	3,686,201
5	3,480,892	3,762,629	3,623,308	3,243,820	3,440,538
6	3,267,827	4,500,906	3,212,772	3,266,966	2,767,736
7	3,577,906	3,658,166	5,227,219	2,546,747	3,511,022
8	3,534,699	4,265,917	4,284,469	3,059,868	3,282,796
9	2,791,390	3,007,032	3,386,909	2,587,113	2,691,415
10	1,101,253	1,351,915	1,277,109	1,276,247	889,633

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	-0.40	0.05	-1.91	-2.39	-0.34
2	0.18	0.37	-0.68	-2.31	0.79
3	0.10	0.81	-0.61	-2.24	0.46
4	0.18	0.79	-0.65	-2.21	0.75
5	0.21	0.74	-0.81	-2.43	0.98
6	0.27	1.21	-0.82	-1.89	0.86
7	0.07	1.12	-1.01	-2.32	0.69
8	0.09	1.45	-1.07	-2.61	0.67
9	0.32	0.98	-0.94	-1.86	0.95
10	-0.59	0.36	-2.14	-2.61	-0.43

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	-0.28	0.09	-0.82	-1.70	0.48
2	-0.12	-0.01	-0.39	-0.67	0.20
3	-0.07	-0.01	-0.24	-0.32	0.10
4	-0.02	-0.01	-0.14	-0.11	0.07
5	0.00	-0.03	-0.05	0.06	0.01
6	0.03	-0.05	0.03	0.22	-0.03
7	0.07	-0.07	0.10	0.42	-0.06
8	0.09	-0.10	0.19	0.60	-0.15
9	0.13	-0.16	0.31	0.96	-0.27
10	0.40	-0.25	0.74	2.44	-0.52

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.80	2.32	2.41	3.54	2.76
2	2.47	1.70	2.14	2.76	2.71
3	2.67	1.51	2.15	3.24	2.83
4	3.05	1.73	2.80	3.92	3.09
5	3.15	1.66	2.38	3.78	3.53
6	3.13	1.45	2.66	3.68	3.31
7	3.44	1.55	2.08	4.30	4.12
8	3.27	1.53	3.21	4.14	3.43
9	2.83	1.80	1.96	3.33	3.28
10	3.28	2.10	2.40	5.64	2.87

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.59	3.47	3.77	6.66	4.00
2	2.88	2.14	2.37	4.35	2.49
3	2.39	1.71	1.94	3.65	2.06
4	2.12	1.46	1.73	3.36	1.78
5	1.93	1.29	1.53	3.20	1.62
6	1.95	1.30	1.50	3.23	1.68
7	2.13	1.42	1.64	3.39	1.88
8	2.46	1.69	1.89	3.82	2.19
9	2.98	2.19	2.27	4.51	2.68
10	4.70	3.48	3.56	7.11	4.22

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	1.79	2.40	2.98	2.38	0.80
2	1.31	1.96	1.80	1.58	0.74
3	1.11	1.33	1.35	1.32	0.84
4	0.94	0.92	1.19	1.09	0.77
5	0.84	0.88	0.79	0.99	0.75
6	0.82	0.82	0.71	0.77	0.87
7	0.83	0.84	0.58	0.73	0.95
8	0.88	0.88	0.43	0.64	1.11
9	1.00	0.98	0.24	0.69	1.42
10	1.12	1.01	-0.65	0.55	2.01

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.67	1.78	0.59	-4.60	1.23
2	-0.22	0.29	-0.78	-4.03	0.85
3	-0.45	0.49	-0.86	-3.48	0.33
4	-0.25	0.38	-0.77	-3.13	0.71
5	-0.19	0.36	-0.79	-2.85	0.73
6	-0.08	0.38	-0.71	-2.62	0.75
7	-0.03	0.42	-0.75	-2.92	1.05
8	-0.26	0.33	-0.56	-3.71	0.74
9	-0.36	0.50	-0.87	-4.05	0.66
10	0.38	1.46	-1.05	-4.74	1.57

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	2.99	2.39	2.52	4.18	2.57
2	1.75	1.44	1.54	2.54	1.44
3	1.38	1.13	1.20	2.03	1.12
4	1.18	0.96	1.06	1.77	0.92
5	1.04	0.82	0.92	1.63	0.80
6	1.05	0.85	0.87	1.70	0.82
7	1.18	0.94	0.97	1.81	0.97
8	1.41	1.12	1.14	2.09	1.19
9	1.79	1.48	1.46	2.61	1.53
10	3.05	2.41	2.39	4.46	2.69

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-14.90	-53.05	-4.45	-6.01	-8.14
2	-6.28	-22.63	-1.94	-2.70	-3.28
3	-3.63	-12.92	-1.20	-1.66	-1.87
4	-1.91	-6.53	-0.71	-0.98	-1.00
5	-0.58	-1.66	-0.32	-0.40	-0.30
6	0.59	2.54	0.00	0.17	0.33
7	1.91	7.33	0.32	0.78	1.06
8	3.67	13.70	0.76	1.53	2.07
9	6.47	23.73	1.44	2.70	3.70
10	15.50	55.13	3.63	6.47	9.00

Table 5.30: Decile portfolios sorted by ABX BBB- factor loadings (Model 1 using unorthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regressions as shown in Equation 5.22 (Model 1) and the *unorthogonalised* ABX index returns. In this table, the decile portfolios contain only stocks with significant F-statistics of null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX index. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t + 1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX BBB- index.

ABX BBB- Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,073,632	1,214,477	1,563,974	925,368	997,525
2	2,712,531	3,709,495	3,059,095	2,312,261	2,569,907
3	3,654,032	4,330,415	3,833,026	2,923,088	3,903,706
4	3,739,381	4,007,805	3,998,076	3,240,027	3,962,656
5	3,084,474	3,031,869	3,900,740	2,462,678	3,131,338
6	3,248,217	3,070,161	3,471,677	3,376,144	3,238,231
7	3,702,833	3,113,097	5,222,475	3,389,142	3,691,517
8	3,621,859	3,810,214	5,311,186	2,893,797	3,316,354
9	2,758,955	2,997,384	3,176,629	2,257,961	2,815,233
10	1,034,689	1,055,371	1,426,537	965,991	938,216

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.45	0.44	-2.33	-1.46	0.77
2	0.37	0.53	-0.82	-2.39	1.04
3	0.59	1.14	-0.62	-2.06	1.24
4	0.19	1.09	-1.10	-2.68	0.99
5	0.35	1.03	-0.55	-2.20	0.87
6	0.16	0.87	-0.96	-1.90	0.62
7	0.15	0.64	-0.87	-2.26	0.65
8	-0.18	0.55	-1.44	-2.43	0.26
9	0.04	1.24	-1.54	-2.76	0.45
10	-0.02	0.79	-1.27	-2.53	-0.01

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	-0.33	0.29	-0.96	-1.99	0.39
2	-0.17	0.10	-0.47	-0.85	0.13
3	-0.09	0.04	-0.29	-0.41	0.07
4	-0.03	0.01	-0.17	-0.15	0.05
5	-0.01	-0.02	-0.06	0.01	0.01
6	0.05	-0.04	0.05	0.24	-0.01
7	0.09	-0.07	0.13	0.48	-0.06
8	0.13	-0.10	0.26	0.73	-0.12
9	0.20	-0.17	0.40	1.16	-0.19
10	0.53	-0.28	0.99	2.70	-0.35

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.60	2.06	2.42	2.60	2.93
2	2.69	1.73	2.25	3.17	2.89
3	2.79	1.86	2.43	3.41	2.88
4	3.14	1.70	3.15	3.21	3.43
5	3.18	1.46	2.58	3.87	3.61
6	3.32	1.84	2.78	4.06	3.54
7	3.39	1.63	2.38	4.22	4.00
8	3.04	1.67	2.87	3.94	2.92
9	2.92	1.84	1.92	3.74	3.12
10	3.25	2.22	2.58	3.59	3.82

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.65	3.43	3.75	6.65	4.11
2	2.94	2.13	2.31	4.41	2.56
3	2.41	1.68	1.96	3.60	2.09
4	2.12	1.47	1.67	3.34	1.80
5	1.96	1.28	1.58	3.14	1.66
6	1.96	1.33	1.52	3.26	1.64
7	2.17	1.49	1.68	3.46	1.88
8	2.49	1.75	1.90	3.87	2.18
9	2.99	2.14	2.26	4.53	2.63
10	4.71	3.36	3.54	7.20	4.08

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	1.80	1.96	3.11	2.08	1.16
2	1.31	1.48	1.90	1.44	0.99
3	1.10	1.20	1.44	1.16	0.93
4	0.94	0.93	1.19	1.01	0.82
5	0.83	0.73	0.97	0.83	0.80
6	0.76	0.69	0.68	0.79	0.79
7	0.75	0.72	0.56	0.72	0.82
8	0.82	0.86	0.46	0.68	0.97
9	0.85	0.77	0.23	0.67	1.10
10	0.81	0.90	-0.70	0.35	1.36

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.42	0.72	1.80	-5.76	0.62
2	-0.55	0.53	-0.89	-4.92	0.02
3	-0.20	0.25	-0.78	-3.49	0.54
4	0.04	0.42	-0.71	-3.04	0.75
5	-0.13	0.11	-0.73	-3.26	0.70
6	0.08	0.31	-0.57	-3.06	0.92
7	0.03	0.38	-0.85	-2.52	0.58
8	0.06	0.69	-0.67	-3.24	0.76
9	0.06	0.22	-0.79	-3.48	0.77
10	1.73	2.45	-0.17	-3.00	2.18

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.06	2.39	2.51	4.22	2.63
2	1.79	1.43	1.49	2.58	1.47
3	1.41	1.10	1.23	2.03	1.14
4	1.19	0.95	1.02	1.82	0.91
5	1.07	0.82	0.94	1.66	0.82
6	1.06	0.85	0.90	1.68	0.82
7	1.21	0.98	1.01	1.86	0.97
8	1.43	1.15	1.17	2.13	1.17
9	1.81	1.45	1.44	2.63	1.51
10	3.07	2.31	2.38	4.54	2.60

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-12.85	-33.70	-3.13	-6.08	-7.43
2	-5.37	-14.37	-1.36	-2.62	-2.99
3	-3.12	-8.31	-0.82	-1.53	-1.70
4	-1.67	-4.33	-0.47	-0.82	-0.88
5	-0.56	-1.30	-0.20	-0.22	-0.26
6	0.47	1.63	0.05	0.34	0.32
7	1.60	4.78	0.30	0.96	1.00
8	3.10	8.92	0.63	1.73	1.88
9	5.44	15.30	1.14	2.86	3.25
10	13.15	34.17	2.71	6.53	7.93

Table 5.31: Decile portfolios sorted by ABX AAA factor loadings (Model 2 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3}\beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3}\gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the orthogonalised ABX AAA index.

ABX AAA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,102,660	1,139,443	1,398,455	1,195,477	1,013,886
2	2,763,735	3,224,598	3,225,689	2,357,187	2,782,846
3	3,424,733	3,706,232	3,656,993	2,708,421	3,763,202
4	3,341,220	3,322,777	3,631,383	2,722,172	3,592,997
5	3,115,173	2,896,602	3,648,092	2,698,599	3,276,383
6	3,172,544	3,265,419	3,802,291	2,779,229	3,171,514
7	3,349,704	3,321,713	4,017,068	2,876,230	3,431,784
8	3,146,872	3,191,440	3,570,899	2,732,158	3,292,501
9	2,519,956	2,935,176	2,900,524	2,363,218	2,397,366
10	1,060,734	1,366,001	1,132,392	1,097,036	999,109

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.26	0.55	-1.53	-2.06	0.54
2	0.47	0.84	-1.30	-1.97	1.17
3	0.40	0.90	-0.78	-2.29	1.11
4	0.41	0.81	-0.66	-2.02	1.00
5	0.27	0.74	-0.88	-1.98	0.93
6	0.16	0.56	-0.88	-2.24	0.82
7	0.15	0.66	-1.01	-1.99	0.68
8	0.13	0.58	-1.22	-2.03	0.66
9	0.17	0.72	-1.29	-2.37	0.60
10	-0.08	0.52	-1.94	-2.19	-0.03

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.42	-0.02	-0.07	0.02	0.91
2	0.11	-0.06	-0.08	0.00	0.28
3	0.06	-0.04	-0.05	0.01	0.15
4	0.04	-0.02	-0.04	0.04	0.08
5	0.02	-0.01	-0.03	0.06	0.03
6	0.00	-0.01	-0.03	0.07	-0.02
7	-0.02	-0.01	-0.03	0.09	-0.08
8	-0.05	-0.03	-0.03	0.13	-0.16
9	-0.11	-0.03	-0.03	0.18	-0.31
10	-0.18	0.03	0.09	0.55	-0.75

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.67	2.30	2.43	2.71	2.93
2	2.78	1.59	2.05	2.98	3.44
3	2.88	1.58	2.25	3.25	3.39
4	3.06	1.46	2.14	3.65	3.59
5	3.46	1.52	2.94	4.06	3.84
6	3.15	1.54	2.38	3.91	3.52
7	2.99	1.56	2.54	3.55	3.26
8	2.85	1.63	2.62	3.16	3.17
9	2.66	1.78	2.00	3.10	3.00
10	2.88	2.30	2.61	3.15	3.13

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.08	3.74	3.91	7.47	4.44
2	3.15	2.23	2.46	4.78	2.74
3	2.59	1.84	2.01	3.97	2.27
4	2.22	1.50	1.70	3.50	1.94
5	1.99	1.34	1.54	3.22	1.71
6	2.03	1.40	1.58	3.26	1.74
7	2.29	1.60	1.81	3.61	1.97
8	2.66	1.92	2.07	4.14	2.28
9	3.20	2.35	2.49	4.88	2.77
10	5.16	3.82	4.00	7.73	4.45

β_{ABX}	Average sum of marker risk factor loadings				
Portfolio	full	pre	subprime	global	post
1	0.10	-5.83	-1.40	2.28	1.52
2	0.66	-1.55	0.08	1.50	1.18
3	0.77	-0.46	0.42	1.26	1.05
4	0.76	0.05	0.59	1.08	0.90
5	0.77	0.55	0.70	0.93	0.79
6	0.88	1.01	0.90	0.93	0.78
7	1.03	1.65	1.20	0.92	0.80
8	1.25	2.56	1.53	0.93	0.85
9	1.60	4.00	2.09	0.97	0.87
10	2.71	9.02	4.09	0.83	0.92

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.53	1.74	0.04	-3.52	1.75
2	-0.01	0.47	-0.72	-3.71	0.39
3	-0.05	0.42	-0.69	-3.58	0.58
4	-0.01	0.43	-0.69	-3.21	0.69
5	0.00	0.40	-0.49	-3.08	0.68
6	-0.04	0.31	-0.67	-3.56	0.91
7	-0.10	0.39	-0.82	-3.87	0.94
8	-0.19	0.20	-0.87	-4.21	0.90
9	-0.35	0.07	-1.01	-4.65	0.64
10	1.48	0.91	-0.12	-3.85	2.23

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.75	2.90	2.95	5.35	3.25
2	2.19	1.69	1.80	3.23	1.82
3	1.73	1.39	1.44	2.58	1.43
4	1.45	1.13	1.19	2.23	1.18
5	1.25	0.99	1.04	1.99	0.99
6	1.29	1.04	1.07	2.02	1.03
7	1.49	1.21	1.26	2.29	1.21
8	1.79	1.46	1.47	2.72	1.45
9	2.24	1.79	1.81	3.33	1.85
10	3.85	2.93	3.02	5.69	3.26

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-36.34	-131.76	-54.57	-7.90	-11.97
2	-14.04	-51.73	-20.77	-3.21	-4.36
3	-7.74	-28.84	-11.30	-1.79	-2.33
4	-3.92	-14.94	-5.53	-0.91	-1.14
5	-1.16	-4.99	-1.32	-0.24	-0.28
6	1.32	3.89	2.61	0.39	0.48
7	4.18	14.23	6.96	1.08	1.37
8	8.16	28.59	13.03	2.02	2.63
9	14.73	52.68	22.71	3.52	4.74
10	38.20	138.38	57.09	8.56	12.60

Table 5.32: Decile portfolios sorted by ABX AA factor loadings (Model 2 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3}\beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3}\gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the orthogonalised ABX AA index.

ABX AA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,057,719	1,029,841	1,297,032	1,127,198	1,006,281
2	2,540,137	2,499,817	2,936,008	2,101,298	2,710,168
3	3,324,333	3,136,454	3,537,495	3,022,493	3,590,796
4	3,426,931	3,580,990	4,028,515	2,731,488	3,507,210
5	3,213,878	2,941,893	3,771,641	2,902,762	3,355,964
6	3,190,026	3,498,755	3,427,186	2,987,039	3,261,647
7	3,391,290	3,644,326	3,788,219	2,851,465	3,515,795
8	3,266,945	3,717,634	3,871,901	2,814,787	3,203,169
9	2,501,796	2,931,464	3,040,657	2,047,204	2,508,117
10	1,078,735	1,354,336	1,276,663	942,772	1,056,968

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.22	0.32	-2.06	-1.69	0.50
2	0.35	0.71	-1.35	-2.10	0.99
3	0.33	1.01	-0.86	-2.24	0.91
4	0.28	0.94	-0.72	-2.18	0.85
5	0.29	0.83	-0.76	-1.96	0.86
6	0.24	0.59	-0.93	-2.12	0.90
7	0.12	0.71	-0.96	-2.40	0.77
8	0.14	0.71	-1.27	-2.43	0.84
9	0.26	0.65	-1.12	-2.22	0.75
10	0.13	0.41	-1.45	-1.76	0.09

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	1.19	4.42	1.61	-0.54	0.87
2	0.42	1.75	0.55	-0.24	0.28
3	0.24	1.00	0.28	-0.13	0.16
4	0.13	0.53	0.13	-0.05	0.08
5	0.05	0.21	0.02	0.01	0.03
6	-0.01	-0.08	-0.06	0.08	-0.01
7	-0.08	-0.42	-0.18	0.16	-0.06
8	-0.19	-0.87	-0.34	0.27	-0.15
9	-0.37	-1.70	-0.59	0.44	-0.29
10	-0.89	-4.35	-1.43	1.11	-0.66

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.68	2.20	2.43	2.60	3.06
2	2.65	1.57	1.93	3.07	2.98
3	3.00	1.50	2.21	3.34	3.70
4	3.01	1.48	2.31	3.65	3.40
5	3.38	1.62	2.54	4.14	3.85
6	3.41	1.58	2.84	4.13	3.86
7	3.03	1.46	2.94	3.63	3.21
8	2.81	1.67	2.13	3.42	3.13
9	2.66	1.83	2.04	2.97	2.98
10	2.76	2.35	2.61	2.63	3.08

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.09	3.72	3.94	7.55	4.47
2	3.14	2.27	2.44	4.74	2.75
3	2.61	1.86	2.03	3.98	2.27
4	2.25	1.60	1.73	3.49	1.96
5	1.99	1.40	1.53	3.18	1.71
6	2.01	1.34	1.54	3.30	1.71
7	2.27	1.56	1.78	3.61	1.93
8	2.66	1.85	2.09	4.18	2.26
9	3.21	2.33	2.47	4.87	2.78
10	5.16	3.80	4.02	7.65	4.46

β_{ABX}	Average sum of market risk factors				
Portfolio	full	pre	subprime	global	post
1	0.03	-7.79	-1.44	2.63	1.73
2	0.60	-2.54	0.04	1.68	1.26
3	0.68	-1.13	0.37	1.33	1.06
4	0.74	-0.21	0.56	1.10	0.93
5	0.75	0.37	0.71	0.91	0.81
6	0.84	0.96	0.86	0.91	0.74
7	1.00	1.72	1.14	0.92	0.75
8	1.22	2.77	1.45	0.89	0.78
9	1.56	4.66	1.96	0.73	0.82
10	2.65	10.66	3.85	0.43	0.69

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.40	1.66	0.02	-3.77	1.80
2	-0.01	0.45	-0.93	-3.84	0.61
3	-0.11	0.33	-1.07	-3.71	0.67
4	-0.13	0.25	-0.88	-3.42	0.67
5	-0.12	0.34	-0.71	-3.31	0.68
6	-0.05	0.41	-0.64	-3.45	0.77
7	0.00	0.22	-0.72	-3.49	0.93
8	-0.07	0.56	-0.79	-3.84	0.72
9	-0.22	-0.06	-0.64	-4.28	0.59
10	1.57	1.14	0.32	-4.07	2.27

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.78	2.89	2.95	5.49	3.28
2	2.18	1.72	1.78	3.20	1.84
3	1.75	1.40	1.46	2.60	1.44
4	1.46	1.20	1.21	2.21	1.18
5	1.25	1.03	1.04	1.95	0.99
6	1.27	1.00	1.03	2.02	1.00
7	1.47	1.17	1.24	2.27	1.18
8	1.79	1.41	1.48	2.74	1.43
9	2.25	1.79	1.80	3.33	1.86
10	3.85	2.97	3.06	5.61	3.27

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-18.17	-72.56	-27.81	-2.86	-3.73
2	-7.16	-29.29	-10.49	-1.12	-1.40
3	-4.07	-16.95	-5.82	-0.63	-0.77
4	-2.18	-9.23	-3.04	-0.32	-0.39
5	-0.81	-3.63	-1.04	-0.09	-0.12
6	0.36	1.11	0.65	0.12	0.11
7	1.69	6.51	2.58	0.36	0.39
8	3.57	14.18	5.27	0.69	0.77
9	6.70	27.05	9.64	1.22	1.42
10	17.68	71.74	25.24	3.02	3.79

Table 5.33: Decile portfolios sorted by ABX A factor loadings (Model 2 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the orthogonalised ABX A index.

ABX A Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,056,586	1,102,649	1,386,385	1,203,874	926,708
2	2,526,964	2,950,447	2,954,014	2,361,574	2,384,022
3	3,257,612	3,321,111	3,985,740	2,719,247	3,312,010
4	3,419,342	3,499,054	3,834,095	3,221,055	3,422,790
5	3,235,029	3,302,573	3,348,175	3,045,876	3,374,628
6	3,219,968	3,469,358	3,440,219	2,823,857	3,331,709
7	3,372,246	3,351,556	4,352,950	2,661,145	3,453,571
8	3,198,080	3,317,433	3,602,622	2,501,853	3,496,648
9	2,557,354	2,560,170	2,960,619	1,936,915	2,836,363
10	1,159,990	1,500,922	1,127,738	1,075,914	1,173,124

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.28	0.32	-1.73	-1.37	0.33
2	0.33	0.48	-1.00	-1.86	0.77
3	0.30	0.74	-0.83	-2.39	0.91
4	0.46	0.84	-0.83	-1.94	1.10
5	0.25	0.66	-0.74	-1.97	0.87
6	0.10	0.62	-0.89	-2.37	0.76
7	0.13	0.74	-1.14	-2.55	0.88
8	0.20	0.78	-1.14	-2.18	0.80
9	0.29	0.95	-1.26	-2.25	0.87
10	0.00	0.75	-1.91	-2.25	0.18

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	2.10	11.02	0.61	-0.96	0.99
2	0.80	4.40	0.20	-0.39	0.34
3	0.45	2.48	0.09	-0.19	0.18
4	0.25	1.35	0.04	-0.08	0.10
5	0.11	0.52	0.01	0.02	0.05
6	-0.02	-0.20	-0.03	0.10	0.00
7	-0.16	-1.01	-0.07	0.20	-0.08
8	-0.35	-2.16	-0.12	0.36	-0.16
9	-0.70	-4.11	-0.22	0.58	-0.33
10	-1.78	-10.93	-0.44	1.67	-0.82

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.82	2.24	2.37	3.06	3.23
2	2.50	1.61	1.97	2.91	2.73
3	2.88	1.51	2.06	3.60	3.29
4	3.14	1.39	2.34	3.91	3.55
5	3.39	1.54	2.91	4.43	3.65
6	3.21	1.65	2.63	3.80	3.61
7	3.16	1.54	2.29	3.37	3.83
8	2.74	1.64	2.21	3.00	3.09
9	2.76	1.80	2.53	2.94	3.02
10	2.81	2.34	2.66	2.54	3.25

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.09	3.74	3.91	7.38	4.52
2	3.17	2.26	2.44	4.69	2.83
3	2.62	1.85	2.02	3.98	2.32
4	2.26	1.55	1.70	3.48	2.00
5	1.99	1.35	1.52	3.11	1.77
6	2.00	1.38	1.57	3.29	1.67
7	2.27	1.58	1.78	3.63	1.91
8	2.63	1.88	2.08	4.18	2.19
9	3.18	2.34	2.51	4.90	2.69
10	5.19	3.82	4.02	7.91	4.39

β_{ABX}	Average sum of market risk factors				
Portfolio	full	pre	subprime	global	post
1	0.27	-6.08	2.15	2.72	0.81
2	0.72	-1.87	1.46	1.70	0.95
3	0.78	-0.59	1.14	1.34	0.90
4	0.78	0.01	0.95	1.07	0.85
5	0.77	0.46	0.82	0.93	0.78
6	0.82	0.95	0.74	0.85	0.77
7	0.96	1.60	0.69	0.80	0.86
8	1.13	2.44	0.60	0.72	0.97
9	1.42	3.99	0.53	0.57	1.11
10	2.33	8.94	0.02	0.09	1.56

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.31	1.55	-0.17	-3.98	2.09
2	0.01	0.63	-0.76	-3.83	0.59
3	-0.09	0.33	-0.90	-3.30	0.51
4	-0.06	0.57	-0.66	-3.34	0.55
5	0.01	0.36	-0.55	-3.16	0.77
6	-0.09	0.26	-0.71	-3.54	0.87
7	-0.09	0.21	-0.82	-3.70	0.80
8	-0.05	0.19	-0.79	-3.92	0.87
9	-0.18	0.10	-0.75	-4.61	0.69
10	1.50	1.16	0.10	-3.83	1.97

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.78	2.90	2.93	5.36	3.34
2	2.22	1.73	1.79	3.17	1.92
3	1.77	1.40	1.46	2.60	1.50
4	1.47	1.17	1.19	2.19	1.23
5	1.25	1.00	1.04	1.90	1.04
6	1.26	1.03	1.07	2.03	0.98
7	1.48	1.19	1.25	2.31	1.16
8	1.78	1.43	1.48	2.77	1.40
9	2.22	1.79	1.82	3.35	1.81
10	3.88	2.96	3.06	5.83	3.23

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-18.14	-87.30	-7.74	-2.70	-4.81
2	-7.18	-34.98	-3.03	-1.02	-1.86
3	-4.07	-19.98	-1.73	-0.55	-1.04
4	-2.19	-10.86	-0.93	-0.25	-0.55
5	-0.83	-4.26	-0.35	-0.04	-0.20
6	0.33	1.37	0.15	0.17	0.09
7	1.64	7.75	0.69	0.42	0.40
8	3.49	16.80	1.44	0.76	0.85
9	6.63	32.09	2.68	1.31	1.61
10	17.95	86.55	7.16	3.29	4.57

Table 5.34: Decile portfolios sorted by ABX BBB factor loadings (Model 2 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas $(\sum_{j=1}^{3}\beta_j)$, and the sum of ABX factor loadings $(\sum_{j=1}^{3}\gamma_j)$ of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the orthogonalised ABX BBB index.

ABX BBB Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,042,092	1,264,674	1,198,292	983,374	1,017,495
2	2,570,128	3,114,614	2,806,318	2,143,637	2,694,480
3	3,204,923	3,424,359	3,335,541	2,797,190	3,495,282
4	3,415,380	3,155,614	3,885,377	2,939,630	3,666,869
5	3,319,634	3,619,041	3,597,519	2,882,918	3,377,809
6	3,159,227	3,142,126	3,411,733	2,798,960	3,324,871
7	3,449,274	3,516,572	4,293,214	2,923,711	3,512,921
8	3,214,595	3,264,427	4,159,060	2,641,207	3,152,321
9	2,507,431	2,492,300	3,065,947	2,277,918	2,471,919
10	1,111,967	1,387,389	1,265,613	1,128,284	981,981

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.23	0.22	-1.86	-1.81	0.25
2	0.51	0.82	-0.94	-1.60	0.85
3	0.40	0.81	-0.78	-1.73	0.82
4	0.26	0.82	-0.80	-2.43	0.94
5	0.23	0.71	-0.78	-2.13	0.86
6	0.14	0.64	-0.98	-2.21	0.82
7	0.17	0.83	-1.05	-2.24	0.83
8	0.24	0.81	-1.24	-2.26	0.91
9	0.22	0.76	-1.41	-2.39	0.97
10	-0.06	0.46	-1.65	-2.34	0.22

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	2.11	6.66	-0.12	-0.50	1.73
2	0.76	2.57	-0.11	-0.18	0.60
3	0.43	1.42	-0.08	-0.07	0.33
4	0.23	0.72	-0.05	0.01	0.17
5	0.09	0.21	-0.03	0.07	0.05
6	-0.03	-0.26	0.00	0.13	-0.06
7	-0.17	-0.79	0.01	0.22	-0.18
8	-0.38	-1.57	0.02	0.33	-0.39
9	-0.73	-2.84	0.06	0.50	-0.72
10	-1.80	-7.19	0.25	1.44	-1.79

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.66	2.32	2.49	2.51	2.97
2	2.57	1.68	2.06	2.73	2.97
3	2.69	1.50	2.15	3.17	3.04
4	2.99	1.46	2.21	3.85	3.34
5	3.28	1.56	2.59	4.06	3.62
6	3.27	1.63	2.60	4.04	3.58
7	3.13	1.52	2.39	3.75	3.57
8	2.99	1.55	2.10	3.12	3.71
9	2.86	1.73	2.27	3.01	3.47
10	2.94	2.31	3.10	3.27	2.98

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.09	3.77	4.00	7.41	4.39
2	3.12	2.24	2.49	4.64	2.67
3	2.57	1.81	2.07	3.92	2.18
4	2.25	1.53	1.75	3.51	1.93
5	2.01	1.37	1.56	3.25	1.70
6	2.01	1.37	1.55	3.24	1.73
7	2.28	1.59	1.72	3.62	2.00
8	2.65	1.88	2.03	4.12	2.35
9	3.21	2.36	2.43	4.93	2.83
10	5.20	3.81	3.96	7.92	4.52

β_{ABX}	Average sum of market risk factors				
Portfolio	full	pre	subprime	global	post
1	0.90	2.15	2.66	1.33	0.62
2	0.99	1.55	1.68	1.20	0.79
3	0.93	1.26	1.34	1.07	0.79
4	0.86	1.05	1.02	0.94	0.77
5	0.79	0.79	0.87	0.86	0.76
6	0.79	0.76	0.72	0.85	0.77
7	0.86	0.72	0.62	0.90	0.91
8	1.02	0.83	0.60	0.98	1.11
9	1.16	0.78	0.40	1.06	1.31
10	1.61	0.55	-0.41	1.35	1.99

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.09	0.97	-0.54	-5.20	1.99
2	-0.15	0.34	-0.97	-4.46	0.63
3	-0.08	0.40	-1.06	-3.96	0.93
4	0.03	0.49	-0.83	-3.22	0.76
5	0.06	0.37	-0.56	-3.04	0.79
6	-0.05	0.15	-0.51	-3.20	0.74
7	0.06	0.36	-0.62	-3.26	0.92
8	-0.04	0.40	-0.65	-3.51	0.65
9	-0.28	0.23	-0.69	-4.22	0.39
10	1.64	1.65	0.43	-3.13	1.93

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.80	2.94	3.02	5.41	3.26
2	2.18	1.71	1.84	3.17	1.80
3	1.73	1.36	1.48	2.57	1.39
4	1.46	1.15	1.24	2.22	1.18
5	1.26	1.02	1.07	2.01	0.98
6	1.26	1.02	1.05	1.97	1.02
7	1.48	1.20	1.20	2.27	1.21
8	1.79	1.43	1.45	2.70	1.50
9	2.25	1.81	1.77	3.37	1.90
10	3.89	2.98	3.04	5.84	3.31

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-12.92	-38.31	-3.38	-5.38	-6.65
2	-4.92	-15.00	-1.33	-2.09	-2.43
3	-2.75	-8.35	-0.76	-1.20	-1.32
4	-1.44	-4.30	-0.41	-0.65	-0.66
5	-0.50	-1.33	-0.16	-0.22	-0.19
6	0.32	1.29	0.05	0.15	0.23
7	1.27	4.34	0.28	0.57	0.75
8	2.60	8.67	0.60	1.14	1.48
9	4.83	15.80	1.13	2.10	2.74
10	12.84	41.05	3.02	5.41	7.32

Table 5.35: Decile portfolios sorted by ABX BBB- factor loadings (Model 2 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the lagged excess returns of the CRSP value-weighted market index and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics for the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3}\beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3}\gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the orthogonalised ABX BBB- index.

ABX BBB- Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,049,499	1,246,779	1,223,824	953,481	1,053,677
2	2,485,558	2,943,168	2,955,664	2,147,723	2,475,292
3	3,180,447	3,494,163	3,149,857	2,700,978	3,465,564
4	3,354,833	3,449,566	3,712,619	3,125,740	3,432,378
5	3,244,234	3,628,346	3,486,976	2,728,332	3,370,241
6	3,227,385	3,088,597	3,645,670	2,933,413	3,381,860
7	3,433,699	3,361,618	4,149,497	2,838,680	3,551,245
8	3,387,272	3,333,936	4,449,333	3,020,953	3,304,697
9	2,526,702	2,520,510	2,888,489	2,160,129	2,578,420
10	1,122,537	1,323,188	1,354,696	929,915	1,110,587

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.25	0.32	-2.07	-1.64	0.52
2	0.39	0.63	-1.01	-2.13	1.03
3	0.53	0.98	-0.70	-2.05	1.16
4	0.43	0.87	-0.80	-1.95	1.00
5	0.34	0.83	-0.68	-2.19	1.05
6	0.19	0.68	-0.92	-2.10	0.86
7	0.23	0.79	-0.97	-1.98	0.78
8	0.08	0.70	-1.20	-1.97	0.56
9	0.07	0.80	-1.49	-2.36	0.54
10	-0.18	0.29	-1.62	-2.73	-0.03

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	1.61	4.72	-0.48	-0.77	1.53
2	0.57	1.76	-0.24	-0.32	0.51
3	0.32	0.97	-0.15	-0.15	0.28
4	0.18	0.49	-0.09	-0.03	0.15
5	0.08	0.12	-0.04	0.04	0.06
6	-0.01	-0.20	0.00	0.12	-0.04
7	-0.12	-0.56	0.04	0.21	-0.15
8	-0.27	-1.08	0.09	0.33	-0.30
9	-0.52	-1.96	0.19	0.55	-0.56
10	-1.30	-4.76	0.58	1.54	-1.40

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.81	2.24	2.48	2.65	3.32
2	2.54	1.60	2.15	2.54	3.02
3	2.68	1.57	2.06	3.09	3.00
4	3.11	1.53	2.66	3.76	3.54
5	3.21	1.55	2.43	3.98	3.59
6	3.41	1.54	2.43	4.36	3.95
7	3.03	1.60	2.32	3.67	3.43
8	2.87	1.58	2.06	3.36	3.21
9	2.68	1.75	2.24	3.30	2.83
10	3.05	2.28	3.14	2.88	3.38

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.10	3.78	3.98	7.41	4.48
2	3.17	2.26	2.51	4.70	2.78
3	2.60	1.86	2.06	3.90	2.27
4	2.25	1.55	1.76	3.49	1.94
5	2.02	1.38	1.55	3.24	1.72
6	2.00	1.37	1.53	3.24	1.70
7	2.25	1.55	1.75	3.63	1.94
8	2.63	1.88	2.04	4.13	2.27
9	3.19	2.37	2.44	4.93	2.75
10	5.18	3.74	3.95	7.88	4.44

β_{ABX}	Average sum of market risk factors				
Portfolio	full	pre	subprime	global	post
1	0.88	0.25	2.61	1.50	0.80
2	0.97	0.83	1.67	1.19	0.91
3	0.90	0.82	1.30	1.02	0.87
4	0.85	0.75	1.08	0.95	0.83
5	0.80	0.77	0.87	0.86	0.78
6	0.79	0.80	0.71	0.86	0.78
7	0.88	0.89	0.65	0.92	0.88
8	1.01	1.08	0.63	0.94	1.01
9	1.21	1.52	0.46	1.03	1.21
10	1.66	2.30	-0.35	1.13	1.65

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.57	0.99	-0.90	-5.71	1.56
2	-0.40	0.52	-0.93	-5.02	0.39
3	-0.16	0.45	-1.01	-3.80	0.69
4	-0.02	0.45	-0.87	-3.47	0.83
5	0.06	0.47	-0.59	-3.26	0.86
6	-0.01	0.31	-0.64	-3.23	0.81
7	-0.07	0.24	-0.63	-3.27	0.61
8	0.05	0.08	-0.55	-3.37	0.73
9	0.13	0.15	-0.55	-3.71	0.78
10	2.12	1.67	0.65	-2.36	2.45

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.80	2.94	3.02	5.43	3.30
2	2.21	1.73	1.85	3.20	1.86
3	1.76	1.41	1.49	2.55	1.45
4	1.46	1.17	1.23	2.21	1.18
5	1.28	1.03	1.06	2.00	1.00
6	1.25	1.02	1.03	1.98	0.99
7	1.46	1.17	1.22	2.27	1.18
8	1.76	1.43	1.45	2.69	1.44
9	2.22	1.82	1.78	3.33	1.84
10	3.87	2.92	3.02	5.80	3.26

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-10.56	-25.89	-2.44	-5.36	-6.15
2	-4.04	-9.81	-0.96	-2.11	-2.27
3	-2.29	-5.46	-0.54	-1.20	-1.23
4	-1.21	-2.77	-0.28	-0.63	-0.62
5	-0.42	-0.77	-0.10	-0.19	-0.20
6	0.26	0.97	0.05	0.21	0.17
7	1.03	2.95	0.22	0.66	0.62
8	2.09	5.72	0.47	1.27	1.24
9	3.89	10.39	0.87	2.23	2.29
10	10.46	26.16	2.32	5.62	6.28

Table 5.36: Decile portfolios sorted by ABX AAA factor loadings (Model 2 using orthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. In this table, the decile portfolios contain only stocks with significant F-statistics of null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX index. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX AAA index.

ABX AAA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,138,961	1,143,326	1,779,754	1,040,286	1,045,705
2	3,150,694	4,261,204	3,730,685	2,549,257	3,089,211
3	4,121,121	5,423,084	4,928,724	3,237,447	3,877,896
4	3,703,527	3,871,840	4,548,053	2,952,885	3,491,971
5	3,159,799	3,484,707	4,416,844	2,397,010	2,943,333
6	3,387,993	4,033,050	4,584,304	2,510,770	3,316,941
7	3,308,900	4,074,234	4,105,209	2,546,472	3,208,420
8	3,389,836	3,773,882	3,912,584	2,957,875	3,197,059
9	2,644,394	2,770,210	3,003,046	2,886,958	2,430,835
10	1,152,731	1,676,519	1,158,086	1,172,114	1,071,353

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.60	1.03	-1.46	-1.01	0.36
2	0.65	1.03	-1.08	-2.15	1.46
3	0.40	1.14	-0.99	-2.22	1.18
4	0.53	0.97	-0.66	-1.61	1.04
5	0.26	0.90	-0.78	-2.35	0.98
6	0.23	0.70	-0.83	-2.19	0.85
7	0.08	0.75	-0.98	-2.41	0.69
8	0.03	1.00	-1.31	-2.22	0.42
9	-0.01	0.78	-1.55	-2.46	0.54
10	-0.23	0.17	-2.41	-2.25	-0.23

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.45	-0.07	-0.04	-0.08	1.04
2	0.15	-0.08	-0.05	-0.01	0.37
3	0.08	-0.06	-0.04	0.02	0.21
4	0.05	-0.05	-0.03	0.05	0.11
5	0.02	-0.01	-0.05	0.07	0.04
6	0.00	0.00	-0.05	0.11	-0.02
7	-0.03	0.03	-0.04	0.16	-0.12
8	-0.09	-0.03	-0.05	0.15	-0.23
9	-0.16	-0.03	-0.08	0.25	-0.42
10	-0.34	-0.01	0.00	0.51	-0.99

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.66	2.15	2.33	2.88	2.93
2	2.71	1.54	2.16	3.17	3.14
3	2.91	1.89	2.24	3.39	3.29
4	2.98	1.84	2.44	3.03	3.62
5	3.27	1.76	2.80	3.39	3.65
6	3.69	1.77	3.24	5.20	3.65
7	3.42	1.97	4.93	3.03	3.37
8	2.78	2.28	1.93	3.57	2.98
9	2.91	1.80	1.94	3.32	3.64
10	2.82	2.34	2.58	3.19	2.98

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.62	3.40	3.58	6.98	3.99
2	2.93	2.09	2.26	4.51	2.51
3	2.43	1.69	1.88	3.83	2.07
4	2.08	1.50	1.60	3.23	1.77
5	1.90	1.28	1.48	3.07	1.59
6	1.94	1.36	1.54	3.07	1.64
7	2.16	1.54	1.75	3.37	1.83
8	2.48	1.83	1.96	3.77	2.13
9	2.97	2.23	2.38	4.36	2.57
10	4.70	3.59	3.68	6.94	4.07

β_{ABX}	Average sum of market risk factors				
Portfolio	full	pre	subprime	global	post
1	-0.22	-7.42	-2.00	2.60	1.45
2	0.53	-2.67	-0.29	1.78	1.26
3	0.62	-1.18	0.09	1.35	1.05
4	0.70	-0.30	0.44	1.10	0.93
5	0.77	0.42	0.68	1.01	0.78
6	0.92	1.08	0.99	1.01	0.78
7	1.11	1.96	1.35	0.99	0.80
8	1.40	3.32	1.75	1.01	0.78
9	1.90	5.46	2.51	1.05	0.89
10	3.12	10.95	4.47	0.98	1.05

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.53	2.30	1.10	-2.95	0.72
2	0.22	0.61	-0.33	-3.28	0.21
3	0.14	0.70	-0.57	-2.65	0.39
4	0.18	0.56	-0.39	-2.80	0.70
5	0.00	0.54	-0.61	-3.22	0.62
6	0.08	0.24	-0.84	-3.41	1.03
7	0.11	0.80	-0.87	-3.73	1.12
8	-0.22	0.10	-0.91	-4.25	0.90
9	-0.22	0.05	-1.19	-4.39	0.82
10	0.68	-0.23	-0.91	-5.00	1.70

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	2.98	2.34	2.37	4.38	2.53
2	1.74	1.39	1.46	2.60	1.41
3	1.38	1.10	1.18	2.13	1.09
4	1.15	0.98	0.97	1.75	0.89
5	1.02	0.81	0.86	1.63	0.78
6	1.04	0.86	0.90	1.60	0.81
7	1.20	1.00	1.05	1.81	0.94
8	1.43	1.19	1.22	2.09	1.16
9	1.80	1.47	1.53	2.54	1.48
10	3.05	2.45	2.47	4.41	2.57

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-44.01	-159.82	-66.13	-9.84	-14.28
2	-18.95	-70.78	-27.43	-4.54	-5.67
3	-11.11	-42.40	-15.69	-2.70	-3.13
4	-5.93	-23.67	-7.73	-1.49	-1.52
5	-1.79	-8.64	-1.24	-0.55	-0.29
6	1.97	5.25	4.29	0.37	0.85
7	6.22	20.71	10.77	1.37	2.15
8	11.72	40.97	18.83	2.69	3.88
9	20.45	74.09	31.15	4.53	6.53
10	46.34	170.35	66.76	10.21	15.41

Table 5.37: Decile portfolios sorted by ABX AA factor loadings (Model 2 using orthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. In this table, the decile portfolios contain only stocks with significant F-statistics of null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX index. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX AA index.

ABX AA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,086,446	908,057	1,344,883	1,074,658	1,129,462
2	2,744,808	2,650,041	3,003,292	2,271,670	3,037,346
3	3,931,510	3,349,826	3,904,386	3,180,914	4,630,838
4	3,627,756	3,055,589	4,627,950	3,185,481	3,611,245
5	3,192,304	3,619,860	4,085,146	2,652,119	3,141,021
6	3,044,842	3,177,180	3,731,253	2,440,979	3,178,048
7	3,656,890	3,720,886	4,729,430	2,627,060	3,753,096
8	3,470,250	4,539,261	4,271,659	2,723,096	3,294,391
9	2,901,129	3,356,897	3,489,906	2,602,250	2,831,071
10	1,091,066	1,472,735	1,122,750	1,096,066	1,041,842

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.41	0.35	-2.60	-1.03	0.52
2	0.41	1.12	-1.27	-2.11	0.95
3	0.38	1.39	-1.00	-2.17	0.93
4	0.26	0.95	-0.86	-2.54	1.05
5	0.34	0.93	-0.93	-1.94	0.88
6	0.13	0.78	-0.84	-2.24	0.75
7	0.13	0.70	-1.30	-2.12	0.88
8	0.22	0.85	-0.89	-2.54	0.94
9	0.47	1.05	-0.86	-1.36	0.60
10	-0.16	-0.21	-0.66	-2.49	-0.07

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	1.33	5.13	2.02	-0.72	0.93
2	0.57	2.34	0.79	-0.33	0.37
3	0.36	1.46	0.46	-0.14	0.22
4	0.21	0.89	0.25	-0.08	0.13
5	0.12	0.44	0.10	0.07	0.05
6	0.02	0.00	-0.04	0.12	-0.01
7	-0.10	-0.52	-0.18	0.24	-0.11
8	-0.24	-1.14	-0.39	0.37	-0.21
9	-0.45	-2.10	-0.68	0.60	-0.37
10	-1.08	-5.07	-1.67	1.31	-0.82

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.65	1.92	2.41	2.58	3.06
2	2.85	1.56	2.12	2.86	3.44
3	2.76	1.38	2.10	3.40	3.14
4	3.10	1.66	2.49	3.88	3.41
5	3.36	1.69	2.70	4.22	3.57
6	3.39	1.71	3.52	3.97	3.48
7	2.92	1.64	2.55	3.47	3.15
8	2.75	1.68	1.98	3.15	3.19
9	2.55	1.92	2.05	2.76	2.84
10	2.82	2.29	2.21	2.28	3.63

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.60	3.38	3.66	6.83	4.04
2	2.92	2.13	2.35	4.36	2.56
3	2.43	1.78	1.93	3.74	2.11
4	2.10	1.51	1.63	3.30	1.79
5	1.96	1.36	1.51	3.17	1.65
6	1.97	1.31	1.51	3.22	1.66
7	2.12	1.42	1.64	3.41	1.81
8	2.45	1.68	1.93	3.83	2.10
9	2.98	2.10	2.27	4.52	2.60
10	4.72	3.40	3.59	7.09	4.12

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	-0.20	-9.58	-2.09	3.06	1.85
2	0.42	-3.92	-0.37	1.97	1.36
3	0.54	-2.13	0.14	1.43	1.12
4	0.58	-1.10	0.23	1.21	0.95
5	0.70	-0.06	0.54	1.05	0.84
6	0.86	0.91	0.86	1.02	0.75
7	1.02	1.97	1.12	0.90	0.74
8	1.29	3.55	1.48	0.71	0.77
9	1.65	5.51	2.16	0.59	0.69
10	2.86	12.15	4.18	0.28	0.61

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.67	1.62	1.48	-4.23	-0.04
2	-0.10	0.02	-0.50	-4.00	0.47
3	0.13	0.28	-0.88	-2.81	0.62
4	-0.01	0.29	-0.90	-3.11	0.77
5	0.27	0.61	-0.76	-2.68	1.10
6	0.09	0.40	-0.62	-3.62	1.13
7	-0.03	0.08	-0.60	-3.62	1.00
8	-0.01	0.36	-0.94	-3.70	1.01
9	0.21	0.33	-0.65	-3.82	1.14
10	1.62	1.40	-0.82	-3.98	2.64

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	2.98	2.31	2.41	4.30	2.58
2	1.74	1.41	1.50	2.52	1.45
3	1.40	1.15	1.20	2.12	1.14
4	1.17	0.96	0.99	1.79	0.92
5	1.06	0.87	0.88	1.68	0.83
6	1.07	0.82	0.88	1.70	0.83
7	1.17	0.91	0.97	1.81	0.94
8	1.42	1.10	1.21	2.16	1.14
9	1.80	1.41	1.45	2.64	1.49
10	3.09	2.37	2.42	4.56	2.60

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-21.50	-84.55	-34.12	-3.45	-4.38
2	-9.69	-39.75	-14.30	-1.52	-1.83
3	-5.96	-24.79	-8.73	-0.90	-1.06
4	-3.47	-14.83	-4.94	-0.48	-0.55
5	-1.56	-7.07	-2.13	-0.15	-0.18
6	0.12	-0.13	0.19	0.17	0.17
7	2.02	7.91	2.58	0.52	0.57
8	4.49	18.10	5.94	0.97	1.08
9	8.36	34.14	11.18	1.62	1.90
10	20.39	83.69	27.56	3.65	4.57

Table 5.38: Decile portfolios sorted by ABX A factor loadings (Model 2 using orthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. In this table, the decile portfolios contain only stocks with significant F-statistics of null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX index. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX A index.

ABX A Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	975,662	1,186,407	1,511,720	918,012	805,528
2	2,690,038	3,020,214	3,405,886	2,704,207	2,386,082
3	3,628,703	3,342,545	4,583,746	3,096,275	3,703,086
4	3,612,424	3,795,374	4,544,186	2,839,364	3,618,992
5	3,319,650	3,514,597	3,684,189	3,369,201	3,330,096
6	3,355,022	3,449,380	3,606,813	2,719,800	3,711,367
7	3,617,897	3,878,797	4,957,999	2,785,187	3,557,936
8	3,473,400	3,086,848	4,002,400	2,234,127	4,105,101
9	2,708,458	2,932,775	3,317,340	1,846,468	2,937,091
10	1,307,959	1,453,379	1,239,125	1,608,396	1,202,265

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.16	-0.10	-1.54	-1.89	0.25
2	0.40	0.47	-1.20	-1.43	0.86
3	0.57	0.72	-0.99	-1.78	1.36
4	0.52	0.90	-0.38	-2.06	1.33
5	0.48	0.94	-0.48	-1.64	1.03
6	0.36	0.70	-0.64	-1.56	0.91
7	0.38	0.96	-0.86	-1.89	1.10
8	0.09	1.07	-1.18	-2.27	0.73
9	0.06	0.77	-1.35	-2.91	0.92
10	-0.13	0.00	-1.54	-2.20	-0.20

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	2.48	13.27	0.96	-1.22	1.02
2	1.10	6.09	0.41	-0.58	0.43
3	0.67	3.74	0.24	-0.32	0.25
4	0.40	2.10	0.15	-0.11	0.15
5	0.20	0.91	0.09	0.03	0.06
6	0.00	-0.09	0.00	0.13	-0.02
7	-0.19	-1.25	-0.07	0.26	-0.10
8	-0.47	-2.81	-0.18	0.46	-0.22
9	-0.93	-5.40	-0.30	0.71	-0.42
10	-2.22	-13.11	-0.68	1.81	-1.01

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.94	2.05	2.21	4.81	2.84
2	2.59	1.60	1.95	3.31	2.79
3	2.76	1.64	2.08	3.55	2.86
4	3.01	1.62	2.50	4.24	3.07
5	3.26	1.61	3.21	4.32	3.34
6	3.35	1.64	3.54	3.28	3.91
7	3.33	1.53	2.47	4.21	3.63
8	2.90	1.59	2.23	3.94	2.87
9	2.67	2.01	2.05	2.99	2.79
10	2.81	2.17	2.54	2.73	3.25

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.69	3.36	3.73	6.79	4.17
2	2.98	2.10	2.28	4.46	2.66
3	2.45	1.75	1.90	3.62	2.21
4	2.14	1.44	1.65	3.30	1.89
5	1.95	1.29	1.47	3.13	1.69
6	1.97	1.34	1.51	3.30	1.64
7	2.13	1.45	1.69	3.46	1.77
8	2.49	1.75	1.99	4.01	2.08
9	2.96	2.20	2.31	4.56	2.53
10	4.72	3.49	3.70	7.17	4.11

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	0.08	-7.44	2.09	3.11	0.82
2	0.54	-2.97	1.43	1.95	0.88
3	0.64	-1.63	1.19	1.39	0.95
4	0.65	-0.51	0.91	1.07	0.76
5	0.70	0.19	0.71	0.96	0.74
6	0.78	0.81	0.70	0.81	0.75
7	0.90	1.69	0.58	0.63	0.82
8	1.10	2.68	0.48	0.52	0.94
9	1.40	4.55	0.24	0.32	1.04
10	2.40	10.19	-0.19	-0.32	1.51

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.40	1.80	1.39	-3.05	1.14
2	-0.22	0.78	-0.41	-4.08	0.24
3	-0.13	0.71	-0.91	-3.06	0.35
4	0.06	0.64	-0.51	-2.73	0.34
5	0.18	0.43	-0.25	-2.65	0.66
6	-0.11	0.20	-0.94	-3.38	0.82
7	0.02	0.12	-0.92	-3.77	1.09
8	0.03	0.51	-0.82	-3.74	1.04
9	-0.08	-0.01	-0.93	-4.10	0.95
10	0.98	0.63	-1.31	-4.67	2.22

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.05	2.32	2.47	4.27	2.67
2	1.80	1.39	1.47	2.61	1.54
3	1.42	1.15	1.18	2.02	1.21
4	1.20	0.94	0.99	1.79	1.00
5	1.06	0.83	0.87	1.64	0.86
6	1.06	0.85	0.88	1.73	0.82
7	1.19	0.94	1.02	1.87	0.93
8	1.45	1.16	1.23	2.27	1.15
9	1.79	1.47	1.48	2.67	1.47
10	3.09	2.41	2.48	4.56	2.64

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-22.14	-105.65	-10.47	-3.24	-5.83
2	-9.99	-48.55	-4.57	-1.34	-2.52
3	-6.06	-29.65	-2.87	-0.75	-1.49
4	-3.45	-16.95	-1.74	-0.35	-0.83
5	-1.47	-7.43	-0.79	-0.04	-0.33
6	0.22	0.56	0.03	0.29	0.12
7	2.10	9.61	0.83	0.65	0.59
8	4.72	22.39	1.84	1.09	1.23
9	8.81	42.52	3.42	1.76	2.22
10	21.58	103.95	8.49	3.99	5.74

Table 5.39: Decile portfolios sorted by ABX BBB factor loadings (Model 2 using orthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. In this table, the decile portfolios contain only stocks with significant F-statistics of null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX index. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3}\beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3}\gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX BBB index.

ABX BBB Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,085,559	1,291,876	1,312,656	1,007,191	1,057,582
2	2,721,617	3,617,960	2,753,696	2,299,426	2,816,008
3	3,755,900	4,365,756	4,242,782	3,146,594	3,946,355
4	3,602,325	3,886,650	3,859,572	3,286,726	3,744,514
5	3,330,102	3,334,280	3,517,488	3,119,689	3,281,998
6	3,243,568	3,456,032	3,338,914	3,162,393	3,218,165
7	3,684,704	4,524,173	5,080,753	3,001,789	3,312,843
8	3,413,749	3,806,503	4,413,161	2,937,384	3,238,842
9	2,778,993	2,642,902	3,468,661	2,759,231	2,585,465
10	1,149,944	1,279,922	1,312,187	1,346,172	939,383

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.03	0.71	-1.90	-2.37	-0.24
2	0.45	0.94	-0.84	-2.11	0.88
3	0.24	0.56	-0.57	-1.85	0.54
4	0.29	0.71	-0.82	-1.95	0.71
5	0.35	1.00	-0.61	-2.33	0.98
6	0.10	0.94	-0.94	-2.28	0.73
7	0.24	1.30	-0.84	-2.30	0.66
8	0.12	1.11	-1.20	-2.70	0.70
9	0.34	0.81	-0.91	-2.22	1.10
10	-0.41	0.53	-2.12	-2.44	-0.45

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	2.41	7.82	-0.07	-0.65	2.02
2	1.00	3.41	-0.06	-0.20	0.80
3	0.58	2.01	-0.04	-0.06	0.44
4	0.34	1.09	-0.02	0.05	0.24
5	0.14	0.31	0.01	0.14	0.06
6	-0.05	-0.37	0.02	0.19	-0.10
7	-0.23	-1.16	0.04	0.31	-0.27
8	-0.52	-2.13	0.04	0.39	-0.56
9	-0.97	-3.78	0.06	0.55	-0.97
10	-2.25	-8.60	0.12	1.42	-2.25

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.85	2.18	2.39	3.25	3.11
2	2.56	1.85	2.10	3.03	2.67
3	2.69	2.16	2.12	3.48	2.65
4	2.82	1.51	2.81	3.57	2.89
5	3.34	1.59	2.35	3.98	3.80
6	3.25	1.64	2.57	4.21	3.15
7	3.63	1.51	2.19	4.09	4.43
8	3.03	1.60	3.28	4.10	2.85
9	2.99	1.84	1.93	3.68	3.47
10	3.29	2.31	2.35	5.65	2.85

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.66	3.37	3.78	6.78	3.99
2	2.92	2.11	2.36	4.37	2.48
3	2.42	1.69	1.95	3.69	2.04
4	2.13	1.50	1.72	3.34	1.79
5	1.97	1.33	1.52	3.25	1.62
6	1.97	1.33	1.50	3.24	1.66
7	2.13	1.45	1.64	3.37	1.88
8	2.48	1.76	1.91	3.83	2.21
9	3.00	2.18	2.25	4.51	2.71
10	4.70	3.48	3.53	7.04	4.20

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	0.96	2.35	2.95	1.43	0.64
2	0.93	1.65	1.74	1.22	0.66
3	0.93	1.31	1.34	1.12	0.77
4	0.86	1.13	1.10	0.98	0.73
5	0.84	1.01	0.85	0.93	0.77
6	0.82	0.80	0.67	0.81	0.86
7	0.85	0.73	0.61	0.79	0.93
8	0.96	0.70	0.47	0.79	1.14
9	1.20	0.77	0.28	1.02	1.46
10	1.64	0.55	-0.53	1.37	2.09

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.30	2.08	0.63	-4.73	1.48
2	0.13	0.81	-0.81	-3.81	0.80
3	-0.17	0.55	-0.93	-3.61	0.26
4	0.12	0.77	-0.67	-2.84	0.68
5	0.17	0.58	-0.74	-2.92	0.81
6	0.10	0.28	-0.81	-2.73	0.87
7	0.12	0.30	-0.71	-3.15	1.03
8	-0.04	0.75	-0.63	-3.65	0.69
9	-0.31	0.18	-0.83	-4.52	0.70
10	0.61	1.32	-0.74	-4.94	1.51

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.04	2.33	2.52	4.28	2.55
2	1.77	1.40	1.53	2.55	1.42
3	1.40	1.09	1.21	2.06	1.10
4	1.19	0.98	1.05	1.78	0.93
5	1.06	0.85	0.91	1.66	0.81
6	1.05	0.86	0.87	1.67	0.81
7	1.18	0.96	0.97	1.79	0.96
8	1.42	1.16	1.15	2.09	1.20
9	1.80	1.46	1.44	2.61	1.56
10	3.05	2.39	2.37	4.42	2.67

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-15.07	-45.13	-4.34	-6.21	-7.97
2	-6.35	-19.88	-1.89	-2.72	-3.17
3	-3.72	-11.78	-1.16	-1.68	-1.80
4	-2.04	-6.45	-0.68	-0.98	-0.93
5	-0.74	-2.10	-0.30	-0.41	-0.25
6	0.44	1.83	0.01	0.14	0.37
7	1.75	6.28	0.33	0.73	1.09
8	3.47	11.92	0.77	1.47	2.09
9	6.23	21.12	1.44	2.60	3.67
10	14.99	49.01	3.55	6.18	8.86

Table 5.40: Decile portfolios sorted by ABX BBB- factor loadings (Model 2 using orthogonalised ABX index returns and only stocks with significant F-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted based on the sum of ABX factor loadings estimated using the time series regression as shown in Equation 5.23 (Model 2) and the *orthogonalised* ABX innovations. In this table, the decile portfolios contain only stocks with significant F-statistics of null hypothesis: $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$, i.e. I screen out all stocks with insignificant F-statistics and sort only those stocks with significant exposure to the ABX index. I then sort the significant stocks into decile portfolios based on the sum of ABX factor loadings at the end of each month and report the equally weighted average summary statistics. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), average α, sum of market betas ($\sum_{j=1}^{3} \beta_j$), and the sum of ABX factor loadings ($\sum_{j=1}^{3} \gamma_j$) of each portfolio are reported. I also report the summary statistics grouped by crisis subperiods. The findings are based on the ABX BBB- index.

ABX BBB- Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	1,074,772	1,269,320	1,537,446	919,407	1,006,320
2	2,689,478	3,436,525	3,205,823	2,265,652	2,609,302
3	3,666,655	4,490,843	3,896,903	2,859,610	3,838,992
4	3,654,014	3,371,773	4,067,088	3,350,495	3,899,579
5	3,302,861	3,279,989	3,939,082	2,768,752	3,396,596
6	3,256,553	3,500,141	3,503,975	3,232,130	3,210,967
7	3,730,091	3,171,809	5,295,243	3,375,607	3,646,618
8	3,660,871	3,632,912	5,233,816	2,977,999	3,441,413
9	2,797,735	2,892,872	3,297,634	2,382,242	2,766,890
10	1,104,961	1,216,222	1,393,588	1,014,164	1,004,206

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.38	0.04	-2.52	-1.46	0.70
2	0.39	0.73	-0.73	-2.27	0.88
3	0.41	1.03	-0.55	-2.70	1.24
4	0.42	1.52	-0.97	-2.25	1.05
5	0.21	0.69	-0.63	-2.30	0.80
6	0.15	0.69	-0.81	-2.00	0.58
7	0.14	0.97	-0.88	-2.15	0.51
8	-0.13	0.91	-1.42	-2.73	0.38
9	-0.06	1.17	-1.71	-2.53	0.32
10	-0.03	0.57	-1.21	-2.78	0.05

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	1.85	5.76	-0.44	-0.93	1.79
2	0.76	2.45	-0.25	-0.38	0.70
3	0.46	1.44	-0.16	-0.16	0.39
4	0.27	0.80	-0.09	-0.03	0.21
5	0.13	0.24	-0.02	0.07	0.07
6	-0.01	-0.24	0.04	0.15	-0.07
7	-0.18	-0.78	0.07	0.28	-0.26
8	-0.38	-1.49	0.15	0.42	-0.46
9	-0.70	-2.57	0.22	0.64	-0.79
10	-1.68	-5.83	0.54	1.55	-1.84

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.61	2.13	2.53	2.56	2.85
2	2.84	1.59	2.23	3.56	3.01
3	2.75	1.96	2.47	3.22	2.83
4	3.16	1.79	3.20	3.44	3.42
5	3.22	1.51	2.46	3.91	3.62
6	3.38	1.76	2.83	4.16	3.77
7	3.29	1.63	2.29	3.89	3.98
8	3.00	1.63	2.88	3.65	2.99
9	3.06	1.74	1.95	4.26	3.19
10	3.28	2.27	2.54	3.59	3.88

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	4.66	3.44	3.77	6.67	4.14
2	2.94	2.07	2.30	4.43	2.55
3	2.43	1.74	1.97	3.68	2.09
4	2.14	1.48	1.69	3.33	1.81
5	1.96	1.36	1.55	3.16	1.64
6	1.96	1.36	1.52	3.22	1.65
7	2.16	1.48	1.69	3.47	1.87
8	2.47	1.72	1.88	3.91	2.18
9	2.97	2.13	2.27	4.48	2.64
10	4.70	3.41	3.52	7.20	4.07

β_{ABX}	Average sum of market betas				
Portfolio	full	pre	subprime	global	post
1	0.81	-0.02	2.86	1.39	0.76
2	0.88	0.59	1.80	1.12	0.82
3	0.86	0.72	1.41	0.98	0.85
4	0.80	0.63	1.18	0.86	0.80
5	0.79	0.75	0.90	0.80	0.81
6	0.78	0.78	0.70	0.81	0.78
7	0.86	0.91	0.61	0.82	0.88
8	1.01	1.19	0.48	0.81	1.10
9	1.22	1.69	0.27	0.90	1.27
10	1.80	2.91	-0.51	1.05	1.82

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.27	0.39	1.76	-6.25	0.65
2	-0.54	0.63	-0.90	-4.58	-0.07
3	-0.20	0.68	-0.85	-3.73	0.53
4	0.08	0.72	-0.75	-2.84	0.66
5	-0.01	0.18	-0.75	-3.14	0.90
6	-0.01	0.39	-0.46	-3.35	0.90
7	-0.09	0.53	-0.91	-2.76	0.53
8	0.01	0.17	-0.56	-3.23	0.77
9	0.06	0.50	-0.70	-3.63	0.81
10	1.63	2.78	-0.12	-2.90	1.99

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.06	2.39	2.52	4.25	2.65
2	1.78	1.39	1.48	2.60	1.46
3	1.41	1.13	1.23	2.05	1.14
4	1.19	0.95	1.03	1.79	0.92
5	1.06	0.87	0.92	1.67	0.81
6	1.06	0.86	0.90	1.66	0.83
7	1.19	0.96	1.02	1.84	0.96
8	1.42	1.13	1.15	2.16	1.17
9	1.79	1.43	1.44	2.59	1.52
10	3.06	2.36	2.36	4.53	2.60

β_{ABX}	Average sum of ABX factor loadings				
Portfolio	full	pre	subprime	global	post
1	-12.31	-31.62	-3.11	-6.36	-7.42
2	-5.30	-13.61	-1.34	-2.78	-2.98
3	-3.14	-8.01	-0.81	-1.64	-1.69
4	-1.76	-4.37	-0.46	-0.91	-0.88
5	-0.68	-1.54	-0.19	-0.30	-0.26
6	0.31	1.14	0.05	0.25	0.31
7	1.41	4.17	0.31	0.84	0.99
8	2.82	7.90	0.64	1.62	1.86
9	5.05	13.78	1.14	2.75	3.22
10	12.35	31.97	2.71	6.50	7.83

Table 5.41: Decile portfolios sorted by ABX AAA factor loadings (Model 3 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.24 (Model 3). All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the excess returns of the CRSP value-weighted market index, the Fama and French (1993) SMB and HML factors, the Cahart (1997) Momentum factor and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and the β_{ABX} of each portfolio are reported. I also report the summary statistics based on my crisis subperiods. The findings are based on the ABX AAA index.

ABX AAA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	865,759	1,068,618	1,207,737	654,067	806,698
2	2,335,461	2,349,027	2,863,431	1,966,390	2,447,237
3	3,233,799	3,216,956	3,844,539	2,740,320	3,379,786
4	3,485,327	3,654,290	3,831,691	2,856,714	3,701,114
5	3,495,367	3,652,401	3,706,307	3,201,056	3,624,631
6	3,362,414	3,646,045	4,117,652	2,911,042	3,254,497
7	3,704,114	4,103,631	4,363,223	3,176,989	3,701,266
8	3,134,163	3,250,113	3,401,361	3,015,704	3,192,718
9	2,276,762	2,319,262	2,599,303	2,127,413	2,265,165
10	934,351	1,086,762	1,076,543	893,094	908,718

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.11	0.03	-1.18	-2.59	0.48
2	0.23	0.85	-1.28	-2.41	0.84
3	0.27	0.74	-1.09	-2.26	0.98
4	0.33	1.06	-0.80	-2.06	0.88
5	0.23	0.78	-0.88	-2.06	0.82
6	0.10	0.70	-0.92	-2.27	0.66
7	0.30	0.87	-0.90	-1.79	0.85
8	0.26	0.75	-1.08	-2.21	0.93
9	0.41	0.82	-1.27	-1.66	0.87
10	0.04	0.25	-2.08	-1.81	0.04

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.09	0.05	-0.10	-0.21	0.22
2	-0.01	0.00	-0.07	-0.15	0.05
3	0.00	0.00	-0.04	-0.08	0.03
4	0.00	0.00	-0.03	-0.06	0.02
5	0.00	0.00	-0.01	-0.03	0.01
6	0.00	-0.01	-0.02	0.00	0.00
7	-0.01	0.00	0.00	-0.01	-0.01
8	0.00	0.00	0.01	0.03	-0.03
9	0.00	0.00	0.03	0.09	-0.06
10	0.08	0.08	0.13	0.34	-0.08

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.57	2.12	2.41	2.16	3.03
2	2.57	1.78	1.97	2.59	3.04
3	2.64	1.55	2.04	2.99	3.03
4	3.20	1.67	2.50	3.86	3.67
5	3.61	1.68	2.91	4.37	4.02
6	3.67	1.72	2.47	4.60	4.22
7	3.12	1.51	2.71	4.08	3.31
8	2.75	1.49	2.10	3.56	3.04
9	2.68	1.65	2.54	2.99	2.86
10	2.74	2.10	2.33	2.38	3.41

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.11	3.74	3.91	7.45	4.51
2	3.18	2.34	2.43	4.80	2.76
3	2.61	1.90	2.03	4.00	2.22
4	2.26	1.62	1.77	3.54	1.91
5	2.01	1.40	1.56	3.25	1.70
6	1.99	1.36	1.58	3.11	1.73
7	2.25	1.56	1.76	3.56	1.94
8	2.62	1.85	2.06	4.10	2.26
9	3.18	2.25	2.48	4.89	2.76
10	5.16	3.74	3.99	7.85	4.44

β_{ABX}	Average β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	-1.74	-12.52	-0.85	0.68	0.38
2	-0.13	-4.31	0.23	0.76	0.70
3	0.28	-2.05	0.47	0.74	0.75
4	0.47	-0.73	0.58	0.72	0.73
5	0.60	0.21	0.64	0.65	0.70
6	0.76	1.04	0.74	0.69	0.72
7	0.99	2.01	0.91	0.75	0.79
8	1.28	3.36	1.15	0.79	0.87
9	1.72	5.61	1.45	0.85	0.95
10	3.10	13.47	2.46	0.77	1.06

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.07	0.75	0.51	-4.81	1.63
2	0.01	0.37	-0.59	-4.28	0.78
3	0.15	0.53	-0.44	-3.61	0.95
4	0.13	0.65	-0.57	-3.50	0.96
5	0.09	0.46	-0.43	-3.19	0.91
6	0.03	0.38	-0.66	-3.04	0.81
7	-0.07	0.38	-0.73	-3.61	0.80
8	-0.11	0.30	-0.90	-3.60	0.61
9	-0.16	0.32	-1.09	-3.94	0.51
10	1.10	1.18	-1.10	-3.61	1.64

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.95	2.99	3.08	5.64	3.47
2	2.28	1.84	1.81	3.35	1.93
3	1.80	1.48	1.49	2.70	1.46
4	1.50	1.25	1.26	2.30	1.19
5	1.28	1.05	1.09	2.02	1.00
6	1.25	1.03	1.11	1.86	1.03
7	1.48	1.20	1.27	2.24	1.21
8	1.79	1.43	1.52	2.68	1.49
9	2.27	1.76	1.89	3.35	1.93
10	3.99	3.00	3.16	5.89	3.41

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-30.93	-161.98	-21.73	-3.05	-3.49
2	-11.79	-62.02	-8.20	-1.22	-1.24
3	-6.52	-34.30	-4.50	-0.72	-0.67
4	-3.36	-17.83	-2.21	-0.41	-0.33
5	-1.07	-5.78	-0.57	-0.17	-0.09
6	0.92	4.69	0.81	0.03	0.11
7	3.13	16.28	2.41	0.25	0.35
8	6.27	32.69	4.64	0.56	0.70
9	11.54	60.32	8.36	1.07	1.28
10	30.41	159.02	21.65	2.86	3.51

Table 5.42: Decile portfolios sorted by ABX AA factor loadings (Model 3 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.24 (Model 3). All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the excess returns of the CRSP value-weighted market index, the Fama and French (1993) SMB and HML factors, the Cahart (1997) Momentum factor and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and the β_{ABX} of each portfolio are reported. I also report the summary statistics based on my crisis subperiods. The findings are based on the ABX AA index.

ABX AA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	910,970	1,072,338	1,249,462	695,485	886,002
2	2,308,147	2,357,822	2,877,514	1,870,656	2,444,722
3	3,183,659	2,808,126	3,833,084	2,721,158	3,369,405
4	3,560,174	3,426,469	3,937,612	3,145,784	3,782,581
5	3,412,498	3,736,302	3,954,980	3,016,334	3,366,240
6	3,333,384	3,586,610	3,952,230	2,974,572	3,304,406
7	3,520,220	3,980,397	3,706,669	3,210,776	3,533,148
8	3,258,923	3,633,734	3,573,132	2,975,731	3,248,844
9	2,380,999	2,643,097	2,782,933	2,094,012	2,374,071
10	962,443	1,128,071	1,149,898	838,368	960,822

β_{ABX}	Equally weighted Month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.17	0.43	-1.58	-2.61	0.56
2	0.28	0.64	-0.99	-2.51	1.02
3	0.33	1.11	-0.88	-2.38	0.89
4	0.33	0.81	-0.75	-2.19	1.06
5	0.28	0.96	-0.79	-1.99	0.85
6	0.16	0.72	-0.87	-2.06	0.65
7	0.27	0.76	-0.94	-2.11	0.91
8	0.23	0.73	-1.29	-1.86	0.72
9	0.26	0.59	-1.18	-2.00	0.76
10	-0.01	0.15	-2.22	-1.40	-0.05

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.70	3.81	0.46	-0.57	0.28
2	0.24	1.51	0.14	-0.28	0.08
3	0.12	0.85	0.07	-0.19	0.04
4	0.07	0.44	0.03	-0.11	0.03
5	0.02	0.15	0.00	-0.05	0.01
6	-0.01	-0.08	-0.03	0.00	0.00
7	-0.06	-0.34	-0.06	0.04	-0.02
8	-0.12	-0.71	-0.11	0.10	-0.05
9	-0.22	-1.30	-0.18	0.21	-0.08
10	-0.49	-3.35	-0.43	0.64	-0.14

β_{ABX}	Turnover ratios				
Portfolio	full	pre	subprime	global	post
1	2.52	2.11	2.34	2.26	2.90
2	2.45	1.72	1.97	2.41	2.89
3	2.79	1.47	2.27	3.46	3.16
4	3.01	1.46	2.53	3.46	3.35
5	3.59	1.64	2.48	4.29	4.27
6	3.70	1.77	2.55	4.90	4.13
7	3.23	1.65	2.54	4.43	3.38
8	2.95	1.58	2.33	3.51	3.30
9	2.42	1.66	1.96	2.55	2.79
10	2.89	2.21	2.99	2.26	3.47

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.16	3.80	3.94	7.67	4.50
2	3.18	2.34	2.47	4.77	2.77
3	2.61	1.91	2.04	4.01	2.23
4	2.27	1.62	1.77	3.54	1.94
5	1.99	1.39	1.55	3.22	1.68
6	1.98	1.35	1.54	3.14	1.72
7	2.25	1.55	1.77	3.58	1.93
8	2.62	1.82	2.06	4.09	2.26
9	3.16	2.27	2.47	4.83	2.75
10	5.13	3.69	3.96	7.71	4.44

β_{ABX}	Average Market β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	-1.02	-8.42	-0.76	0.69	0.56
2	0.12	-2.93	0.24	0.80	0.77
3	0.41	-1.32	0.50	0.78	0.77
4	0.54	-0.38	0.59	0.73	0.75
5	0.62	0.26	0.65	0.68	0.70
6	0.73	0.88	0.73	0.68	0.70
7	0.90	1.52	0.88	0.74	0.77
8	1.12	2.47	1.13	0.78	0.83
9	1.42	3.94	1.43	0.83	0.87
10	2.30	8.87	2.39	0.66	0.89

β_{ABX}	Equally weighted Month t returns				
Portfolio	full	pre	subprime	global	post
1	1.03	0.92	-0.19	-4.68	1.89
2	0.16	0.34	-0.66	-3.87	0.96
3	0.04	0.37	-0.52	-3.73	0.81
4	0.05	0.31	-0.56	-3.57	0.95
5	0.04	0.40	-0.52	-3.19	0.87
6	0.14	0.46	-0.52	-3.04	0.91
7	-0.08	0.54	-0.56	-3.35	0.56
8	-0.11	0.52	-0.79	-3.66	0.53
9	-0.09	0.34	-0.86	-4.14	0.60
10	1.04	1.14	-0.85	-3.99	1.52

β_{ABX}	Average idiosyncratic volatilities				
Portfolio	full	pre	subprime	global	post
1	3.99	3.04	3.09	5.84	3.48
2	2.29	1.84	1.86	3.35	1.95
3	1.81	1.49	1.50	2.68	1.47
4	1.51	1.26	1.27	2.28	1.21
5	1.26	1.06	1.07	1.98	0.98
6	1.25	1.01	1.07	1.89	1.02
7	1.48	1.19	1.28	2.26	1.20
8	1.80	1.42	1.53	2.68	1.48
9	2.26	1.77	1.88	3.30	1.92
10	3.95	2.95	3.13	5.75	3.42

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-12.05	-60.79	-10.73	-1.25	-1.24
2	-4.75	-24.33	-4.05	-0.49	-0.44
3	-2.65	-13.65	-2.20	-0.27	-0.24
4	-1.38	-7.20	-1.09	-0.15	-0.12
5	-0.48	-2.57	-0.31	-0.05	-0.03
6	0.28	1.27	0.35	0.03	0.04
7	1.14	5.55	1.17	0.12	0.12
8	2.33	11.52	2.31	0.24	0.24
9	4.28	21.18	4.14	0.45	0.45
10	11.25	55.57	10.86	1.18	1.24

Table 5.43: Decile portfolios sorted by ABX A factor loadings (Model 3 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.24 (Model 3). All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the excess returns of the CRSP value-weighted market index, the Fama and French (1993) SMB and HML factors, the Cahart (1997) Momentum factor and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and the β_{ABX} of each portfolio are reported. I also report the summary statistics based on my crisis subperiods. The findings are based on the ABX A index.

ABX A Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	901,343	1,052,775	1,212,717	714,800	853,687
2	2,303,448	2,538,217	2,648,412	1,994,226	2,362,130
3	3,362,699	3,586,377	3,698,080	2,923,033	3,505,546
4	3,464,814	3,743,196	4,110,945	2,999,600	3,420,609
5	3,301,748	3,509,408	3,748,672	2,883,637	3,348,428
6	3,406,180	3,382,607	3,903,704	3,074,983	3,506,371
7	3,518,981	3,791,210	4,016,043	3,155,253	3,477,319
8	3,239,040	3,379,400	3,532,627	2,886,812	3,393,161
9	2,415,595	2,470,293	2,916,699	2,102,462	2,493,789
10	926,384	940,355	1,203,776	806,258	939,175

β_{ABX}	Equally weighted Month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.08	0.55	-1.62	-2.46	0.27
2	0.19	0.46	-1.21	-2.26	0.77
3	0.21	0.74	-0.94	-2.35	0.78
4	0.22	0.86	-0.78	-2.24	0.77
5	0.17	0.51	-0.86	-2.11	0.83
6	0.25	0.86	-0.93	-2.18	0.93
7	0.32	0.95	-0.82	-2.15	0.88
8	0.32	0.86	-1.35	-1.91	0.92
9	0.39	0.86	-1.09	-1.73	0.78
10	0.14	0.21	-1.88	-1.73	0.44

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	1.16	6.50	0.16	-0.43	0.40
2	0.41	2.50	0.03	-0.24	0.12
3	0.23	1.40	0.02	-0.14	0.06
4	0.11	0.70	0.00	-0.09	0.04
5	0.03	0.19	-0.01	-0.03	0.02
6	-0.04	-0.25	-0.02	-0.01	0.00
7	-0.12	-0.75	-0.02	0.03	-0.02
8	-0.24	-1.43	-0.03	0.09	-0.07
9	-0.43	-2.60	-0.07	0.18	-0.12
10	-1.03	-6.71	-0.10	0.58	-0.24

β_{ABX}	Turnover ratios				
Portfolio	full	pre	subprime	global	post
1	2.60	2.09	2.34	2.10	3.18
2	2.54	1.59	2.18	2.45	2.97
3	2.75	1.58	2.26	3.37	3.01
4	3.05	1.65	2.20	3.79	3.34
5	3.51	1.61	2.48	4.84	3.89
6	3.69	1.59	2.55	4.43	4.44
7	3.31	1.56	2.56	4.44	3.55
8	2.84	1.62	2.36	3.53	3.17
9	2.58	1.74	2.57	2.53	2.89
10	2.67	2.22	2.47	2.12	3.20

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.08	3.65	4.01	7.43	4.51
2	3.16	2.26	2.49	4.76	2.76
3	2.61	1.87	2.07	4.03	2.23
4	2.26	1.60	1.77	3.53	1.94
5	1.99	1.37	1.53	3.20	1.71
6	1.99	1.38	1.52	3.19	1.69
7	2.27	1.59	1.73	3.59	1.96
8	2.62	1.87	2.02	4.11	2.25
9	3.19	2.33	2.43	4.87	2.75
10	5.20	3.82	3.98	7.83	4.42

β_{ABX}	Average Market β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	-0.36	-5.67	0.37	0.70	0.75
2	0.40	-1.65	0.69	0.78	0.82
3	0.56	-0.60	0.70	0.78	0.80
4	0.62	0.01	0.69	0.72	0.74
5	0.65	0.47	0.66	0.67	0.69
6	0.73	0.90	0.69	0.69	0.71
7	0.86	1.43	0.78	0.76	0.74
8	1.01	2.11	0.87	0.82	0.79
9	1.22	3.28	0.98	0.82	0.80
10	1.80	7.21	1.23	0.69	0.69

β_{ABX}	Equally weighted Month t returns				
Portfolio	full	pre	subprime	global	post
1	0.65	0.88	-0.44	-5.01	1.67
2	-0.08	0.56	-1.04	-4.00	0.66
3	-0.03	0.50	-0.57	-3.83	0.71
4	-0.02	0.41	-0.67	-3.51	0.74
5	0.02	0.50	-0.49	-3.27	0.73
6	0.00	0.31	-0.53	-3.36	0.84
7	0.05	0.44	-0.58	-3.55	0.87
8	-0.02	0.34	-0.67	-3.72	0.71
9	0.04	0.28	-0.94	-3.78	0.69
10	1.62	1.11	-0.12	-3.16	1.96

β_{ABX}	Average idiosyncratic volatilities				
Portfolio	full	pre	subprime	global	post
1	3.92	2.92	3.14	5.58	3.51
2	2.27	1.77	1.88	3.33	1.95
3	1.80	1.44	1.53	2.71	1.48
4	1.50	1.22	1.28	2.26	1.23
5	1.26	1.03	1.07	1.96	1.01
6	1.25	1.05	1.05	1.94	0.99
7.00	1.49	1.23	1.24	2.25	1.21
8.00	1.79	1.46	1.49	2.70	1.48
9.00	2.29	1.84	1.84	3.38	1.92
10.00	4.03	3.09	3.15	5.93	3.40

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-8.92	-48.69	-2.77	-0.97	-1.31
2	-3.44	-18.87	-1.10	-0.38	-0.47
3	-1.91	-10.51	-0.59	-0.21	-0.25
4	-0.96	-5.31	-0.28	-0.11	-0.13
5	-0.26	-1.43	-0.07	-0.03	-0.04
6	0.33	1.86	0.11	0.03	0.03
7.00	1.02	5.66	0.30	0.10	0.12
8.00	1.96	10.87	0.58	0.20	0.25
9.00	3.57	19.77	1.03	0.37	0.46
10.00	9.29	51.26	2.58	0.99	1.28

Table 5.44: Decile portfolios sorted by ABX BBB factor loadings (Model 3 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.24 (Model 3). All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the excess returns of the CRSP value-weighted market index, the Fama and French (1993) SMB and HML factors, the Cahart (1997) Momentum factor and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and the β_{ABX} of each portfolio are reported. I also report the summary statistics based on my crisis subperiods. The findings are based on the ABX BBB index.

ABX BBB Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	861,215	1,021,023	1,058,625	777,460	801,197
2	2,320,590	2,395,652	2,568,681	1,858,331	2,522,183
3	3,305,891	3,134,130	3,957,931	2,762,420	3,467,635
4	3,456,631	3,564,038	4,121,466	2,951,790	3,475,718
5	3,523,790	3,852,815	3,942,177	3,055,395	3,483,219
6	3,321,512	3,668,198	3,636,655	2,837,315	3,386,686
7	3,588,575	3,691,512	3,845,848	3,228,133	3,700,570
8	3,271,985	3,546,482	3,703,054	3,121,619	3,126,019
9	2,429,622	2,522,391	2,962,369	2,148,445	2,424,205
10	925,693	996,299	1,219,379	800,545	896,514

β_{ABX}	Equally weighted Month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.01	0.31	-1.58	-2.07	0.51
2	0.21	0.77	-1.39	-2.07	0.96
3	0.22	0.86	-0.95	-2.19	0.85
4	0.31	0.94	-0.71	-1.76	0.80
5	0.09	0.71	-0.69	-2.38	0.75
6	0.20	0.83	-0.94	-1.82	0.83
7	0.16	0.98	-0.82	-2.33	0.86
8	0.11	0.81	-1.32	-2.21	0.87
9	0.04	0.47	-1.37	-2.28	0.77
10	-0.18	0.19	-1.71	-2.00	0.17

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.60	2.53	-0.12	-0.06	0.49
2	0.18	0.96	-0.08	-0.10	0.15
3	0.10	0.54	-0.05	-0.07	0.08
4	0.05	0.28	-0.04	-0.05	0.05
5	0.02	0.09	-0.01	-0.02	0.02
6	-0.02	-0.07	-0.01	-0.01	-0.01
7	-0.05	-0.25	0.01	0.00	-0.03
8	-0.10	-0.52	0.03	0.03	-0.08
9	-0.19	-0.93	0.03	0.05	-0.15
10	-0.43	-2.39	0.15	0.23	-0.33

β_{ABX}	Turnover ratios				
Portfolio	full	pre	subprime	global	post
1	2.70	2.31	2.38	2.27	3.21
2	2.55	1.66	2.04	2.62	2.94
3	2.68	1.55	2.08	3.15	3.04
4	3.07	1.60	2.33	3.85	3.49
5	3.52	1.63	2.65	4.38	4.09
6	3.67	1.63	2.73	4.68	4.28
7	3.21	1.50	2.44	4.20	3.64
8	2.82	1.55	2.29	3.50	3.11
9	2.53	1.68	1.94	2.79	2.89
10	2.64	2.15	3.07	2.13	2.94

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.09	3.76	4.04	7.64	4.49
2	3.14	2.33	2.51	4.81	2.73
3	2.58	1.87	2.07	4.00	2.23
4	2.24	1.58	1.78	3.55	1.93
5	1.98	1.37	1.53	3.19	1.71
6	1.96	1.36	1.53	3.15	1.70
7	2.24	1.54	1.72	3.54	1.96
8	2.60	1.85	2.02	4.08	2.25
9	3.15	2.31	2.41	4.86	2.76
10	5.10	3.77	3.96	7.73	4.47

β_{ABX}	Average Market β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	0.55	0.18	0.78	0.75	0.55
2	0.75	0.61	0.83	0.83	0.74
3	0.75	0.64	0.77	0.78	0.78
4	0.72	0.63	0.71	0.73	0.75
5	0.67	0.61	0.67	0.67	0.70
6	0.68	0.65	0.69	0.66	0.70
7	0.74	0.73	0.72	0.73	0.76
8	0.81	0.79	0.81	0.78	0.83
9	0.87	0.92	0.85	0.82	0.89
10	0.87	1.08	0.88	0.64	0.88

β_{ABX}	Equally weighted Month t returns				
Portfolio	full	pre	subprime	global	post
1	0.53	0.61	-0.25	-4.49	1.67
2	-0.35	0.09	-0.76	-4.52	0.85
3	-0.24	0.33	-0.76	-4.11	0.96
4	-0.15	0.34	-0.72	-3.55	0.92
5	-0.06	0.41	-0.46	-2.99	0.86
6	-0.16	0.39	-0.62	-2.98	0.77
7	-0.12	0.45	-0.45	-3.29	0.84
8	-0.23	0.46	-0.57	-3.48	0.66
9	-0.33	0.92	-1.04	-4.08	0.54
10	0.68	1.34	-0.40	-3.72	1.54

β_{ABX}	Average idiosyncratic volatilities				
Portfolio	full	pre	subprime	global	post
1	3.93	3.01	3.17	5.73	3.47
2	2.25	1.82	1.90	3.35	1.92
3	1.76	1.45	1.53	2.65	1.46
4	1.49	1.21	1.29	2.29	1.20
5	1.26	1.03	1.07	1.96	1.01
6	1.24	1.03	1.05	1.92	0.99
7	1.47	1.19	1.24	2.23	1.23
8	1.78	1.45	1.48	2.68	1.49
9	2.26	1.82	1.81	3.35	1.94
10	3.95	3.04	3.14	5.85	3.45

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-3.67	-14.81	-1.32	-1.71	-1.41
2	-1.40	-5.72	-0.52	-0.67	-0.50
3	-0.78	-3.22	-0.29	-0.38	-0.28
4	-0.41	-1.66	-0.15	-0.21	-0.14
5	-0.13	-0.54	-0.05	-0.08	-0.04
6	0.10	0.41	0.04	0.03	0.04
7	0.36	1.52	0.13	0.15	0.13
8	0.74	3.06	0.26	0.32	0.27
9	1.37	5.62	0.48	0.59	0.51
10	3.61	14.57	1.24	1.62	1.43

Table 5.45: Decile portfolios sorted by ABX BBB- factor loadings (Model 3 using orthogonalised ABX index returns)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using the time series regression as shown in Equation 5.24 (Model 3). All available stocks from the major US exchanges have been included with a time series regression run at the end of each trading month for each stock (I screen out stocks with less than 15 daily observations in any months) to obtain time-varying monthly estimates of the factor loadings. The factors in the regression include the excess returns of the CRSP value-weighted market index, the Fama and French (1993) SMB and HML factors, the Cahart (1997) Momentum factor and an *orthogonalised* ABX factor. I sort the stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and the β_{ABX} of each portfolio are reported. I also report the summary statistics based on my crisis subperiods. The findings are based on the ABX BBB- index.

ABX BBB- Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	877,037	1,094,102	1,083,629	678,448	875,230
2	2,254,164	2,403,723	2,772,126	1,869,680	2,333,505
3	3,277,993	3,181,319	3,629,410	2,758,320	3,572,489
4	3,366,532	3,535,235	3,797,092	2,879,126	3,522,363
5	3,362,197	3,438,377	3,807,080	2,831,972	3,459,647
6	3,414,987	3,759,494	3,952,332	3,192,145	3,250,660
7	3,518,245	3,760,215	4,101,927	3,308,167	3,441,177
8	3,366,317	3,422,941	3,732,308	3,017,521	3,462,629
9	2,412,633	2,664,782	2,916,698	2,090,793	2,410,091
10	989,577	1,117,823	1,210,139	910,771	971,258

β_{ABX}	Equally weighted Month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.29	0.31	-1.90	-1.41	0.44
2	0.29	0.86	-1.13	-2.57	0.94
3	0.27	0.71	-0.99	-2.10	0.79
4	0.28	1.11	-0.82	-2.33	0.81
5	0.25	0.79	-0.75	-2.12	0.84
6	0.24	0.78	-0.73	-2.12	0.86
7	0.29	0.79	-0.92	-1.87	0.87
8	0.25	0.73	-1.08	-2.08	0.84
9	0.11	0.51	-1.32	-2.36	0.76
10	0.02	0.28	-1.85	-2.15	0.21

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.53	1.96	-0.20	-0.13	0.42
2	0.16	0.72	-0.10	-0.13	0.12
3	0.09	0.40	-0.06	-0.07	0.07
4	0.04	0.21	-0.05	-0.04	0.04
5	0.01	0.06	-0.03	-0.02	0.02
6	-0.01	-0.05	-0.01	-0.01	0.00
7	-0.04	-0.19	0.00	0.00	-0.03
8	-0.09	-0.39	0.02	0.04	-0.07
9	-0.16	-0.71	0.06	0.07	-0.13
10	-0.35	-1.77	0.22	0.26	-0.25

β_{ABX}	Turnover ratios				
Portfolio	full	pre	subprime	global	post
1	2.66	2.30	2.41	2.21	3.15
2	2.50	1.66	2.03	2.54	2.87
3	2.70	1.55	2.25	2.93	3.08
4	3.16	1.51	2.24	3.69	3.74
5	3.60	1.65	2.54	4.65	4.14
6	3.62	1.64	2.77	4.82	4.02
7	3.24	1.60	2.41	4.28	3.46
8	2.80	1.54	2.12	3.51	3.13
9	2.59	1.67	2.22	2.81	2.96
10	2.67	2.14	2.97	2.10	3.07

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.19	3.80	4.05	7.73	4.51
2	3.20	2.33	2.52	4.83	2.77
3	2.61	1.86	2.07	4.04	2.24
4	2.27	1.59	1.77	3.54	1.95
5	2.01	1.39	1.55	3.21	1.72
6	1.98	1.35	1.54	3.16	1.69
7	2.23	1.56	1.75	3.52	1.91
8	2.59	1.82	1.99	4.04	2.24
9	3.17	2.30	2.44	4.85	2.74
10	5.10	3.75	3.89	7.62	4.46

β_{ABX}	Average Market β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	0.47	0.15	0.70	0.56	0.51
2	0.72	0.58	0.81	0.73	0.74
3	0.73	0.66	0.77	0.72	0.75
4	0.70	0.61	0.70	0.70	0.73
5	0.67	0.62	0.67	0.67	0.70
6	0.69	0.64	0.68	0.68	0.72
7	0.75	0.71	0.75	0.74	0.77
8	0.83	0.83	0.82	0.83	0.83
9	0.88	0.91	0.88	0.89	0.87
10	0.95	1.11	0.97	0.83	0.93

β_{ABX}	Equally weighted Month t returns				
Portfolio	full	pre	subprime	global	post
1	0.73	0.77	-0.57	-5.09	1.71
2	-0.14	0.00	-0.66	-4.40	0.61
3	0.11	0.32	-0.47	-3.71	0.85
4	0.07	0.42	-0.73	-3.30	0.81
5	0.08	0.35	-0.59	-3.19	0.88
6	0.10	0.49	-0.59	-3.06	0.86
7	0.05	0.58	-0.66	-3.36	0.85
8	-0.04	0.52	-0.78	-3.65	0.65
9	-0.01	0.56	-0.85	-3.81	0.58
10	1.28	1.34	-0.13	-3.61	1.81

β_{ABX}	Average idiosyncratic volatilities				
Portfolio	full	pre	subprime	global	post
1	4.00	3.05	3.19	5.80	3.48
2	2.31	1.83	1.92	3.38	1.94
3	1.80	1.44	1.52	2.69	1.48
4	1.51	1.22	1.28	2.29	1.22
5	1.28	1.05	1.08	1.98	1.02
6	1.25	1.02	1.06	1.91	0.99
7	1.47	1.20	1.26	2.22	1.19
8	1.77	1.42	1.47	2.64	1.48
9	2.26	1.81	1.84	3.33	1.91
10	3.94	3.01	3.06	5.75	3.45

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-3.33	-11.54	-1.03	-1.60	-1.40
2	-1.29	-4.49	-0.40	-0.64	-0.51
3	-0.71	-2.49	-0.22	-0.38	-0.28
4	-0.37	-1.28	-0.11	-0.22	-0.14
5	-0.13	-0.41	-0.03	-0.10	-0.04
6	0.08	0.32	0.03	0.01	0.03
7	0.32	1.18	0.11	0.12	0.13
8	0.65	2.36	0.21	0.27	0.26
9	1.21	4.32	0.38	0.52	0.49
10	3.27	11.18	0.98	1.41	1.39

Table 5.46: Decile portfolios sorted by ABX AAA factor loadings (Model 3 using orthogonalised ABX index returns and only stocks with significant t-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using time series regressions as shown in Equation 5.24 (Model 3). The decile portfolios contain only stocks with significant t-statistics on the ABX factor (with null hypothesis: $H_0 : \beta_{ABX} = 0$) at the 5% significance level. I screen out stocks with insignificant F-statistics (threshold p-value of 0.05) and sort the significant stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and β_{ABX} of each portfolio are reported. I also report the summary statistics in each crisis subperiod. The findings are based on the ABX AAA index.

ABX AAA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	458,255	594,651	523,110	389,340	460,179
2	1,355,555	1,358,155	2,154,320	856,038	1,375,798
3	2,895,787	3,112,486	4,596,250	1,919,310	2,891,111
4	4,608,071	3,882,462	6,703,693	3,166,725	5,134,411
5	3,829,073	3,916,242	4,262,382	4,147,698	3,399,556
6	4,061,205	3,761,857	5,769,360	3,565,899	3,815,333
7	4,762,704	5,851,448	4,960,507	4,169,539	4,603,060
8	3,026,586	3,226,099	2,670,218	3,090,999	2,903,891
9	1,554,536	1,975,357	1,637,848	1,555,313	1,482,504
10	524,326	637,362	603,027	429,107	544,831

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.02	-1.16	-1.81	-2.93	0.84
2	0.43	0.45	-1.01	-2.15	1.31
3	0.19	0.71	-0.86	-2.95	1.15
4	0.33	1.33	-0.55	-2.83	1.36
5	0.30	1.07	-0.37	-2.50	1.12
6	0.11	1.03	-0.37	-2.66	0.75
7	0.19	0.60	-1.02	-1.31	0.42
8	0.49	1.05	-0.95	-1.41	0.73
9	0.45	0.19	-2.43	-0.39	0.82
10	-0.34	0.33	-3.55	-0.01	-1.21

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.10	0.03	-0.20	-0.31	0.33
2	-0.04	-0.03	-0.10	-0.36	0.09
3	-0.02	-0.01	-0.09	-0.19	0.06
4	0.00	-0.02	-0.06	-0.07	0.06
5	-0.01	0.01	-0.05	-0.07	0.02
6	0.00	0.02	-0.03	0.06	-0.02
7	-0.01	0.01	0.01	0.12	-0.07
8	-0.04	-0.01	0.01	0.14	-0.12
9	-0.02	0.01	0.08	0.23	-0.16
10	0.00	0.01	0.10	0.41	-0.22

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.23	2.08	2.43	2.02	2.36
2	2.12	1.71	1.93	2.03	2.17
3	2.27	1.72	1.82	2.62	2.32
4	3.35	1.84	1.96	3.08	4.51
5	3.28	1.82	3.23	3.91	3.45
6	3.69	1.48	2.50	5.23	4.21
7	3.61	1.43	1.86	4.35	3.79
8	3.41	1.54	1.71	3.93	4.72
9	3.16	1.50	1.95	2.58	4.63
10	2.55	1.83	2.31	2.43	3.00

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.45	4.06	4.17	8.04	4.76
2	3.22	2.46	2.41	4.89	2.76
3	2.50	1.86	1.91	3.82	2.14
4	1.92	1.42	1.42	3.08	1.58
5	1.39	0.90	0.98	2.42	1.17
6	1.33	0.68	1.07	2.13	1.22
7	1.89	1.24	1.54	2.98	1.64
8	2.50	1.71	2.00	3.90	2.21
9	3.21	2.28	2.56	4.91	2.82
10	5.38	3.84	4.31	8.25	4.66

β_{ABX}	Average β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	-3.41	-21.13	-2.16	0.59	0.10
2	-1.13	-9.88	-0.53	0.80	0.62
3	-0.47	-6.44	-0.03	0.75	0.76
4	-0.14	-4.18	0.15	0.71	0.68
5	0.16	-2.00	0.36	0.54	0.62
6	0.87	1.80	0.93	0.54	0.71
7	1.58	4.94	1.39	0.79	0.90
8	2.13	7.47	1.74	0.97	1.06
9	2.69	10.57	2.20	0.99	1.05
10	4.44	20.62	3.53	0.86	1.16

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	1.03	0.84	1.50	-4.52	0.85
2	-0.24	0.04	0.45	-5.33	0.17
3	0.25	0.30	0.03	-3.14	0.64
4	0.58	0.19	-0.19	-1.63	1.21
5	0.40	0.71	-0.12	-1.57	0.67
6	0.28	0.66	-0.90	-1.71	0.79
7	-0.13	0.45	-1.33	-2.87	0.59
8	-0.46	-0.07	-1.66	-2.99	0.28
9	-0.45	0.12	-1.60	-3.71	0.02
10	0.18	-0.55	-2.39	-4.06	1.21

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.88	3.02	3.03	5.63	3.37
2	2.11	1.79	1.65	3.15	1.73
3	1.50	1.31	1.21	2.26	1.20
4	1.07	0.97	0.85	1.69	0.80
5	0.67	0.57	0.48	1.18	0.50
6	0.62	0.43	0.59	0.85	0.55
7	0.99	0.83	0.96	1.38	0.83
8	1.46	1.18	1.32	2.11	1.23
9	2.06	1.63	1.78	2.97	1.78
10	3.83	2.90	3.14	5.66	3.30

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-51.69	-267.57	-38.64	-5.13	-6.02
2	-25.26	-131.86	-18.18	-2.56	-2.80
3	-17.03	-88.95	-12.40	-1.79	-1.78
4	-11.51	-60.42	-8.34	-1.28	-1.06
5	-5.88	-32.22	-3.28	-0.85	-0.33
6	3.41	16.18	4.16	-0.11	0.53
7	10.20	52.48	8.24	0.72	1.21
8	15.89	82.07	11.92	1.54	1.95
9	23.48	121.06	17.57	2.33	2.95
10	47.82	247.16	34.93	4.87	6.04

Table 5.47: Decile portfolios sorted by ABX AA factor loadings (Model 3 using orthogonalised ABX index returns and only stocks with significant t-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using time series regressions as shown in Equation 5.24 (Model 3). The decile portfolios contain only stocks with significant t-statistics on the ABX factor (with null hypothesis: $H_0 : \beta_{ABX} = 0$) at the 5% significance level. I screen out stocks with insignificant F-statistics (threshold p-value of 0.05) and sort the significant stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and β_{ABX} of each portfolio are reported. I also report the summary statistics in each crisis subperiod. The findings are based on the ABX AA factor.

ABX AA Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	482,109	464,442	574,337	378,924	545,356
2	1,312,073	1,521,307	1,826,571	746,782	1,391,180
3	3,062,974	2,573,133	3,994,348	2,544,939	3,405,100
4	4,724,368	4,148,932	6,720,699	3,299,724	5,377,184
5	4,039,884	4,051,598	4,461,773	3,550,812	3,733,797
6	4,523,437	5,717,479	4,988,746	5,078,645	3,949,126
7	4,485,887	5,774,962	4,994,242	3,440,579	4,265,299
8	3,571,893	3,794,547	3,853,915	3,285,937	3,769,407
9	1,401,676	1,624,154	1,518,574	1,377,190	1,407,365
10	510,793	672,129	658,038	446,015	442,494

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.72	-0.20	-2.13	-2.96	2.17
2	0.49	1.13	-0.81	-2.57	1.20
3	0.26	0.49	-0.38	-2.62	1.01
4	0.28	0.64	-0.40	-2.78	1.22
5	0.32	1.06	-0.21	-2.21	0.97
6	0.17	0.99	-0.66	-1.84	0.65
7	0.35	1.26	-1.28	-2.00	1.15
8	0.47	1.52	-1.53	-1.64	0.77
9	0.28	0.40	-1.22	-1.81	0.70
10	-0.04	0.14	-3.07	-0.92	-0.11

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	1.10	6.41	0.77	-1.01	0.38
2	0.49	3.22	0.37	-0.62	0.12
3	0.34	2.24	0.25	-0.44	0.09
4	0.26	1.62	0.12	-0.25	0.07
5	0.13	0.93	0.02	-0.17	0.03
6	-0.04	-0.08	-0.11	0.03	-0.03
7	-0.18	-1.03	-0.22	0.25	-0.09
8	-0.32	-1.79	-0.29	0.36	-0.14
9	-0.48	-2.70	-0.43	0.50	-0.20
10	-0.92	-5.49	-0.80	0.91	-0.32

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.23	1.99	2.13	2.18	2.34
2	2.37	1.54	1.99	2.73	2.58
3	2.26	1.56	1.92	2.20	2.49
4	3.11	1.59	2.34	4.26	3.14
5	3.23	1.40	2.89	3.44	3.96
6	4.07	1.60	3.03	5.20	4.27
7	3.48	1.46	2.28	4.38	3.78
8	3.65	1.32	5.66	2.88	4.24
9	2.23	1.59	2.00	2.45	2.29
10	2.58	2.06	2.40	2.31	3.08

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.41	4.13	4.36	7.86	4.70
2	3.26	2.47	2.48	4.90	2.83
3	2.50	1.89	1.96	3.72	2.14
4	1.94	1.46	1.48	3.10	1.58
5	1.40	0.97	0.91	2.37	1.17
6	1.31	0.77	1.00	2.07	1.18
7	1.87	1.10	1.50	3.11	1.63
8	2.49	1.61	1.95	3.94	2.17
9	3.22	2.25	2.55	4.85	2.84
10	5.44	3.82	4.25	8.35	4.72

β_{ABX}	Average β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	-2.29	-14.79	-1.95	0.62	0.43
2	-0.64	-7.12	-0.37	0.75	0.76
3	-0.17	-4.66	0.01	0.76	0.80
4	0.06	-3.15	0.19	0.75	0.75
5	0.22	-1.56	0.28	0.58	0.61
6	0.68	0.86	0.84	0.56	0.61
7	1.27	3.26	1.35	0.81	0.81
8	1.72	5.13	1.77	0.87	0.97
9	2.12	7.39	2.09	0.87	1.00
10	3.23	14.11	3.36	0.56	0.86

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.55	2.11	-0.07	-4.59	0.55
2	-0.28	-0.23	-0.20	-4.49	0.02
3	-0.12	-0.11	-0.15	-3.82	0.67
4	0.36	0.47	-0.55	-2.19	1.12
5	0.19	0.72	-0.42	-2.43	0.82
6	0.45	0.80	-0.48	-2.42	1.38
7	-0.09	0.62	-1.18	-3.56	0.90
8	-0.22	0.35	-0.96	-3.80	0.72
9	-0.19	0.45	-1.63	-3.32	0.19
10	0.95	1.87	-2.60	-4.27	1.43

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.85	3.06	3.15	5.50	3.35
2	2.13	1.77	1.68	3.17	1.78
3	1.51	1.30	1.26	2.24	1.22
4	1.06	0.99	0.88	1.66	0.79
5	0.67	0.62	0.47	1.12	0.49
6	0.60	0.45	0.54	0.84	0.52
7	0.99	0.71	0.92	1.51	0.82
8	1.46	1.09	1.28	2.18	1.22
9	2.07	1.58	1.79	2.94	1.78
10	3.86	2.80	3.07	5.76	3.35

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-20.27	-101.56	-18.55	-2.08	-2.15
2	-10.35	-52.78	-8.87	-1.07	-1.00
3	-7.13	-36.62	-6.01	-0.73	-0.64
4	-5.01	-26.14	-3.98	-0.51	-0.39
5	-2.64	-14.79	-1.47	-0.29	-0.08
6	0.67	1.56	1.94	0.09	0.20
7	3.61	16.93	4.13	0.45	0.43
8	6.00	29.04	6.25	0.69	0.67
9	9.05	44.06	9.26	0.99	1.02
10	18.37	90.59	17.52	2.05	2.12

Table 5.48: Decile portfolios sorted by ABX A factor loadings (Model 3 using orthogonalised ABX index returns and only stocks with significant t-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using time series regressions as shown in Equation 5.24 (Model 3). The decile portfolios contain only stocks with significant t-statistics on the ABX index returns (with null hypothesis: $H_0 : \beta_{ABX} = 0$) at the 5% significance level. I screen out stocks with insignificant F-statistics (threshold p-value of 0.05) and sort the significant stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and β_{ABX} of each portfolio are reported. I also report the summary statistics in each crisis subperiod. The findings are based on the ABX A index.

ABX A Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	463,342	558,128	602,520	321,773	483,348
2	1,397,902	1,461,084	1,874,690	1,035,292	1,467,169
3	3,100,637	3,396,097	3,932,755	2,024,935	3,374,541
4	4,635,680	4,861,828	5,230,183	3,286,063	5,265,817
5	4,416,040	5,086,657	5,282,887	4,313,163	3,956,626
6	4,264,319	3,913,970	4,684,306	3,787,506	4,656,860
7	4,937,474	5,226,155	5,534,866	4,326,436	4,955,386
8	3,174,891	2,391,990	4,030,437	2,885,376	3,306,389
9	1,475,906	1,642,244	1,927,725	1,449,857	1,288,586
10	518,852	426,689	769,296	484,748	512,527

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	-0.75	1.08	-2.19	-3.83	-0.68
2	0.43	0.74	-0.74	-2.83	1.03
3	0.53	0.40	-0.18	-2.95	1.24
4	0.21	0.34	-1.03	-2.57	1.39
5	0.33	1.08	-0.04	-2.35	1.02
6	0.23	0.88	-0.58	-1.76	0.69
7	0.35	1.14	-0.43	-2.06	0.84
8	0.48	0.62	-1.08	-1.32	1.36
9	0.68	0.24	-0.65	-0.99	1.06
10	-0.01	-0.76	-3.13	-1.37	0.40

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	1.87	10.63	0.35	-0.69	0.58
2	0.86	5.31	0.11	-0.47	0.22
3	0.58	3.58	0.08	-0.30	0.15
4	0.38	2.36	0.05	-0.21	0.11
5	0.17	1.00	0.01	-0.10	0.06
6	-0.18	-1.08	-0.03	0.01	-0.02
7	-0.39	-2.46	-0.05	0.20	-0.10
8	-0.63	-3.80	-0.07	0.31	-0.19
9	-0.95	-5.65	-0.12	0.43	-0.30
10	-1.84	-11.41	-0.27	0.86	-0.47

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.15	2.06	2.28	2.19	2.25
2	2.12	1.55	2.21	2.38	2.13
3	2.91	1.30	2.04	2.73	3.52
4	2.86	1.50	2.09	2.62	3.46
5	4.32	1.73	4.77	5.98	4.05
6	4.39	1.92	3.78	5.97	4.59
7	3.15	1.32	1.74	4.26	3.69
8	2.43	1.36	1.60	2.85	2.70
9	2.53	1.67	1.86	2.22	3.39
10	2.25	2.17	2.34	2.23	2.24

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.40	3.88	4.42	8.01	4.71
2	3.23	2.36	2.61	4.90	2.77
3	2.51	1.77	2.08	3.87	2.11
4	1.94	1.32	1.63	3.03	1.64
5	1.37	0.85	1.07	2.32	1.17
6	1.32	0.72	0.94	2.32	1.15
7	1.88	1.25	1.39	3.04	1.66
8	2.50	1.74	1.87	3.92	2.23
9	3.24	2.40	2.44	4.89	2.87
10	5.50	4.04	4.08	8.43	4.72

β_{ABX}	Average β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	-1.08	-9.63	0.14	0.69	0.68
2	-0.04	-4.37	0.56	0.79	0.86
3	0.25	-2.69	0.69	0.79	0.84
4	0.39	-1.49	0.68	0.69	0.79
5	0.44	-0.32	0.55	0.56	0.59
6	0.74	1.56	0.60	0.62	0.56
7	1.19	3.16	0.85	0.84	0.78
8	1.49	4.48	1.05	0.90	0.90
9	1.73	6.27	1.17	0.85	0.78
10	2.49	11.58	1.42	0.66	0.59

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.94	0.68	0.86	-4.21	1.12
2	-0.58	-0.14	-0.28	-4.46	-0.10
3	-0.06	0.14	-0.64	-2.92	0.47
4	0.13	0.78	-0.12	-2.57	0.43
5	0.39	0.87	-0.41	-2.19	1.05
6	0.25	0.25	-0.62	-1.89	1.19
7	0.22	0.10	-1.25	-2.41	1.26
8	-0.02	0.42	-1.04	-3.12	0.99
9	0.31	0.19	-1.55	-2.31	0.89
10	1.39	1.36	-2.08	-4.14	2.51

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.84	2.85	3.13	5.55	3.40
2	2.11	1.66	1.79	3.13	1.76
3	1.52	1.21	1.35	2.29	1.22
4	1.06	0.87	0.98	1.63	0.82
5	0.64	0.50	0.56	1.08	0.48
6	0.61	0.45	0.49	1.03	0.48
7	0.99	0.85	0.82	1.51	0.82
8	1.47	1.22	1.19	2.22	1.24
9	2.09	1.72	1.66	3.06	1.82
10	3.94	3.04	2.97	5.92	3.35

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-14.75	-80.02	-4.74	-1.66	-2.23
2	-7.39	-40.31	-2.43	-0.83	-1.04
3	-5.00	-27.29	-1.74	-0.56	-0.67
4	-3.29	-17.96	-1.19	-0.38	-0.42
5	-1.38	-7.58	-0.49	-0.18	-0.14
6	1.46	8.24	0.36	0.10	0.18
7	3.32	18.45	0.87	0.35	0.45
8	5.17	28.73	1.37	0.55	0.71
9	7.72	42.84	2.00	0.81	1.09
10	15.73	87.07	3.97	1.68	2.26

Table 5.49: Decile portfolios sorted by ABX BBB factor loadings (Model 3 using orthogonalised ABX index returns and only stocks with significant t-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using time series regressions as shown in Equation 5.24 (Model 3). The decile portfolios contain only stocks with significant t-statistics on the ABX index returns (with null hypothesis: $H_0 : \beta_{ABX} = 0$) at the 5% significance level. I screen out stocks with insignificant F-statistics (threshold p-value of 0.05) and sort the significant stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and β_{ABX} of each portfolio are reported. I also report the summary statistics in each crisis subperiod. The findings are based on the ABX BBB index.

ABX BBB Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	468,848	684,313	483,245	373,142	459,971
2	1,359,614	1,464,512	1,435,693	1,041,838	1,501,740
3	2,898,472	2,549,949	2,995,215	2,671,430	3,202,636
4	4,865,036	4,528,078	4,899,650	4,302,911	5,443,911
5	3,805,916	3,823,140	4,518,673	3,206,064	3,889,291
6	3,890,121	4,684,206	4,410,494	3,910,955	3,469,095
7	5,082,641	4,807,112	6,133,315	4,340,383	5,360,079
8	3,249,153	3,459,228	4,328,090	2,260,233	3,355,965
9	1,479,879	1,201,431	2,024,986	1,286,693	1,555,917
10	522,689	614,156	872,023	378,987	451,232

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.26	1.16	-1.97	-1.27	0.36
2	0.63	0.49	-0.50	-1.95	1.34
3	0.11	0.66	-1.00	-3.03	1.12
4	0.14	1.00	-1.20	-2.76	1.14
5	0.26	0.70	-0.27	-2.04	0.87
6	-0.32	0.79	-1.25	-2.81	0.32
7	0.05	0.80	-0.73	-1.62	0.33
8	0.05	0.73	-1.59	-1.99	0.86
9	0.25	0.90	-1.04	-1.99	0.74
10	-0.18	-0.36	-1.93	-0.92	-0.23

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.97	4.28	-0.09	-0.14	0.71
2	0.42	2.10	-0.12	-0.18	0.31
3	0.27	1.46	-0.11	-0.13	0.20
4	0.20	1.02	-0.08	-0.04	0.15
5	0.11	0.62	-0.03	-0.07	0.08
6	-0.03	-0.14	-0.01	0.00	-0.01
7	-0.16	-0.81	0.04	0.06	-0.11
8	-0.28	-1.36	0.07	0.09	-0.21
9	-0.45	-2.08	0.08	0.07	-0.35
10	-0.86	-4.18	0.14	0.18	-0.63

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.29	2.28	2.37	1.95	2.48
2	2.14	1.66	1.88	2.57	2.19
3	2.47	1.68	2.11	2.77	2.77
4	2.83	1.31	2.21	3.63	3.07
5	3.61	1.50	2.27	4.73	4.44
6	4.57	1.64	5.20	5.86	4.92
7	3.22	1.49	1.99	4.58	3.53
8	2.43	1.34	1.87	3.29	2.55
9	3.81	1.82	8.90	1.87	3.58
10	2.20	2.02	2.21	2.02	2.45

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.44	4.04	4.40	8.26	4.71
2	3.25	2.37	2.60	5.03	2.82
3	2.52	1.86	2.05	4.02	2.12
4	1.93	1.43	1.56	3.14	1.58
5	1.41	0.93	1.07	2.33	1.21
6	1.32	0.67	0.96	2.28	1.20
7	1.79	1.14	1.39	2.95	1.54
8	2.44	1.69	1.86	3.90	2.13
9	3.16	2.36	2.41	4.85	2.78
10	5.30	4.05	4.07	8.01	4.67

β_{ABX}	Average β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	0.42	-0.18	0.81	0.82	0.38
2	0.73	0.42	0.86	0.90	0.71
3	0.80	0.61	0.89	0.86	0.80
4	0.76	0.73	0.79	0.76	0.76
5	0.60	0.50	0.57	0.53	0.68
6	0.61	0.58	0.57	0.53	0.65
7	0.77	0.85	0.74	0.74	0.76
8	0.92	1.05	0.88	0.86	0.91
9	0.96	1.24	0.87	0.78	0.97
10	0.89	1.27	0.80	0.50	0.96

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.54	1.37	1.05	-3.41	0.33
2	-0.44	0.34	-0.41	-5.38	0.48
3	-0.58	-0.29	-0.86	-4.40	0.53
4	-0.05	0.13	-0.24	-3.26	0.99
5	0.05	0.43	-0.49	-2.21	0.72
6	0.02	0.52	-0.56	-2.47	0.98
7	-0.15	0.56	-0.87	-2.41	0.78
8	-0.31	0.54	-0.80	-2.93	0.48
9	-0.43	0.41	-1.06	-3.62	0.34
10	-0.65	0.53	-1.61	-6.16	0.77

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.87	2.94	3.13	5.74	3.38
2	2.10	1.66	1.77	3.15	1.77
3	1.49	1.26	1.32	2.31	1.18
4	1.05	0.92	0.95	1.65	0.80
5	0.66	0.59	0.58	1.10	0.47
6	0.57	0.39	0.49	0.97	0.44
7	0.94	0.75	0.83	1.42	0.76
8	1.41	1.15	1.17	2.12	1.18
9	2.03	1.64	1.60	3.02	1.74
10	3.80	3.03	2.96	5.63	3.32

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-6.19	-24.73	-2.28	-2.86	-2.46
2	-3.06	-12.51	-1.14	-1.49	-1.11
3	-2.12	-8.85	-0.79	-1.02	-0.71
4	-1.46	-6.25	-0.55	-0.70	-0.45
5	-0.82	-3.72	-0.27	-0.36	-0.19
6	0.20	0.73	0.13	0.06	0.09
7	1.15	4.79	0.45	0.47	0.43
8	1.94	8.03	0.69	0.85	0.72
9	2.95	12.23	1.00	1.28	1.13
10	6.10	24.97	2.05	2.66	2.42

Table 5.50: Decile portfolios sorted by ABX BBB- factor loadings (Model 3 using orthogonalised ABX index returns and only stocks with significant t-statistics)

This table reports the equally weighted average summary statistics of the decile portfolios sorted by the ABX factor loadings estimated using time series regressions as shown in Equation 5.24 (Model 3). The decile portfolios contain only stocks with significant t-statistics on the ABX index returns (with null hypothesis: $H_0 : \beta_{ABX} = 0$) at the 5% significance level. I screen out stocks with insignificant F-statistics (threshold p-value of 0.05) and sort the significant stocks into decile portfolios based on the ABX factor loadings at the end of each month and report the equally weighted average summary statistics of the decile portfolios. Portfolios 1 and 10 contain stocks with the lowest and highest ABX factor loadings respectively. The market capitalisation, turnover ratios, month t and $t+1$ returns, standard deviations, idiosyncratic volatilities (based on daily observations), the average α, β_{MKT}, and β_{ABX} of each portfolio are reported. I also report the summary statistics in each crisis subperiod. The findings are based on the ABX BBB- index.

ABX BBB- Factor loadings

β_{ABX}	Market capitalisation				
Portfolio	full	pre	subprime	global	post
1	450,032	672,592	481,767	269,206	473,188
2	1,373,887	1,548,570	1,725,058	1,111,383	1,374,855
3	2,666,409	3,220,321	3,202,063	2,001,897	2,748,625
4	4,664,202	4,758,937	5,606,494	4,265,124	4,751,363
5	3,774,628	4,230,124	4,397,050	2,742,342	4,067,308
6	4,155,540	4,438,993	4,629,812	4,415,023	3,931,687
7	4,395,648	4,881,536	6,088,836	3,572,490	4,137,529
8	3,378,400	3,007,345	4,334,317	2,949,251	3,487,893
9	1,667,587	1,864,797	1,851,382	1,435,427	1,790,165
10	496,454	553,783	692,360	449,970	444,150

β_{ABX}	Equally weighted month t+1 returns				
Portfolio	full	pre	subprime	global	post
1	0.10	-0.30	-2.06	-1.55	-0.14
2	0.35	-0.16	-0.56	-2.11	0.71
3	0.46	0.84	-0.81	-2.69	1.39
4	0.45	0.93	-0.73	-2.09	1.24
5	0.31	0.89	-0.43	-1.91	0.78
6	0.34	0.82	-0.44	-2.15	1.19
7	0.18	0.41	-1.25	-2.52	1.37
8	0.23	1.01	-1.03	-1.91	0.80
9	0.46	0.98	-0.43	-2.65	1.20
10	-0.52	-0.95	-1.76	-2.47	-0.05

β_{ABX}	Average α				
Portfolio	full	pre	subprime	global	post
1	0.81	3.40	-0.32	-0.28	0.61
2	0.34	1.62	-0.18	-0.22	0.26
3	0.21	1.09	-0.15	-0.20	0.17
4	0.15	0.76	-0.13	-0.09	0.12
5	0.08	0.41	-0.07	-0.06	0.08
6	-0.05	-0.23	0.01	-0.03	-0.01
7	-0.13	-0.69	0.05	0.12	-0.09
8	-0.22	-1.02	0.08	0.13	-0.19
9	-0.34	-1.52	0.13	0.11	-0.24
10	-0.73	-3.16	0.21	0.30	-0.56

β_{ABX}	Turnover ratio				
Portfolio	full	pre	subprime	global	post
1	2.90	2.23	2.27	1.64	4.20
2	2.27	1.87	1.74	2.23	2.65
3	2.30	1.62	2.15	2.30	2.53
4	2.84	1.27	2.51	2.77	3.47
5	3.42	1.73	2.86	3.79	4.01
6	4.69	1.87	7.39	5.71	4.07
7	3.61	1.49	1.97	5.90	3.55
8	2.43	1.54	1.73	2.73	2.83
9	3.22	1.73	7.11	2.44	2.68
10	2.37	2.00	2.33	1.74	2.94

β_{ABX}	Average standard deviations				
Portfolio	full	pre	subprime	global	post
1	5.55	4.14	4.41	8.32	4.71
2	3.33	2.36	2.57	5.14	2.88
3	2.60	1.80	2.04	4.06	2.24
4	2.03	1.38	1.59	3.22	1.73
5	1.45	0.88	1.05	2.43	1.25
6	1.29	0.67	0.95	2.21	1.14
7	1.76	1.24	1.40	2.75	1.55
8	2.41	1.74	1.84	3.74	2.08
9	3.12	2.28	2.42	4.71	2.73
10	5.29	4.04	4.09	7.87	4.60

β_{ABX}	Average β_{MKT}				
Portfolio	full	pre	subprime	global	post
1	0.26	-0.28	0.68	0.36	0.37
2	0.67	0.41	0.77	0.71	0.71
3	0.77	0.55	0.88	0.78	0.81
4	0.72	0.63	0.75	0.72	0.75
5	0.58	0.53	0.64	0.52	0.58
6	0.61	0.61	0.60	0.53	0.62
7	0.82	0.98	0.77	0.79	0.80
8	0.98	1.12	0.91	0.97	0.95
9	1.03	1.26	1.00	0.94	1.00
10	1.09	1.52	1.07	0.93	1.00

β_{ABX}	Equally weighted month t returns				
Portfolio	full	pre	subprime	global	post
1	0.10	1.51	-0.46	-5.30	0.41
2	-0.42	-0.05	-0.50	-5.23	0.31
3	-0.32	-0.07	-0.79	-4.70	0.78
4	0.11	0.36	-0.55	-3.39	0.97
5	0.30	0.55	-0.38	-2.44	0.99
6	0.06	0.42	-0.33	-3.00	0.89
7	0.05	0.66	-0.91	-2.14	0.69
8	0.01	1.12	-0.86	-3.03	0.53
9	0.04	1.20	-1.01	-3.97	0.97
10	0.01	0.60	-1.22	-5.21	0.46

β_{ABX}	Average idiosyncratic volatilities (daily)				
Portfolio	full	pre	subprime	global	post
1	3.96	3.03	3.17	5.86	3.34
2	2.18	1.66	1.77	3.27	1.83
3	1.57	1.22	1.32	2.41	1.28
4	1.13	0.92	0.97	1.75	0.88
5	0.70	0.55	0.56	1.18	0.52
6	0.57	0.39	0.49	0.96	0.45
7	0.92	0.81	0.84	1.29	0.75
8	1.41	1.17	1.17	2.05	1.18
9	2.00	1.57	1.63	2.91	1.71
10	3.76	2.98	2.95	5.47	3.25

β_{ABX}	Average β_{ABX}				
Portfolio	full	pre	subprime	global	post
1	-5.58	-19.71	-1.78	-2.70	-2.39
2	-2.74	-9.85	-0.89	-1.34	-1.16
3	-1.85	-6.71	-0.62	-0.94	-0.77
4	-1.27	-4.67	-0.44	-0.67	-0.51
5	-0.68	-2.51	-0.21	-0.41	-0.24
6	0.25	1.22	0.12	-0.11	0.11
7	1.03	4.12	0.33	0.33	0.42
8	1.68	6.36	0.53	0.71	0.70
9	2.56	9.46	0.77	1.11	1.09
10	5.46	19.34	1.55	2.31	2.38

Table 5.51: Summary statistics of the monthly contagion variables and the $\kappa_{AAA,t}$ series

This table reports the summary statistics of the various monthly contagion variables and the $\kappa_{AAA,t}$ series over the sample period February 2006 to December 2011. Panel A reports the full sample statistics while Panel B - E report the crisis subsample statistics, respectively.

Panel A: Full sample

	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
Mean	0.12	-0.21	0.65	1.10	2.87	0.40	0.66	6.70
Median	0.11	-0.01	0.33	0.94	2.79	0.16	0.47	5.84
Maximum	0.29	9.63	5.04	2.77	6.07	2.36	3.15	16.21
Minimum	0.05	-15.01	0.03	0.43	1.57	0.03	0.12	4.50
Std. Dev.	0.04	3.50	0.80	0.59	1.11	0.49	0.61	2.25

Panel B: Pre-crisis subperiod

	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
Mean	0.14	0.01	0.41	0.63	1.68	0.08	0.48	5.56
Median	0.14	0.00	0.37	0.62	1.67	0.09	0.48	5.50
Maximum	0.16	0.19	0.88	0.83	1.74	0.10	0.61	6.34
Minimum	0.11	-0.06	0.14	0.43	1.64	0.03	0.31	4.50
Std. Dev.	0.02	0.06	0.26	0.12	0.03	0.02	0.08	0.47

Panel C: Subprime crisis subperiod

	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
Mean	0.12	-0.56	1.04	0.60	1.89	0.34	0.95	5.74
Median	0.11	-0.13	0.73	0.56	1.80	0.11	0.72	5.53
Maximum	0.25	0.60	2.23	0.85	2.53	1.00	2.05	7.25
Minimum	0.08	-2.40	0.16	0.44	1.57	0.08	0.34	4.69
Std. Dev.	0.05	0.98	0.78	0.14	0.33	0.34	0.58	0.85

Panel D: Global crisis subperiod

	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
Mean	0.12	-2.54	1.43	1.82	4.21	1.08	1.43	9.88
Median	0.11	-2.14	1.30	1.61	3.47	0.88	1.19	10.00
Maximum	0.29	5.76	5.04	2.77	6.07	2.36	3.15	16.21
Minimum	0.05	-15.01	0.25	1.00	2.99	0.38	0.83	6.63
Std. Dev.	0.06	5.45	1.18	0.66	1.23	0.61	0.68	2.71

Panel E: Post-crisis subperiod

	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
Mean	0.11	0.56	0.21	0.97	2.86	0.19	0.24	5.59
Median	0.09	0.63	0.21	0.96	2.88	0.14	0.19	5.50
Maximum	0.21	6.43	0.54	1.35	3.29	0.50	0.56	6.95
Minimum	0.06	-3.94	0.03	0.65	2.41	0.09	0.12	4.79
Std. Dev.	0.04	2.46	0.11	0.21	0.27	0.11	0.12	0.61

Table 5.52: Correlation matrix for the monthly contagion variables and the $\kappa_{AAA,t}$ series

This table reports the correlation matrices of the various monthly contagion variables and the $\kappa_{AAA,t}$ series over the sample period February 2006 to December 2011. Panel A reports the full sample correlation while Panel B - E report the crisis subsample correlations.

Panel A: Full sample

Correlation	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
$\kappa_{AAA,t}$	1.00							
RET_{AAA}	-0.15	1.00						
$ABCP$	-0.02	-0.08	1.00					
$AILLIQ$	-0.19	-0.29	0.20	1.00				
BAA	-0.18	-0.30	0.20	0.95	1.00			
$LIBOR-OIS$	-0.08	-0.30	0.75	0.69	0.72	1.00		
TED	0.01	-0.27	0.90	0.41	0.42	0.90	1.00	
$VW\ IVol$	-0.05	-0.31	0.50	0.84	0.82	0.87	0.72	1.00

Panel B: Pre-crisis subperiod

Correlation	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
$\kappa_{AAA,t}$	1.00							
RET_{AAA}	-0.51	1.00						
$ABCP$	-0.23	-0.09	1.00					
$AILLIQ$	-0.27	-0.29	0.06	1.00				
BAA	-0.01	-0.29	0.26	0.60	1.00			
$LIBOR-OIS$	-0.18	-0.24	0.20	0.29	0.19	1.00		
TED	-0.02	-0.62	0.78	0.34	0.50	0.34	1.00	
$VW\ IVol$	-0.31	-0.23	-0.21	0.69	0.17	-0.07	0.04	1.00

Panel C: Subprime crisis subperiod

Correlation	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
$\kappa_{AAA,t}$	1.00							
RET_{AAA}	0.03	1.00						
$ABCP$	-0.24	-0.05	1.00					
$AILLIQ$	-0.28	-0.46	0.85	1.00				
BAA	-0.19	-0.54	0.77	0.91	1.00			
$LIBOR-OIS$	-0.30	-0.37	0.87	0.96	0.89	1.00		
TED	-0.37	-0.29	0.91	0.94	0.85	0.98	1.00	
$VW\ IVol$	-0.28	-0.63	0.57	0.79	0.75	0.81	0.76	1.00

Panel D: Global crisis subperiod

Correlation	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
$\kappa_{AAA,t}$	1.00							
RET_{AAA}	-0.11	1.00						
$ABCP$	-0.12	0.27	1.00					
$AILLIQ$	-0.27	-0.55	-0.29	1.00				
BAA	-0.17	-0.51	-0.19	0.95	1.00			
$LIBOR-OIS$	-0.18	-0.13	0.63	0.45	0.57	1.00		
TED	-0.06	0.03	0.85	0.13	0.28	0.91	1.00	
$VW\ IVol$	-0.16	-0.35	0.23	0.72	0.81	0.79	0.63	1.00

Panel E: Post-crisis subperiod

Correlation	$\kappa_{AAA,t}$	RET_{AAA}	$ABCP$	$AILLIQ$	BAA	$LIBOR$-OIS	TED	$VW\ IVol$
$\kappa_{AAA,t}$	1.00							
RET_{AAA}	-0.11	1.00						
$ABCP$	0.14	-0.18	1.00					
$AILLIQ$	-0.02	-0.03	0.69	1.00				
BAA	-0.01	-0.40	0.45	0.67	1.00			
$LIBOR-OIS$	0.07	-0.25	0.49	0.35	0.60	1.00		
TED	0.15	-0.30	0.57	0.40	0.60	0.97	1.00	
$VW\ IVol$	0.34	0.05	0.36	0.49	0.18	0.15	0.19	1.00

Table 5.53: Granger causality tests on the contagion variables and the $\kappa_{AAA,t}$ series

This table reports the findings of the Granger-causality tests based on the VAR(1) model of the contagion variables and the $\kappa_{AAA,t}$ series. The F-statistics on the lagged regressors are reported while the p-values are reported in the squared brackets. Abbreviations are as follows: the ABX AAA exposure series ($\kappa_{AAA,t}$), the ABX AAA log returns (RET_{AAA}), the one-month ABCP, the average market illiquidity ($AILLIQ$), the Moody's BAA corporate bond yield spreads (BAA), the LIBOR-OIS spreads ($LIBOR\text{-}OIS$), the TED spreads (TED) and the value-weighted average idiosyncratic volatilities ($VW\ IVol$). All significant coefficients at the 10% level are in bold. Each column corresponds to a VAR equation with the variables listed in the first row of the table as dependent variables.

	$\kappa_{AAA,t}$		RET_{AAA}		$ABCP$		$AILLIQ$		BAA		$LIBOR\text{-}OIS$		TED		$VW\ IVol$	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
$\kappa_{AAA,t}$			0.548	[0.459]	0.345	[0.557]	1.559	[0.212]	2.095	[0.148]	0.549	[0.459]	0.324	[0.569]	1.271	[0.260]
RET_{AAA}	0.006	[0.938]			0.417	[0.518]	0.543	[0.461]	0.977	[0.323]	0.009	[0.925]	0.044	[0.834]	0.001	[0.982]
$ABCP$	0.692	[0.406]	1.271	[0.260]			**2.728**	[0.099]	**5.474**	[0.019]	0.073	[0.787]	0.707	[0.401]	**4.227**	[0.040]
$AILLIQ$	**6.479**	[0.011]	1.478	[0.224]	1.748	[0.186]			0.000	[0.991]	1.860	[0.173]	1.153	[0.283]	**8.145**	[0.004]
BAA	0.295	[0.587]	0.692	[0.406]	0.720	[0.396]	0.093	[0.761]			1.049	[0.306]	2.275	[0.131]	1.417	[0.234]
$LIBOR\text{-}OIS$	**4.690**	[0.030]	**3.247**	[0.072]	0.054	[0.817]	**5.810**	[0.016]	**21.041**	[0.000]			0.432	[0.511]	**6.624**	[0.010]
TED	0.207	[0.649]	0.472	[0.492]	**6.488**	[0.011]	**5.194**	[0.023]	**14.530**	[0.000]	0.003	[0.956]			1.577	[0.209]
$VW\ IVol$	**16.632**	[0.000]	**3.863**	[0.049]	2.431	[0.119]	0.985	[0.321]	0.072	[0.788]	0.945	[0.331]	0.172	[0.679]		
All	**26.596**	[0.000]	**23.077**	[0.002]	**12.206**	[0.094]	**36.637**	[0.000]	**58.208**	[0.000]	3.334	[0.853]	4.183	[0.758]	**47.785**	[0.000]

Table 5.54: Determinants of stocks' exposure to the ABX AAA innovations

This table reports the findings of the logistic, multinomial logistic and multivariate regressions using SIG, SIGN and β_{ABX} as dependent variables respectively. SIG is a dummy variable whose value is 1 when the individual stock has a significant t-statistic (at 5% significance level) on the ABX factor loadings, and 0 otherwise while SIGN is a categorical variable whose value is 1 when the individual stock is significant and has a positive ABX factor loading, 2 when the stock is significant with a negative ABX factor loading, and 0 otherwise. Panel A reports the findings of the logistic regressions using SIG as the dependent variable; Panel B reports the findings of the multinomial logistic regressions of the SIGN=1 model (positive ABX factor loadings and significant exposure) while Panel C reports the results of the multinomial logistic regressions of the SIGN=2 model (negative ABX factor loadings and significant exposure); Panel D reports the findings of the multivariate regressions using the ABX factor loading as the dependent variable. The pseudo R^2 is the McFadden's likelihood ratio index and applies to Panels A - C while the adjusted R^2 is reported for Panel D. Superscripts ***, ** and * denote statistical significance at the 0.1%, 1% and 5% level, respectively. The findings in this table are based on the ABX AAA factor of Model 3. The t-statistics are reported in the parenthesis.

ABX AAA	**Panel A: Logistic**				**Panel B: SIGN=1**				**Panel C: SIGN=2**				**Panel D: Multivariate**			
	Dep. Var.: SIG				*Dep. Var.: SIGN*				*Dep. Var.: SIGN*				*Dep. Var.:* β_{ABX}			
	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post
RET_t	−0.02	−0.01	0.02	0.03	−0.04	−0.03	0.10***	0.02	−0.01	0.01	−0.02	0.05	0.03	−0.00	0.00	−0.00
	(−1.57)	(−1.30)	(0.80)	(0.90)	(−1.06)	(−1.91)	(3.88)	(0.41)	(−0.48)	(0.40)	(−0.60)	(0.64)	(1.41)	(−1.88)	(1.98)	(−0.36)
LN_MCAP	0.13	−0.10	−0.01	−0.04	−0.01	−0.11	0.01	0.13	0.41***	−0.05	−0.01	−0.13	−0.73***	−0.01	0.01	0.01*
	(1.51)	(−1.22)	(−0.12)	(−0.59)	(−0.05)	(−1.10)	(0.13)	(1.28)	(4.95)	(−0.51)	(−0.09)	(−1.44)	(−5.78)	(−0.73)	(1.81)	(2.92)
LN_TURN	−0.04	−0.01	−0.01	−0.05	−0.15	0.01	0.21*	−0.02	0.41**	−0.05	−0.09	−0.11	−0.79***	0.04*	−0.00	0.01
	(−0.43)	(−0.09)	(−0.12)	(−0.44)	(−1.33)	(0.11)	(1.98)	(−0.09)	(3.18)	(−0.60)	(−0.83)	(−0.62)	(−10.22)	(2.95)	(−0.47)	(1.11)
LN_BE/ME	0.10	0.05	−0.17*	0.03	−0.29*	0.23**	−0.22	0.07	0.47***	−0.20	−0.15	0.06	−0.43*	0.03*	−0.00	0.01*
	(1.08)	(0.49)	(−1.99)	(0.33)	(−2.46)	(2.78)	(−1.67)	(0.48)	(3.88)	(−1.06)	(−1.49)	(0.41)	(−3.01)	(2.23)	(−0.12)	(2.20)
IVol	−0.29**	−0.27*	−0.10***	−0.09	0.75***	0.29***	−0.23***	0.10*	−1.11***	−1.03***	0.02	−0.31**	3.36***	0.12***	−0.01	0.02***
	(−2.73)	(−2.07)	(−4.35)	(−1.28)	(8.02)	(3.34)	(−5.79)	(2.06)	(−16.97)	(−8.34)	(0.52)	(−3.14)	(13.26)	(16.29)	(−1.84)	(6.46)
Stdev	1.48**	1.39*	0.42***	0.29	−5.59***	−1.62***	1.17***	−0.39	4.52***	5.22***	−0.22	1.25**	−18.60***	−0.58***	0.05*	−0.09***
	(2.67)	(1.96)	(3.98)	(0.92)	(−10.53)	(−3.43)	(5.62)	(−1.53)	(13.02)	(7.87)	(−1.58)	(2.88)	(−12.11)	(−14.45)	(2.24)	(−5.31)
β_{MKT}	−0.09	−0.04	−0.35**	−0.29	3.55***	1.25***	−0.52	0.71*	−4.00***	−2.07***	0.02	−1.48**	10.48***	0.25***	−0.01	0.08**
	(−0.36)	(−0.11)	(−2.97)	(−0.79)	(15.52)	(4.58)	(−1.05)	(1.98)	(−13.34)	(−4.21)	(0.13)	(−2.92)	(121.03)	(9.12)	(−0.24)	(3.95)
Earn_yield	−0.02*	0.00	0.00	−0.00	−0.03**	0.02	0.00	−0.01	−0.01	−0.02	0.00	0.00	0.00	−0.00*	0.00	−0.00
	(−2.55)	(0.25)	(0.65)	(−0.66)	(−2.63)	(1.46)	(0.49)	(−1.12)	(−0.38)	(−1.33)	(0.61)	(0.91)	(0.22)	(−2.98)	(0.13)	(−1.03)
Sales_growth	0.00	−0.00	−0.00	−0.00	−0.00	0.00	−0.016$*$	−0.00	−0.00	−0.01	−0.00	−0.01*	0.00	0.00	−0.00*	−0.00
	(1.45)	(−0.58)	(−1.34)	(−1.69)	(−0.49)	(0.60)	(−2.48)	(−0.71)	(−0.86)	(−1.64)	(−0.38)	(−2.48)	(0.56)	(2.00)	(−2.56)	(−0.69)
EBITDA_growth	0.01	0.01	0.00	0.00	−0.00	0.00	−0.00	−0.01*	0.02	0.01	0.01	0.02*	0.01	−0.00	0.00	−0.00
	(1.36)	(0.69)	(0.53)	(0.79)	(−0.07)	(0.22)	(−0.25)	(−2.50)	(1.52)	(0.82)	(0.80)	(2.00)	(1.03)	(−0.43)	(0.77)	(−0.06)
Div_yield	−0.04	−0.05	0.01	0.07	−0.01	−0.17*	0.01	0.01	0.06	0.04	0.02	0.07*	−0.01	−0.01	−0.00	−0.00
	(−1.51)	(−1.28)	(0.72)	(1.84)	(−0.08)	(−2.17)	(0.42)	(0.10)	(1.18)	(0.81)	(0.57)	(2.43)	(−0.13)	(−0.83)	(−0.07)	(−0.74)
CAPX_AT	0.04*	0.00	0.01	0.00	0.02	−0.00	−0.02	0.02	0.01	0.02	0.03	−0.01	0.07	−0.00	−0.00	0.00
	(2.53)	(0.34)	(1.51)	(0.07)	(0.67)	(−0.20)	(−0.50)	(0.81)	(0.79)	(1.15)	(1.84)	(−0.27)	(2.01)	(−1.01)	(−0.69)	(1.62)
Leverage	0.00	0.00	−0.00	−0.00	0.00	0.00*	−0.02***	−0.01	0.01	0.00	0.00	−0.00	−0.01***	0.00	−0.00	−0.00*
	(0.34)	(1.54)	(−1.36)	(−1.45)	(0.36)	(2.52)	(−3.61)	(−1.68)	(1.67)	(0.31)	(0.62)	(−0.36)	(−6.32)	(0.46)	(−1.49)	(−2.29)
FCF_AT	0.01	−0.00	−0.00	−0.01*	0.01	−0.01	0.01	−0.02	0.00	0.01	−0.01	−0.00	−0.00	0.00	0.00*	−0.00
	(1.52)	(−0.24)	(−0.48)	(−2.01)	(1.37)	(−0.56)	(0.43)	(−1.76)	(0.10)	(0.64)	(−1.12)	(−0.84)	(−0.16)	(1.52)	(2.61)	(−0.30)
BIG4	−0.23	0.02	−0.13	−0.00	−0.39	−0.10	−0.05	−0.51**	−0.01	0.23	−0.12	0.41	−0.53*	−0.03	−0.01	−0.03**
	(−1.34)	(0.22)	(−1.44)	(−0.01)	(−1.69)	(−0.75)	(−0.22)	(−3.04)	(−0.03)	(1.03)	(−0.78)	(1.81)	(−2.59)	(−1.71)	(−1.01)	(−3.43)
Constant	−4.24***	−1.36	−1.56	−1.55*	−4.77*	−1.93	−2.94**	−5.59***	−7.80***	−2.02	−2.03	−0.17	6.11*	0.05	−0.19	−0.20**
	(−3.90)	(−1.41)	(−1.68)	(−2.27)	(−2.22)	(−1.64)	(−2.92)	(−4.71)	(−8.00)	(−1.31)	(−1.57)	(−0.15)	(2.91)	(0.38)	(−2.02)	(−3.59)
N	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517
Pseudo/Adj. R^2	0.03	0.02	0.02	0.01	0.48	0.06	0.05	0.04	0.48	0.06	0.05	0.04	0.85	0.08	0.04	0.04

Table 5.55: Determinants of stocks' exposure to the ABX AA innovations

This table reports the findings of the logistic, multinomial logistic and multivariate regressions using SIG, SIGN and β_{ABX} as dependent variables respectively. SIG is a dummy variable whose value is 1 when the individual stock has a significant t-statistic (at 5% significance level) on the ABX factor loadings, and 0 otherwise while SIGN is a categorical variable whose value is 1 when the individual stock is significant and has a positive ABX factor loading, 2 when the stock is significant with a negative ABX factor loading, and 0 otherwise. Panel A reports the findings of the logistic regressions using SIG as the dependent variable; Panel B reports the findings of the multinomial logistic regressions of the SIGN=1 model (positive ABX factor loadings and significant exposure) while Panel C reports the results of the multinomial logistic regressions of the SIGN=2 model (negative ABX factor loadings and significant exposure); Panel D reports the findings of the multivariate regressions using the ABX factor loading as the dependent variable. The pseudo R^2 is the McFadden's likelihood ratio index and applies to Panels A - C while the adjusted R^2 is reported for Panel D. Superscripts ***, ** and * denote statistical significance at the 0.1%, 1% and 5% level, respectively. The findings in this table are based on the ABX AA factor of Model 3. The t-statistics are reported in the parenthesis.

ABX AA																
Panel A: Logistic					**Panel B: SIGN=1**				**Panel C: SIGN=2**				**Panel D: Multivariate**			
	Dep. Var.: SIG				*Dep. Var.: SIGN*				*Dep. Var.: SIGN*				*Dep. Var.:* β_{ABX}			
	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post
RET_t	−0.00	0.02	−0.02	0.07**	−0.05	−0.00	0.06	0.03	0.02	0.04	−0.07*	0.13***	0.01	−0.00	0.00*	−0.00
	(−0.02)	(1.21)	(−1.07)	(2.67)	(−1.75)	(−0.02)	(1.90)	(0.51)	(0.58)	(1.84)	(−2.34)	(3.55)	(0.99)	(−1.96)	(2.28)	(−0.47)
LN_MCAP	0.00	0.03	−0.05	0.00	−0.22*	0.05	−0.04	0.10	0.27**	0.02	−0.06	−0.07	−0.34***	0.00	0.00	0.00*
	(0.01)	(0.47)	(−0.76)	(0.00)	(−2.05)	(0.70)	(−0.44)	(0.84)	(2.97)	(0.17)	(−0.58)	(−0.82)	(−5.56)	(0.31)	(1.40)	(2.77)
LN_TURN	−0.11	−0.06	0.04	0.16	−0.21	0.17	0.22	0.33	0.14	−0.31***	−0.08	−0.02	−0.40***	0.02**	0.00	0.01
	(−1.38)	(−0.91)	(0.44)	(1.53)	(−1.25)	(1.50)	(1.47)	(1.78)	(1.35)	(−3.86)	(−0.70)	(−0.12)	(−5.56)	(3.51)	(0.88)	(2.05)
LN_BE/ME	0.05	0.12	−0.04	−0.10	−0.12	0.19***	−0.24	0.04	0.30**	0.04	0.07	−0.21	−0.25*	0.01	0.00	0.00**
	(0.84)	(1.52)	(−0.38)	(−1.03)	(−0.92)	(5.04)	(−1.72)	(0.30)	(2.64)	(0.23)	(0.54)	(−1.51)	(−2.97)	(1.35)	(0.06)	(3.07)
$IVol$	−0.39***	−0.34***	−0.08**	−0.14*	0.79***	0.18	−0.19***	−0.15**	−1.17***	−0.86***	0.03	−0.17	1.56***	0.05***	−0.00	0.00*
	(−6.06)	(−5.54)	(−3.24)	(−2.35)	(5.19)	(1.06)	(−6.81)	(−2.69)	(−8.42)	(−14.19)	(0.62)	(−1.82)	(14.07)	(12.92)	(−1.66)	(2.90)
$Stdev$	1.97***	1.85***	0.35*	0.64*	−6.04***	−0.98	1.04***	0.95***	5.38***	4.61***	−0.35	0.56	−8.72***	−0.26***	0.02	−0.01
	(5.06)	(5.31)	(2.26)	(2.49)	(−6.08)	(−1.00)	(7.21)	(3.63)	(8.23)	(17.67)	(−1.58)	(1.29)	(−13.53)	(−11.68)	(1.78)	(−1.16)
β_{MKT}	−0.31	−0.29	−0.06	−0.58**	4.28***	0.69	−0.69	−0.30	−3.58***	−1.39***	0.65*	−0.84***	5.18***	0.09***	−0.01	0.01
	(−1.64)	(−1.37)	(−0.37)	(−2.94)	(16.16)	(1.92)	(−1.67)	(−0.84)	(−22.39)	(−8.24)	(2.04)	(−3.75)	(74.44)	(6.46)	(−0.95)	(1.02)
$Earn\_yield$	−0.01	0.01	0.01	−0.01	−0.04*	0.00	0.01	−0.01	0.01	0.01	0.01	0.00	−0.01	−0.00	0.00	−0.00
	(−1.77)	(0.77)	(0.99)	(−1.17)	(−2.48)	(0.38)	(1.02)	(−1.77)	(0.92)	(0.65)	(0.67)	(0.67)	(−1.92)	(−0.73)	(1.03)	(−1.98)
$Sales\_growth$	−0.00	0.00	−0.00	−0.00	−0.00	−0.00	−0.01*	−0.00	−0.01	0.00	−0.00	−0.00	0.00	0.00	−0.00*	−0.00
	(−0.05)	(0.16)	(−1.08)	(−0.84)	(−0.82)	(−0.82)	(−2.16)	(−0.28)	(−1.21)	(0.69)	(−0.46)	(−0.77)	(1.11)	(0.72)	(−2.66)	(−0.51)
$EBITDA\_growth$	−0.01	0.02	0.00	0.02***	0.01	0.02	0.00	0.02**	−0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00
	(−1.27)	(1.36)	(0.22)	(3.82)	(0.67)	(1.24)	(0.07)	(3.20)	(−1.39)	(0.73)	(0.35)	(1.42)	(0.32)	(0.42)	(1.12)	(0.50)
Div_yield	0.05	−0.09*	−0.01	0.01	−0.03	−0.23***	−0.01	0.03	0.06	0.01	−0.01	−0.02	0.00	−0.00	0.00	−0.00
	(1.70)	(−2.25)	(−0.58)	(0.27)	(−0.34)	(−4.66)	(−0.70)	(0.58)	(1.59)	(0.14)	(−0.42)	(−0.77)	(0.19)	(−0.71)	(1.85)	(−1.27)
$CAPX\_AT$	−0.01	0.04***	0.02	−0.06**	−0.05**	0.01	−0.02	−0.07**	−0.03	0.07***	0.04*	−0.05	0.04	−0.00	−0.00	0.00
	(−0.66)	(5.55)	(1.92)	(−3.08)	(−2.94)	(0.51)	(−0.44)	(−2.97)	(−1.10)	(4.44)	(2.12)	(−1.60)	(1.83)	(−1.87)	(−0.80)	(1.05)
$Leverage$	0.00	−0.00	−0.00	0.00	0.00	0.01**	−0.01	−0.00	0.00	−0.01**	0.00	0.00	−0.00	0.00	−0.00	−0.00
	(0.76)	(−0.97)	(−0.56)	(0.64)	(0.24)	(3.25)	(−1.91)	(−0.20)	(1.38)	(−3.12)	(0.19)	(0.80)	(−1.82)	(0.61)	(−0.29)	(−0.70)
FCF_AT	−0.00	−0.00	−0.01	−0.00	−0.01	0.00	0.00	−0.01	0.00	−0.01	−0.01	0.00	−0.00	0.00	0.00	−0.00
	(−0.38)	(−0.31)	(−0.75)	(−0.55)	(−1.88)	(0.27)	(0.36)	(−0.72)	(0.30)	(−0.85)	(−1.14)	(0.12)	(−0.52)	(1.66)	(0.95)	(−1.24)
$BIG4$	−0.01	−0.02	−0.13	−0.30	−0.20	−0.14	0.10	−0.58*	0.26	0.14	−0.24	−0.07	−0.14*	−0.02	−0.00	−0.00
	(−0.10)	(−0.10)	(−0.76)	(−1.52)	(−0.60)	(−0.62)	(0.43)	(−2.42)	(0.98)	(1.08)	(−1.24)	(−0.27)	(−2.44)	(−1.76)	(−0.22)	(−1.12)
$Constant$	−2.17**	−2.96***	−1.49	−1.99	−1.31	−3.83***	−3.11**	−4.99**	−5.72***	−3.34*	−1.64	−0.98	2.53*	0.00	−0.07	−0.06**
	(−2.83)	(−4.51)	(−1.48)	(−1.81)	(−0.99)	(−5.60)	(−2.98)	(−2.88)	(−4.98)	(−2.44)	(−1.12)	(−0.79)	(2.57)	(0.03)	(−1.82)	(−3.23)
N	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517
Pseudo/Adj. R^2	0.02	0.03	0.02	0.02	0.42	0.06	0.04	0.04	0.42	0.06	0.04	0.04	0.78	0.04	0.03	0.04

Table 5.56: Determinants of stocks' exposure to the ABX A innovations

This table reports the findings of the logistic, multinomial logistic and multivariate regressions using SIG, SIGN and β_{ABX} as dependent variables respectively. SIG is a dummy variable whose value is 1 when the individual stock has a significant t-statistic (at 5% significance level) on the ABX factor loadings, and 0 otherwise while SIGN is a categorical variable whose value is 1 when the individual stock is significant and has a positive ABX factor loading, 2 when the stock is significant with a negative ABX factor loading, and 0 otherwise. Panel A reports the findings of the logistic regressions using SIG as the dependent variable; Panel B reports the findings of the multinomial logistic regressions of the SIGN=1 model (positive ABX factor loadings and significant exposure) while Panel C reports the results of the multinomial logistic regressions of the SIGN=2 model (negative ABX factor loadings and significant exposure); Panel D reports the findings of the multivariate regressions using the ABX factor loading as the dependent variable. The pseudo R^2 is the McFadden's likelihood ratio index and applies to Panels A - C while the adjusted R^2 is reported for Panel D. Superscripts ***, ** and * denote statistical significance at the 0.1%, 1% and 5% level, respectively. The findings in this table are based on the ABX A factor of Model 3. The t-statistics are reported in the parenthesis.

ABX A																
Panel A: Logistic					**Panel B: SIGN=1**				**Panel C: SIGN=2**				**Panel D: Multivariate**			
	Dep. Var.: SIG				*Dep. Var.: SIGN*				*Dep. Var.: SIGN*				*Dep. Var.:* β_{ABX}			
	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post
RET_t	0.02	0.02	−0.00	0.02	−0.01	−0.01	0.11**	0.02	0.05	0.04	−0.08**	0.03	0.02	−0.00	0.00**	−0.00
	(0.69)	(1.12)	(−0.01)	(0.79)	(−0.13)	(−0.23)	(2.61)	(0.40)	(1.62)	(1.00)	(−2.63)	(0.52)	(1.19)	(−0.72)	(3.18)	(−0.48)
LN_MCAP	−0.07	0.17*	0.08	−0.03	−0.17	0.28	−0.04	−0.12	0.14	0.06	0.17*	0.03	−0.38***	0.00	−0.00	0.00
	(−1.52)	(2.27)	(1.26)	(−0.39)	(−1.93)	(1.82)	(−0.47)	(−0.94)	(1.61)	(0.48)	(2.17)	(0.36)	(−5.39)	(1.44)	(−0.07)	(0.86)
LN_TURN	−0.08	−0.06	−0.01	−0.02	−0.37**	0.21	0.16*	−0.00	0.21	−0.31*	−0.15	−0.02	−0.37***	0.01*	0.00	−0.00
	(−0.89)	(−0.67)	(−0.18)	(−0.25)	(−3.11)	(1.65)	(2.01)	(−0.01)	(1.38)	(−2.40)	(−1.33)	(−0.16)	(−6.24)	(2.98)	(1.34)	(−0.33)
LN_BE/ME	−0.01	0.19	−0.05	0.09	−0.07	0.23*	−0.14*	−0.04	0.15	0.14	0.02	0.16	−0.16	0.00	−0.00	−0.00**
	(−0.10)	(1.95)	(−0.73)	(1.16)	(−0.81)	(2.04)	(−2.13)	(−0.32)	(1.03)	(1.07)	(0.24)	(1.78)	(−1.92)	(0.21)	(−0.01)	(−3.24)
$IVol$	−0.30***	−0.41***	−0.11***	−0.01	0.83***	−0.35**	−0.14***	0.05	−1.67***	−0.46***	−0.07	−0.05	1.72***	0.00	−0.00	0.00
	(−3.33)	(−4.30)	(−5.26)	(−0.26)	(3.82)	(−2.74)	(−6.68)	(0.35)	(−14.52)	(−4.83)	(−1.21)	(−0.48)	(7.69)	(0.33)	(−1.08)	(0.81)
$Stdev$	1.43**	2.28***	0.55***	−0.05	−5.38***	2.10**	0.78***	−0.40	7.92***	2.38***	0.30	0.16	−9.44***	0.00	0.01	−0.01
	(3.18)	(4.62)	(5.03)	(−0.16)	(−4.30)	(3.08)	(6.93)	(−0.44)	(14.63)	(4.72)	(0.96)	(0.26)	(−7.21)	(0.22)	(1.33)	(−0.85)
β_{MKT}	−0.28	−0.92***	−0.08	0.10	3.55***	−1.19***	−0.34	0.17	−3.87***	−0.61**	0.18	0.05	5.44***	−0.01*	−0.01	0.00
	(−1.26)	(−4.41)	(−0.42)	(0.58)	(24.27)	(−3.49)	(−1.16)	(0.29)	(−16.03)	(−2.88)	(0.50)	(0.13)	(57.30)	(−2.80)	(−1.34)	(0.45)
$Earn\_yield$	−0.01	0.02	0.00	0.00	0.02	0.02	0.01	0.01	−0.01	0.01	0.00	0.00	−0.01	0.00	0.00	0.00
	(−0.53)	(1.82)	(0.98)	(0.95)	(1.40)	(1.54)	(1.90)	(0.86)	(−0.50)	(1.27)	(0.24)	(0.54)	(−1.54)	(1.23)	(0.30)	(1.14)
$Sales\_growth$	−0.00	−0.00	−0.01**	0.00	0.00	−0.01**	−0.01	−0.00	−0.01*	0.00	−0.01**	0.00	0.01*	−0.00	−0.00	−0.00
	(−0.03)	(−0.89)	(−3.04)	(0.13)	(0.96)	(−2.65)	(−1.80)	(−0.09)	(−2.10)	(0.21)	(−2.63)	(0.27)	(2.35)	(−0.09)	(−1.27)	(−0.43)
$EBITDA\_growth$	0.00	−0.00	0.01	−0.01	0.01	0.02	−0.02	−0.02	−0.00	−0.01	0.03*	−0.01	0.01	−0.00	0.00	0.00
	(0.36)	(−0.02)	(0.94)	(−1.69)	(0.91)	(0.66)	(−1.29)	(−0.66)	(−0.24)	(−0.40)	(2.20)	(−0.68)	(1.45)	(−0.54)	(0.62)	(0.49)
Div_yield	−0.04	−0.12***	−0.02	−0.07*	0.08	−0.21***	0.00	−0.07	−0.03	−0.07	−0.05	−0.07	0.01	−0.00**	0.00	−0.00
	(−1.16)	(−3.93)	(−0.98)	(−2.12)	(1.06)	(−3.41)	(0.17)	(−0.84)	(−0.70)	(−1.25)	(−1.89)	(−1.83)	(0.45)	(−3.30)	(1.31)	(−1.84)
$CAPX\_AT$	−0.02	0.02*	0.03	0.04**	0.01	−0.03	−0.02	0.00	−0.05*	0.05**	0.06*	0.06**	0.08	−0.00	−0.00	−0.00
	(−1.75)	(2.31)	(1.82)	(2.84)	(0.23)	(−0.98)	(−0.63)	(0.13)	(−2.01)	(2.68)	(2.12)	(3.10)	(2.15)	(−2.02)	(−1.00)	(−0.75)
$Leverage$	−0.00	−0.00	−0.00	0.01**	−0.01	0.01	0.01*	0.01	0.01*	−0.01	−0.01	0.01**	−0.01	0.00	0.00	−0.00
	(−0.15)	(−0.60)	(−0.38)	(3.23)	(−1.88)	(1.63)	(2.11)	(0.99)	(2.25)	(−1.47)	(−1.73)	(3.12)	(−1.86)	(0.45)	(1.42)	(−0.40)
FCF_AT	−0.00	−0.02*	−0.00	−0.00	−0.01	−0.01	0.00	−0.00	−0.01	−0.02**	−0.01	−0.00	−0.01	0.00	0.00	−0.00
	(−0.64)	(−2.00)	(−0.60)	(−0.43)	(−1.76)	(−1.25)	(0.35)	(−0.25)	(−0.46)	(−2.61)	(−0.85)	(−0.13)	(−1.03)	(1.28)	(1.82)	(−0.46)
$BIG4$	0.21**	−0.21	−0.41**	0.12	0.03	−0.49*	−0.10	0.50*	0.31*	0.03	−0.59**	−0.12	−0.28*	−0.01	0.01	−0.00
	(3.15)	(−1.50)	(−3.11)	(0.77)	(0.25)	(−2.48)	(−0.53)	(2.38)	(2.25)	(0.14)	(−3.24)	(−0.65)	(−2.82)	(−1.91)	(1.95)	(−0.69)
$Constant$	−1.47	−4.27***	−3.53***	−2.74**	−2.92*	−6.33***	−3.26**	−2.53	−3.50*	−3.48*	−4.97***	−3.93**	2.77*	−0.02	−0.01	−0.01
	(−1.96)	(−4.52)	(−3.60)	(−3.26)	(−2.00)	(−3.65)	(−3.25)	(−1.41)	(−2.53)	(−2.17)	(−4.13)	(−3.23)	(2.22)	(−1.06)	(−0.48)	(−0.88)
N	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517
Pseudo/Adj. R^2	0.01	0.03	0.03	0.01	0.32	0.04	0.05	0.01	0.32	0.04	0.05	0.01	0.65	0.02	0.02	0.00

Table 5.57: Determinants of stocks' exposure to the ABX BBB innovations

This table reports the findings of the logistic, multinomial logistic and multivariate regressions using SIG, SIGN and β_{ABX} as dependent variables respectively. SIG is a dummy variable whose value is 1 when the individual stock has a significant t-statisti (at 5% significance level) on the ABX factor loadings, and 0 otherwise while SIGN is a categorical variable whose value is 1 when the individual stock is significant and has a positive ABX factor loading, 2 when the stock is significant with a negative ABX factor loading, and 0 otherwise. Panel A reports the findings of the logistic regressions using SIG as the dependent variable; Panel B reports the findings of the multinomial logistic regressions of the SIGN=1 model (positive ABX factor loadings and significant exposure) while Panel C reports the results of the multinomial logistic regressions of the SIGN=2 model (negative ABX factor loadings and significant exposure); Panel D reports the findings of the multivariate regressions using the ABX factor loading as the dependent variable. The pseudo R^2 is the McFadden's likelihood ratio index and applies to Panels A - C while the adjusted R^2 is reported for Panel D. Superscripts ***, ** and * denote statistical significance at the 0.1%, 1% and 5% level respectively. The findings in this table are based on the ABX BBB factor of Model 3. The t-statistics are reported in the parenthesis.

ABX BBB **Panel A: Logistic**					**Panel B: SIGN=1**				**Panel C: SIGN=2**				**Panel D: Multivariate**			
	Dep. Var.: SIG				*Dep. Var.: SIGN*				*Dep. Var.: SIGN*				*Dep. Var.:* β_{ABX}			
	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post
RET_t	0.00	0.03	0.01	−0.04	−0.00	0.02	0.13***	−0.07	0.01	0.04	−0.06**	−0.02	−0.01	−0.00	0.00*	−0.00
	(0.19)	(1.34)	(0.42)	(−1.90)	(−0.06)	(0.63)	(3.54)	(−1.40)	(0.19)	(1.43)	(−2.75)	(−0.80)	(−1.81)	(−0.71)	(2.97)	(−0.12)
LN_MCAP	−0.05	0.04	0.05	0.16**	−0.11	0.17**	−0.20*	−0.05	−0.00	−0.14	0.20**	0.30***	−0.04	0.00*	−0.00	−0.00*
	(−0.87)	(0.94)	(0.69)	(3.00)	(−0.90)	(2.58)	(−2.48)	(−0.61)	(−0.05)	(−1.56)	(3.27)	(6.23)	(−1.56)	(2.86)	(−1.42)	(−2.45)
LN_TURN	−0.01	0.00	−0.09	−0.12	−0.06	0.14	0.02	0.05	0.04	−0.19	−0.16**	−0.23	−0.07**	0.01***	−0.00	0.01***
	(−0.08)	(0.01)	(−1.33)	(−1.15)	(−0.36)	(1.14)	(0.18)	(0.44)	(0.28)	(−1.81)	(−2.62)	(−1.41)	(−3.48)	(5.62)	(−0.39)	(5.17)
LN_BE/ME	−0.09	0.01	0.05	0.07	−0.10	0.10	−0.09	0.02	−0.08	−0.11	0.13	0.10	−0.09*	0.00	−0.00**	0.00
	(−0.73)	(0.15)	(0.75)	(1.61)	(−0.83)	(1.22)	(−0.73)	(0.22)	(−0.42)	(−1.13)	(1.56)	(0.92)	(−2.60)	(1.21)	(−3.73)	(0.74)
$IVol$	−0.14	−0.38***	−0.10***	−0.04	0.28	−0.43**	−0.20***	−0.15**	−0.45**	−0.27*	−0.03	0.04	0.14**	−0.00**	−0.00	−0.00
	(−1.49)	(−3.90)	(−4.20)	(−1.04)	(1.85)	(−2.82)	(−8.15)	(−2.76)	(−3.04)	(−2.16)	(−0.60)	(0.36)	(3.41)	(−3.71)	(−1.72)	(−1.01)
$Stdev$	0.63	2.10***	0.56***	0.31	−1.79*	2.57**	1.05***	0.78*	2.29**	1.05	0.19	−0.09	−0.84**	0.03***	0.02	0.00
	(1.24)	(3.97)	(3.62)	(1.25)	(−2.08)	(3.15)	(6.70)	(2.07)	(2.80)	(1.53)	(0.58)	(−0.15)	(−3.35)	(5.07)	(2.16)	(0.43)
β_{MKT}	−0.17	−0.76***	−0.00	−0.30	0.86**	−1.19***	−0.58*	−0.11	−0.98***	0.10	0.37	−0.43	0.54***	−0.03***	−0.02	0.01
	(−0.79)	(−3.45)	(−0.01)	(−0.98)	(3.01)	(−3.71)	(−2.10)	(−0.20)	(−3.82)	(0.33)	(1.13)	(−0.95)	(9.76)	(−9.57)	(−1.63)	(1.91)
$Earn\_yield$	−0.01	0.00	0.00	−0.00	−0.02	0.02	−0.01	0.00	0.00	−0.02	0.01	−0.00	−0.01	0.00*	−0.00	0.00
	(−0.86)	(0.54)	(0.39)	(−0.30)	(−1.26)	(1.16)	(−0.78)	(0.09)	(0.01)	(−1.36)	(1.05)	(−0.48)	(−1.22)	(2.34)	(−0.09)	(0.80)
$Sales\_growth$	0.00	−0.00*	−0.00	0.00	0.01*	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	0.00	0.00	0.00	−0.00*	0.00
	(1.28)	(−2.54)	(−0.95)	(0.50)	(2.03)	(−1.27)	(−1.23)	(−0.05)	(−1.24)	(−0.93)	(−0.68)	(0.61)	(1.69)	(0.42)	(−2.92)	(0.18)
$EBITDA\_growth$	0.00	0.00	0.01	−0.00	0.00	0.00	0.00	−0.00	0.01	0.01	0.02	−0.01	−0.00	−0.00	0.00	0.00
	(0.49)	(0.39)	(1.00)	(−0.94)	(0.09)	(0.22)	(0.32)	(−0.19)	(0.53)	(0.67)	(1.53)	(−1.05)	(−0.40)	(−0.72)	(0.67)	(1.09)
Div_yield	−0.05	−0.03	0.02	0.01	−0.05	−0.13**	0.07*	−0.09**	−0.04	0.05	−0.02	0.06*	−0.00	−0.00*	0.00	−0.00**
	(−1.21)	(−1.67)	(0.86)	(0.54)	(−1.56)	(−2.65)	(1.96)	(−3.00)	(−0.53)	(1.50)	(−0.55)	(2.02)	(−0.19)	(−2.43)	(1.07)	(−3.08)
$CAPX\_AT$	0.01	0.02*	0.03	−0.01	0.04	−0.02	−0.05	0.00	−0.02	0.06***	0.05*	−0.03	0.01	−0.00	−0.00	0.00
	(0.48)	(2.48)	(1.59)	(−0.85)	(1.61)	(−0.92)	(−1.12)	(0.15)	(−0.79)	(3.45)	(2.15)	(−1.31)	(0.43)	(−1.72)	(−1.01)	(2.02)
$Leverage$	0.00	0.00**	0.00	−0.00	0.01*	0.01*	0.01	−0.00	−0.00	0.00	−0.00	−0.00	0.00	0.00	0.00	0.00
	(1.54)	(2.74)	(0.69)	(−0.56)	(2.50)	(2.44)	(1.16)	(−0.35)	(−0.04)	(0.12)	(−0.82)	(−0.75)	(1.39)	(0.58)	(0.81)	(1.24)
FCF_AT	0.00	−0.00	−0.00	−0.00	0.00	−0.01	0.02	0.00	−0.00	0.01	−0.01	−0.01	−0.00	0.00	0.00*	−0.00
	(0.09)	(−0.81)	(−0.17)	(−0.35)	(0.37)	(−1.59)	(1.24)	(0.09)	(−0.18)	(1.31)	(−0.92)	(−0.87)	(−1.66)	(0.11)	(2.21)	(−0.13)
$BIG4$	0.19	0.05	−0.28	−0.26*	−0.29	0.05	−0.00	0.02	0.66***	0.06	−0.39*	−0.48***	−0.07	−0.01*	0.01**	−0.00*
	(1.31)	(0.31)	(−1.56)	(−2.26)	(−1.84)	(0.22)	(−0.00)	(0.14)	(3.78)	(0.28)	(−2.10)	(−3.83)	(−1.48)	(−3.09)	(3.24)	(−2.21)
$Constant$	−2.23*	−3.16***	−3.32**	−4.35***	−2.44	−5.78***	−0.91	−2.94*	−3.21**	−1.21	−5.69***	−6.51***	0.27	−0.05*	0.01	0.03
	(−2.47)	(−5.19)	(−2.80)	(−5.48)	(−1.41)	(−6.93)	(−1.07)	(−2.48)	(−2.65)	(−0.94)	(−6.36)	(−7.43)	(0.75)	(−2.52)	(0.33)	(1.44)
N	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517
Pseudo/Adj. R^2	0.01	0.02	0.03	0.01	0.03	0.03	0.06	0.02	0.03	0.03	0.06	0.02	0.03	0.03	0.03	0.02

Table 5.58: Determinants of stocks' exposure to the ABX BBB- innovations

This table reports the findings of the logistic, multinomial logistic and multivariate regressions using SIG, SIGN and β_{ABX} as dependent variables respectively. SIG is a dummy variable whose value is 1 when the individual stock has a significant t-statistic (at 5% significance level) on the ABX factor loadings, and 0 otherwise while SIGN is a categorical variable whose value is 1 when the individual stock is significant and has a positive ABX factor loading, 2 when the stock is significant with a negative ABX factor loading, and 0 otherwise. Panel A reports the findings of the logistic regressions using SIG as the dependent variable; Panel B reports the findings of the multinomial logistic regressions of the SIGN=1 model (positive ABX factor loadings and significant exposure) while Panel C reports the results of the multinomial logistic regressions of the SIGN=2 model (negative ABX factor loadings and significant exposure); Panel D reports the findings of the multivariate regressions using the ABX factor loading as the dependent variable. The pseudo R^2 is the McFadden's likelihood ratio index and applies to Panels A - C while the adjusted R^2 is reported for Panel D. Superscripts ***, ** and * denote statistical significance at the 0.1%, 1% and 5% level respectively. The findings in this table are based on the ABX BBB- factor of Model 3. The t-statistics are reported in the parenthesis.

ABX BBB- Panel A: Logistic					Panel B: SIGN=1				Panel C: SIGN=2				Panel D: Multivariate			
	Dep. Var.: SIG				*Dep. Var.: SIGN*				*Dep. Var.: SIGN*				*Dep. Var.:* β_{ABX}			
	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post	Pre	Subp	Global	Post
RET_t	0.01	−0.03	0.02	−0.01	−0.01	−0.02	0.09^{**}	−0.02	0.03	−0.03	−0.02	0.01	−0.01	−0.00	0.00^{**}	−0.00
	(0.72)	(−1.22)	(0.80)	(−0.36)	(−0.35)	(−0.66)	(2.64)	(−0.75)	(0.92)	(−0.98)	(−1.02)	(0.16)	(−1.14)	(−0.39)	(3.27)	(−0.27)
LN_MCAP	−0.10	0.09	0.02	0.10	−0.13	0.21	−0.12	−0.06	−0.09	−0.05	0.09	0.24	−0.04	0.00^{*}	0.00	−0.00
	(−1.23)	(0.98)	(0.27)	(0.85)	(−1.66)	(1.71)	(−1.13)	(−0.55)	(−0.53)	(−0.48)	(1.23)	(1.38)	(−1.41)	(2.33)	(0.56)	(−0.08)
LN_TURN	0.04	0.03	0.02	0.01	−0.14	0.23	0.25^{*}	0.02	0.19	-0.16^{*}	−0.11	0.01	-0.06^{*}	0.01^{**}	−0.00	0.00
	(0.34)	(0.29)	(0.23)	(0.11)	(−1.28)	(1.76)	(2.11)	(0.10)	(1.02)	(−1.99)	(−1.64)	(0.08)	(−2.58)	(3.38)	(−0.14)	(0.32)
LN_BE/ME	0.01	0.02	0.03	0.04	−0.01	−0.02	−0.09	−0.04	0.02	0.03	0.10	0.11	−0.06	−0.00	−0.00	−0.00
	(0.05)	(0.15)	(0.37)	(0.51)	(−0.07)	(−0.24)	(−1.23)	(−0.56)	(0.11)	(0.18)	(0.94)	(0.75)	(−2.15)	(−0.40)	(−1.81)	(−0.85)
$IVol$	−0.19	-0.32^{***}	-0.06^{*}	0.02	0.10	-0.39^{***}	-0.14^{***}	0.04	-0.40^{*}	−0.21	−0.01	0.00	0.11^{**}	-0.01^{*}	−0.00	−0.00
	(−1.69)	(−5.08)	(−2.49)	(0.32)	(0.51)	(−4.26)	(−4.01)	(0.52)	(−2.35)	(−1.93)	(−0.10)	(0.02)	(3.54)	(−2.96)	(−1.33)	(−1.27)
$Stdev$	0.88	1.74^{***}	0.26^{*}	−0.07	−0.76	2.28^{***}	0.66^{***}	−0.22	1.99^{*}	0.89	−0.05	0.10	-0.68^{**}	0.04^{**}	0.02	0.01
	(1.59)	(5.41)	(2.05)	(−0.15)	(−0.73)	(5.19)	(3.63)	(−0.44)	(2.26)	(1.35)	(−0.18)	(0.17)	(−3.63)	(3.31)	(1.72)	(1.05)
β_{MKT}	−0.23	-0.85^{***}	0.15	−0.15	0.87^{***}	-1.30^{***}	−0.35	0.28	-1.07^{***}	−0.26	0.51	−0.58	0.48^{***}	-0.03^{***}	−0.02	−0.00
	(−1.89)	(−3.48)	(0.93)	(−0.58)	(3.33)	(−3.88)	(−1.52)	(0.92)	(−7.08)	(−0.83)	(1.55)	(−1.64)	(9.21)	(−6.59)	(−2.14)	(−0.63)
$Earn\_yield$	−0.01	0.01	0.00	-0.01^{*}	−0.01	0.02	0.00	−0.00	−0.01	−0.01	0.00	-0.01^{*}	−0.00	0.00	0.00	-0.00^{**}
	(−1.15)	(1.25)	(0.17)	(−2.00)	(−0.85)	(1.82)	(0.06)	(−0.93)	(−0.50)	(−0.72)	(0.23)	(−2.01)	(−0.82)	(1.87)	(0.29)	(−4.11)
$Sales\_growth$	0.00	0.00	−0.00	−0.00	0.00	0.00	−0.00	−0.00	0.00	0.00	−0.00	0.00	0.00	0.00	-0.00^{*}	−0.00
	(0.48)	(0.63)	(−1.15)	(−0.07)	(1.01)	(0.00)	(−0.70)	(−1.51)	(0.08)	(0.65)	(−0.57)	(0.74)	(1.01)	(0.05)	(−2.90)	(−0.07)
$EBITDA\_growth$	−0.00	0.01	0.01	−0.00	−0.01	0.02	0.01	0.01	0.01	−0.01	0.01	−0.01	−0.00	0.00	0.00	0.00
	(−0.14)	(0.56)	(0.93)	(−0.35)	(−0.77)	(1.31)	(0.32)	(1.44)	(0.34)	(−0.34)	(1.33)	(−1.01)	(−0.30)	(0.13)	(1.91)	(0.26)
Div_yield	-0.09^{**}	−0.01	0.01	−0.05	−0.08	−0.05	0.01	−0.04	−0.11	0.02	0.01	−0.08	−0.01	−0.00	0.00	0.00
	(−2.74)	(−0.40)	(0.47)	(−1.56)	(−0.96)	(−0.78)	(0.16)	(−1.14)	(−1.30)	(0.39)	(0.41)	(−1.32)	(−1.38)	(−1.03)	(0.00)	(1.07)
$CAPX\_AT$	0.01	0.02^{**}	0.03^{**}	0.01	0.04	−0.03	−0.04	−0.03	−0.02	0.06^{***}	0.05^{*}	0.03	−0.00	-0.00^{*}	−0.00	-0.00^{*}
	(0.69)	(2.85)	(2.71)	(0.30)	(1.95)	(−1.17)	(−0.74)	(−1.80)	(−0.79)	(3.97)	(2.26)	(1.61)	(−0.00)	(−2.33)	(−0.77)	(−2.75)
$Leverage$	0.01^{*}	0.00	0.00	−0.00	0.01^{*}	0.01^{*}	0.00	0.01	0.00	−0.00	0.00	−0.01	0.00	0.00	0.00	0.00
	(2.09)	(1.27)	(1.46)	(−0.10)	(2.32)	(2.41)	(1.62)	(1.37)	(0.48)	(−0.54)	(0.50)	(−1.75)	(1.26)	(0.97)	(0.87)	(1.50)
FCF_AT	−0.00	−0.01	−0.00	0.00	0.00	−0.02	0.01	0.01	−0.00	0.01	−0.01	−0.01	−0.00	−0.00	0.00^{**}	0.00
	(−0.08)	(−0.95)	(−0.75)	(0.25)	(0.66)	(−1.93)	(1.12)	(1.48)	(−0.23)	(1.20)	(−1.14)	(−0.81)	(−0.05)	(−0.39)	(3.72)	(0.42)
$BIG4$	0.02	0.04	-0.25^{*}	0.03	−0.11	−0.08	0.09	0.07	0.13	0.14	-0.39^{**}	0.01	0.03	−0.01	0.01^{*}	−0.00
	(0.13)	(0.30)	(−1.97)	(0.26)	(−0.71)	(−0.38)	(0.31)	(0.53)	(0.50)	(0.91)	(−3.27)	(0.05)	(0.74)	(−1.73)	(2.90)	(−0.73)
$Constant$	−1.47	-3.73^{***}	-2.64^{*}	-3.90^{*}	-2.59^{*}	-6.38^{***}	−1.72	−2.99	−1.66	−2.38	-4.10^{***}	-6.09^{*}	0.22	−0.04	−0.04	0.00
	(−1.27)	(−3.61)	(−2.51)	(−2.33)	(−2.04)	(−3.77)	(−1.39)	(−1.78)	(−0.77)	(−1.82)	(−3.54)	(−2.48)	(0.62)	(−2.07)	(−1.12)	(0.06)
N	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517	4,873	4,803	4,933	8,517
Pseudo/Adj. R^2	0.01	0.02	0.02	0.01	0.03	0.03	0.04	0.02	0.03	0.03	0.04	0.02	0.03	0.02	0.03	0.01

Table 5.59: Determinants of stocks' exposure to the ABX innovations (fixed effects models)

This table reports the findings of the fixed effects panel regressions using β_{ABX} as the dependent variable. Panels A - E report the findings of the ABX AAA, AA, A, BBB and BBB- indices respectively. I report the coefficients, the adjusted R^2, and the t-statistics based on robust standard errors clustered by PERMNO. Superscripts ***, ** and * denote statistical significance at the 0.1%, 1% and 5% level respectively. All five sets of panel regressions have rejected significantly the Hausman test and thus the parameters estimated based on the fixed effects model are consistent (firm fixed effects).

Panel A: ABX AAA

Model	(1)	(2)	(3)	(4)
RET_t	−0.00*			−0.01*
	(−1.96)			(−2.00)
β_{MKT}	0.21***			0.21***
	(4.89)			(4.13)
Stdev	−0.07**			−0.14***
	(−2.67)			(−3.97)
IVol	0.04			0.14**
	(1.27)			(3.20)
LN_MCAP		0.15***		0.15***
		(5.09)		(3.75)
LN_BE/ME		0.02		0.03
		(0.57)		(0.80)
LN_TURN		−0.00		−0.01
		(−0.09)		(−0.22)
Sales_growth			0.00	−0.00
			(0.15)	(−0.74)
Earn_yield			0.00**	0.00
			(2.81)	(0.23)
EBITDA_growth			−0.00	−0.00
			(−0.66)	(−0.55)
Div_yield			−0.01	−0.00
			(−1.71)	(−0.01)
FCF_AT			−0.00	−0.00
			(−0.92)	(−1.51)
CAPX_AT			−0.00	−0.00
			(−0.57)	(−0.46)
Leverage			0.00	0.00
			(1.11)	(1.72)
BIG4			0.20*	0.17
			(2.08)	(1.74)
Constant	−0.01	−1.83***	−0.13	−2.18***
	(−0.16)	(−5.01)	(−1.21)	(−3.93)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.002	0.001	0.001	0.004

Panel B: ABX AA

Model	(1)	(2)	(3)	(4)
RET_t	−0.00			−0.01***
	(−1.19)			(−6.02)
β_{MKT}	0.09***			0.08***
	(4.77)			(3.73)
Stdev	0.10***			0.06***
	(8.35)			(3.75)
IVol	−0.09***			−0.03
	(−6.05)			(−1.67)
LN_MCAP		0.03*		0.12***
		(2.54)		(6.32)
LN_BE/ME		0.12***		0.15***
		(8.37)		(7.88)
LN_TURN		0.04**		−0.02
		(2.70)		(−1.50)
Sales_growth			−0.00	−0.00
			(−0.82)	(−0.79)
Earn_yield			−0.00*	−0.00
			(−2.14)	(−1.74)
EBITDA_growth			−0.00*	−0.00
			(−2.06)	(−1.88)
Div_yield			0.01	0.00
			(1.72)	(0.62)
FCF_AT			0.00**	0.00
			(2.80)	(1.96)
CAPX_AT			−0.00	−0.00
			(−1.12)	(−0.70)
Leverage			0.00	0.00*
			(0.35)	(2.10)
BIG4			−0.02	−0.02
			(−0.48)	(−0.32)
Constant	−0.23***	−0.45**	−0.04	−1.71***
	(−12.77)	(−2.63)	(−0.80)	(−6.75)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.008	0.004	0.001	0.011

Panel C: ABX A

Model	(1)	(2)	(3)	(4)
RET_t	0.00			0.00
	(0.12)			(0.04)
β_{MKT}	−0.09***			−0.10***
	(−5.50)			(−4.99)
Stdev	0.05***			0.02
	(4.25)			(1.79)
IVol	−0.04***			−0.03
	(−3.45)			(−1.62)
LN_MCAP		−0.03*		−0.01
		(−2.31)		(−0.66)
LN_BE/ME		0.00		0.01
		(0.17)		(0.35)
LN_TURN		0.06***		0.05***
		(5.07)		(3.70)
Sales_growth			0.00***	0.00***
			(3.49)	(3.50)
Earn_yield			0.00	0.00
			(0.01)	(0.83)
EBITDA_growth			−0.00	−0.00
			(−0.38)	(−0.71)
Div_yield			0.01***	0.01**
			(3.54)	(2.61)
FCF_AT			−0.00	−0.00
			(−0.40)	(−0.52)
CAPX_AT			−0.00	−0.00
			(−0.32)	(−0.78)
Leverage			0.00	0.00
			(1.91)	(1.71)
BIG4			−0.04	−0.04
			(−1.03)	(−1.00)
Constant	0.03*	0.32*	−0.06	0.16
	(2.16)	(2.20)	(−1.39)	(0.72)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.002	0.002	0.001	0.004

Panel D: ABX BBB

Model	(1)	(2)	(3)	(4)
RET_t	−0.00***			−0.00***
	(−4.26)			(−4.41)
β_{MKT}	0.00			−0.01
	(0.56)			(−0.72)
Stdev	0.01**			0.01
	(2.91)			(1.17)
IVol	−0.01*			−0.01
	(−2.20)			(−0.93)
LN_MCAP		−0.01		0.00
		(−1.68)		(0.15)
LN_BE/ME		0.00		0.01
		(0.22)		(1.21)
LN_TURN		0.02***		0.02**
		(3.81)		(2.92)
Sales_growth			−0.00	−0.00
			(−0.66)	(−0.72)
Earn_yield			0.00	0.00
			(0.97)	(0.81)
EBITDA_growth			−0.00**	−0.00***
			(−2.85)	(−3.53)
Div_yield			0.00**	0.00*
			(2.63)	(1.97)
FCF_AT			−0.00	0.00
			(−0.48)	(0.01)
CAPX_AT			−0.00	−0.00
			(−0.87)	(−0.59)
Leverage			0.00	0.00
			(1.71)	(1.71)
BIG4			0.01	0.02
			(0.71)	(1.20)
Constant	−0.02**	0.09	−0.03	−0.04
	(−3.20)	(1.52)	(−1.78)	(−0.48)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.001	0.001	0.001	0.003

Panel E: ABX BBB-

Model	(1)	(2)	(3)	(4)
RET_t	−0.00***			−0.00***
	(−5.54)			(−5.60)
β_{MKT}	−0.01			−0.01
	(−0.79)			(−1.73)
Stdev	0.01***			0.01
	(3.47)			(1.30)
IVol	−0.01**			−0.00
	(−2.98)			(−0.65)
LN_MCAP		0.01		0.02**
		(1.43)		(2.87)
LN_BE/ME		0.01*		0.02**
		(2.41)		(3.25)
LN_TURN		0.01**		0.01
		(3.03)		(1.42)
Sales_growth			−0.00	−0.00
			(−1.38)	(−1.41)
Earn_yield			0.00	−0.00
			(0.08)	(−0.12)
EBITDA_growth			−0.00	−0.00
			(−1.24)	(−1.57)
Div_yield			0.00	0.00
			(0.44)	(0.34)
FCF_AT			0.00	0.00
			(1.33)	(1.29)
CAPX_AT			−0.00	−0.00
			(−1.26)	(−1.14)
Leverage			0.00	0.00
			(0.60)	(1.71)
BIG4			−0.00	−0.00
			(−0.22)	(−0.11)
Constant	−0.02**	−0.09	−0.01	−0.23**
	(−2.69)	(−1.61)	(−0.60)	(−2.84)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.002	0.001	0.000	0.003

Table 5.60: Determinants of stocks' exposure to the ABX innovations (firm and time fixed effects)

This table reports the findings of the fixed effects panel regressions using β_{ABX} as the dependent variable. Panels A - E report the findings of the ABX AAA, AA, A, BBB and BBB- indices respectively. I report the coefficients, adjusted R^2, and the t-statistics based on robust standard errors clustered by PERMNO. Superscripts ***, ** and * denote statistical significance at the 0.1%, 1% and 5% level respectively. All five sets of panel regressions have rejected significantly the Hausman test and thus the parameters estimated based on the fixed effects model are consistent. Time fixed effects are accounted for in the following panel regressions by including year dummy variables.

Panel A: ABX AAA				
Model	(1)	(2)	(3)	(4)
RET_t	−0.01*			−0.01***
	(−2.43)			(−3.80)
β_{MKT}	0.19***			0.18***
	(4.21)			(3.47)
Stdev	0.02			−0.04
	(0.52)			(−0.82)
IVol	−0.04			0.04
	(−1.03)			(0.93)
LN_MCAP		0.14***		0.19***
		(3.98)		(4.59)
LN_BE/ME		0.06		0.12**
		(1.60)		(2.71)
LN_TURN		0.02		−0.00
		(0.68)		(−0.06)
Sales_growth			−0.00	−0.00
			(−0.74)	(−1.46)
Earn_yield			0.00*	0.00
			(2.09)	(0.44)
EBITDA_growth			−0.00	−0.00
			(−0.60)	(−0.50)
Div_yield			−0.00	−0.00
			(−0.53)	(−0.03)
FCF_AT			−0.00	−0.00
			(−0.65)	(−1.38)
CAPX_AT			−0.00	−0.01
			(−0.62)	(−0.76)
Leverage			0.00	0.00*
			(1.67)	(2.56)
BIG4			0.14	0.12
			(1.48)	(1.21)
Constant	0.05	−1.54***	0.04	−2.54***
	(0.87)	(−3.48)	(0.36)	(−4.47)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.003	0.003	0.004	0.007

Panel B: ABX AA				
Model	(1)	(2)	(3)	(4)
RET_t	−0.00			−0.00*
	(−1.57)			(−2.57)
β_{MKT}	0.09***			0.10***
	(4.74)			(4.30)
Stdev	−0.01			−0.05*
	(−0.37)			(−2.43)
IVol	−0.01			0.05*
	(−0.42)			(2.41)
LN_MCAP		0.07***		0.08***
		(4.23)		(4.57)
LN_BE/ME		0.05**		0.06**
		(3.06)		(3.13)
LN_TURN		−0.02		−0.03*
		(−1.28)		(−2.32)
Sales_growth			0.00*	0.00
			(2.25)	(1.18)
Earn_yield			−0.00	−0.00*
			(−0.59)	(−2.31)
EBITDA_growth			−0.00*	−0.00*
			(−2.09)	(−2.02)
Div_yield			−0.00	−0.00
			(−0.79)	(−0.64)
FCF_AT			0.00*	0.00
			(2.00)	(1.52)
CAPX_AT			−0.00	−0.00
			(−0.89)	(−1.06)
Leverage			−0.00	0.00
			(−1.15)	(0.24)
BIG4			0.06	0.05
			(1.32)	(1.10)
Constant	−0.44***	−1.16***	−0.33***	−1.49***
	(−17.04)	(−5.84)	(−6.07)	(−5.85)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.052	0.039	0.036	0.038

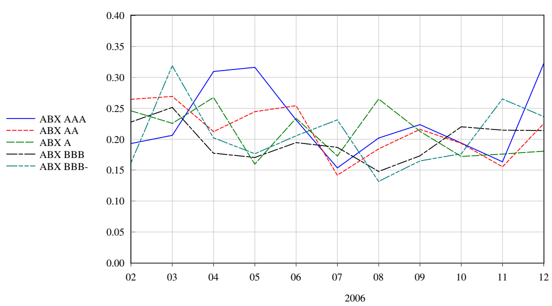
Panel C: ABX A				
Model	(1)	(2)	(3)	(4)
RET_t	−0.00			−0.00
	(−1.72)			(−0.28)
β_{MKT}	−0.11***			−0.10***
	(−6.29)			(−5.11)
Stdev	0.09***			0.04*
	(7.01)			(2.47)
IVol	−0.08***			−0.04*
	(−5.84)			(−2.30)
LN_MCAP		−0.02		−0.01
		(−1.83)		(−0.76)
LN_BE/ME		−0.00		0.00
		(−0.30)		(0.15)
LN_TURN		0.05***		0.04**
		(4.42)		(3.25)
Sales_growth			0.00***	0.00***
			(3.50)	(3.54)
Earn_yield			0.00	0.00
			(0.17)	(1.00)
EBITDA_growth			−0.00	−0.00
			(−0.35)	(−0.65)
Div_yield			0.01**	0.01*
			(3.15)	(2.51)
FCF_AT			−0.00	−0.00
			(−0.45)	(−0.51)
CAPX_AT			−0.00	−0.00
			(−0.48)	(−0.88)
Leverage			0.00	0.00
			(1.82)	(1.63)
BIG4			−0.03	−0.03
			(−0.88)	(−0.91)
Constant	0.02	0.26	−0.08	0.16
	(0.76)	(1.47)	(−1.75)	(0.71)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.003	0.003	0.002	0.004

Panel D: ABX BBB				
Model	(1)	(2)	(3)	(4)
RET_t	−0.00***			−0.00***
	(−6.01)			(−4.50)
β_{MKT}	−0.01			−0.01
	(−0.69)			(−1.33)
Stdev	0.02***			0.02*
	(4.75)			(2.21)
IVol	−0.02***			−0.01
	(−3.83)			(−1.82)
LN_MCAP		−0.01		−0.00
		(−1.26)		(−0.02)
LN_BE/ME		−0.01		0.00
		(−0.92)		(0.35)
LN_TURN		0.01**		0.01*
		(2.62)		(2.11)
Sales_growth			−0.00	−0.00
			(−0.47)	(−0.34)
Earn_yield			0.00	0.00
			(0.99)	(1.09)
EBITDA_growth			−0.00**	−0.00***
			(−2.80)	(−3.54)
Div_yield			0.00*	0.00
			(2.27)	(1.61)
FCF_AT			−0.00	−0.00
			(−0.50)	(−0.01)
CAPX_AT			−0.00	−0.00
			(−1.04)	(−0.77)
Leverage			0.00	0.00
			(1.53)	(1.38)
BIG4			0.02	0.02
			(1.11)	(1.51)
Constant	−0.04***	0.05	−0.05**	−0.05
	(−4.62)	(0.64)	(−3.01)	(−0.55)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.005	0.005	0.004	0.006

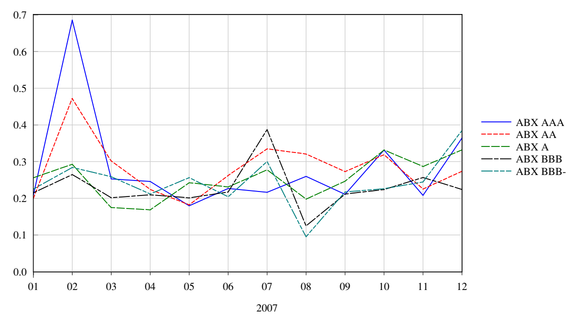
Panel E: ABX BBB-				
Model	(1)	(2)	(3)	(4)
RET_t	−0.00***			−0.00***
	(−6.40)			(−5.19)
β_{MKT}	−0.02*			−0.02*
	(−2.37)			(−2.55)
Stdev	0.03***			0.02***
	(7.00)			(3.47)
IVol	−0.03***			−0.02*
	(−5.56)			(−2.24)
LN_MCAP		0.01		0.02*
		(0.93)		(2.40)
LN_BE/ME		0.00		0.01
		(0.70)		(1.89)
LN_TURN		0.01*		0.00
		(1.99)		(0.29)
Sales_growth			−0.00	−0.00
			(−0.57)	(−0.75)
Earn_yield			−0.00	0.00
			(−0.24)	(0.29)
EBITDA_growth			−0.00	−0.00
			(−1.04)	(−1.50)
Div_yield			0.00	0.00
			(0.80)	(0.39)
FCF_AT			0.00	0.00
			(1.10)	(1.25)
CAPX_AT			−0.00	−0.00
			(−0.97)	(−1.05)
Leverage			0.00	0.00
			(0.43)	(1.29)
BIG4			0.00	0.00
			(0.16)	(0.14)
Constant	−0.04***	−0.10	−0.03*	−0.23**
	(−5.84)	(−1.51)	(−2.15)	(−2.72)
N	35,846	26,890	26,884	25,304
Adj. R^2	0.009	0.005	0.003	0.006

Figure 5-5: The monthly proportion of individual stocks with significant ABX factor loadings - Model 2

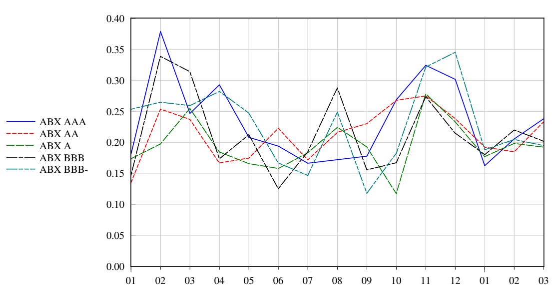
The following figures plot the monthly proportion of individual stocks with significant F-statistics at the 5% significance level (null hypothesis: $H_0 : \gamma_{1,t} = \gamma_{2,t} = \gamma_{3,t} = 0$) in the augmented market model of Equation 5.23 (Model 2 using orthogonalised ABX returns) to the total number of individual stocks in my sample, over the period March 2006 to December 2011 (omitted observations between April - August 2009), grouped by crisis subperiods as defined in Section 2.5. The augmented market model is estimated on the last trading day of each month using all available trading day observations to obtain monthly estimates of the ABX factor loading. Five sets of findings are presented corresponding to the five ABX indices.



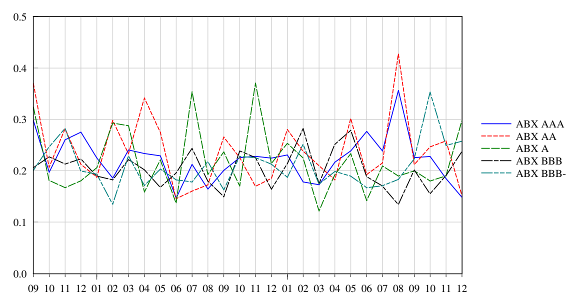
(a) Pre-crisis



(b) Subprime crisis



(c) Global crisis



(d) Post-crisis

Figure 5-6: The spreads of the US Moody's Baa corporate bond yield and the ABCP yield (one-month) (daily)

This figure plots the daily spreads of the US Moody's BAA corporate bond yields and ABCP (one-month) yields between January 2007 and March 2009 (covers both subprime and global crisis subperiods). Both spreads are computed by subtracting the 4-week Treasury bills yields.

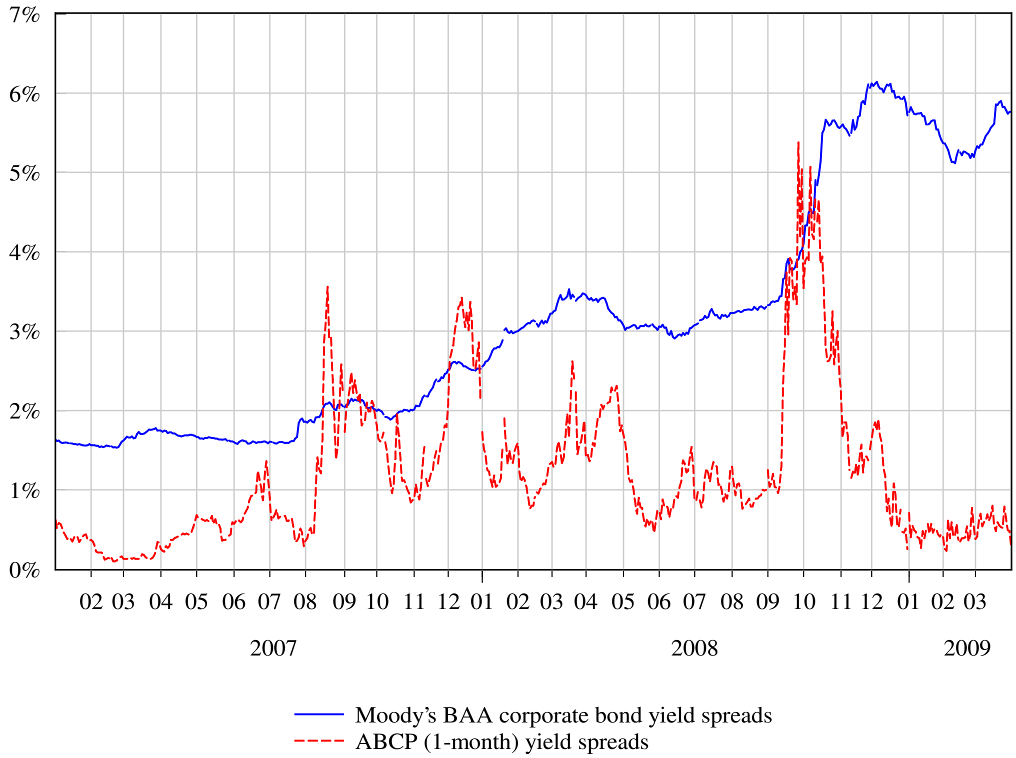
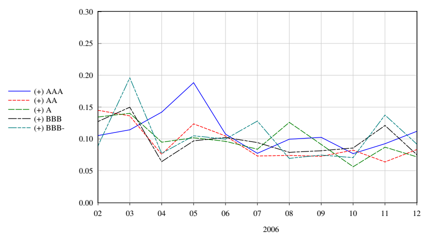
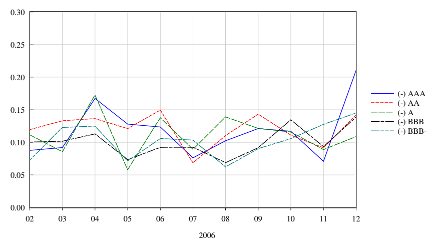


Figure 5-7: The monthly proportion of individual stocks with significant ABX factor loadings - Model 2 and sorted by signs of ABX factor loadings

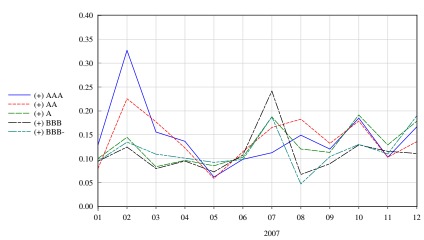
The following figures plot the monthly proportion of individual stocks with significant F-statistics ($H_0 : \gamma_{1,t} = \gamma_{2,t} = \gamma_{3,t} = 0$) in the augmented market model of Equation 5.23 (Model 2 using orthogonalised ABX innovations) to the total number of individual stocks in my sample, over the period March 2006 to December 2011 (omitted observations between April and August 2009), grouped by crisis phases as defined in Section 2.5. The augmented market model is estimated on the last trading day of each month using all available trading day observations to obtain monthly estimates of the ABX factor loading. Five sets of findings are presented corresponding to the five ABX indices. The stocks are also sorted by the signs of the sums of the ABX factor loadings to reflect the direction of exposure to the ABX innovations.



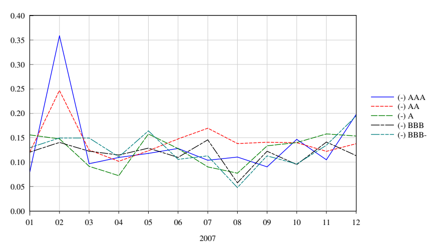
(a) Pre-crisis (+)



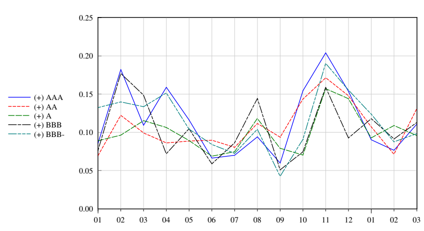
(b) Pre-crisis (-)



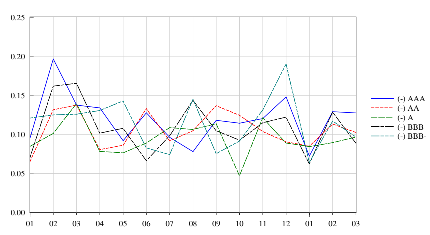
(c) Subprime crisis (+)



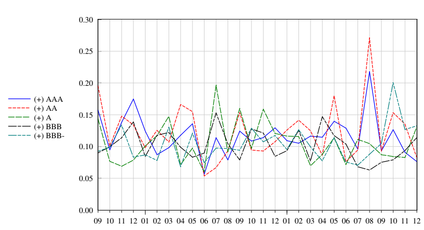
(d) Subprime crisis (-)



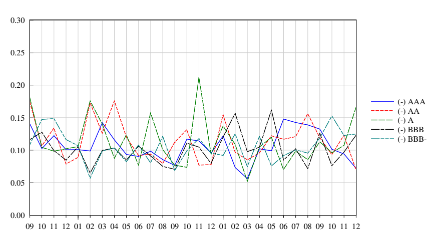
(e) Global crisis (+)



(f) Global crisis (-)



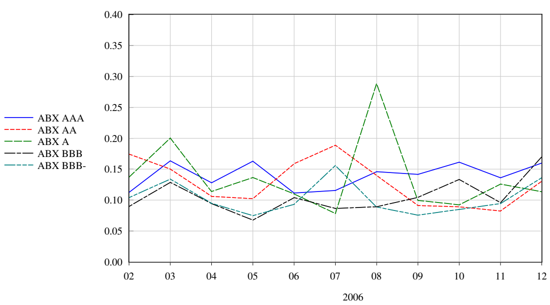
(g) Post-crisis (+)



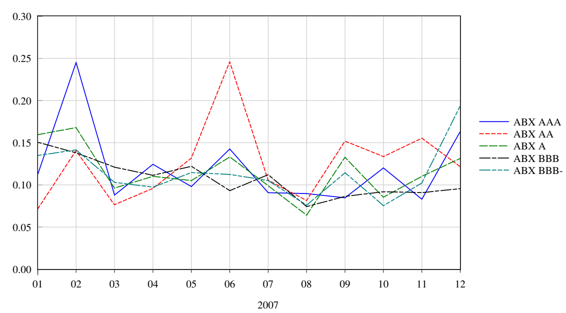
(h) Post-crisis (-)

Figure 5-8: The monthly proportion of individual stocks with significant ABX factor loadings - Model 3

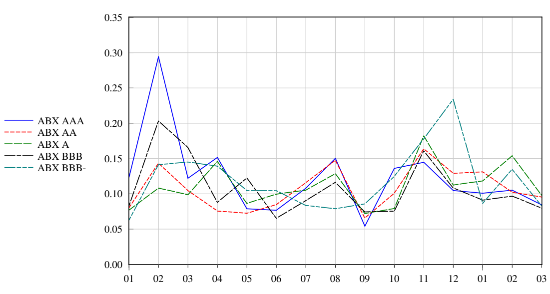
The following figures plot the monthly proportion of individual stocks with significant t-statistics ($H_0 : \beta_{ABX} = 0$) in the augmented FF-4 model of Equation 5.24 (Model 3 using orthogonalised ABX innovations) to the total number of individual stocks in my sample, over the period March 2006 to December 2011 (omitted observations between April and August 2009), grouped by crisis subperiods as defined in Section 2.5. The augmented FF-4 model is estimated on the last trading day of each month using all available trading day observations to obtain monthly estimates of the ABX factor loadings. Five sets of findings are presented corresponding to the five ABX indices.



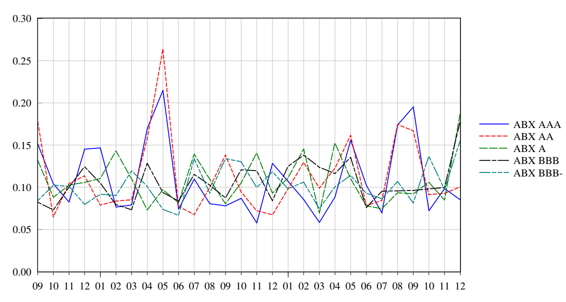
(a) Pre-crisis



(b) Subprime crisis



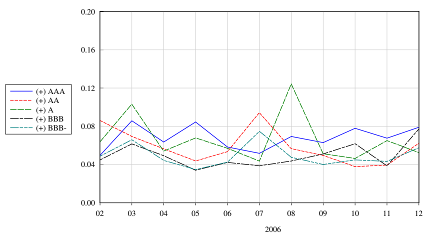
(c) Global crisis



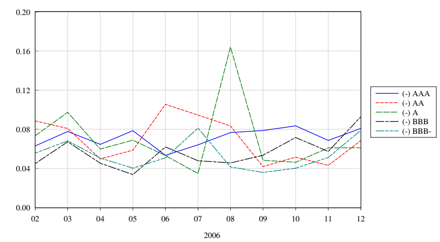
(d) Post-crisis

Figure 5-9: The monthly proportion of individual stocks with significant ABX factor loadings - Model 3 and sorted by signs of ABX factor loadings

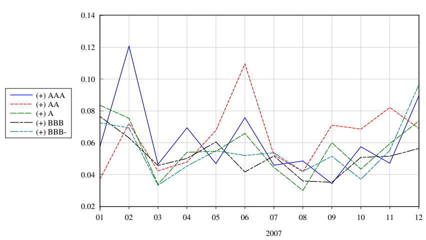
The following figures plot the monthly proportion of individual stocks with significant t-statistics ($H_0 : \beta_{ABX} = 0$) in the augmented FF-4 model of Equation 5.24 (Model 3 using orthogonalised ABX innovations) to the total number of individual stocks in my sample, over the period March 2006 to December 2011 (omitted observations between April and August 2009), grouped by crisis subperiods as defined in Section 2.5. The augmented FF-4 model is estimated on the last trading day of each month using all available trading day observations to obtain monthly estimates of the ABX factor loadings. Five sets of findings are presented corresponding to the five ABX indices. The stocks are also sorted by the signs of the sums of the ABX factor loadings to reflect the direction of exposure to the ABX innovations.



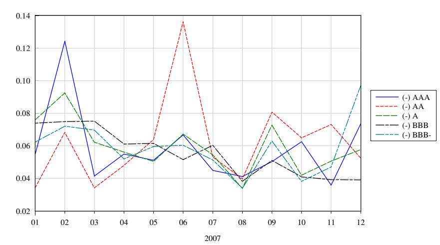
(a) Pre-crisis (+)



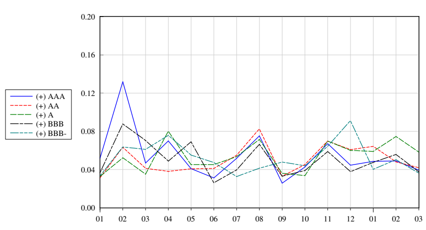
(b) Pre-crisis (-)



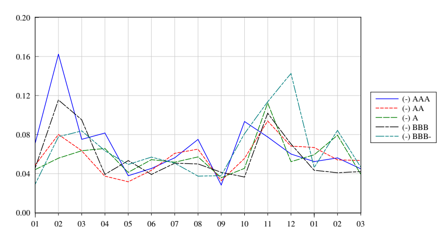
(c) Subprime crisis (+)



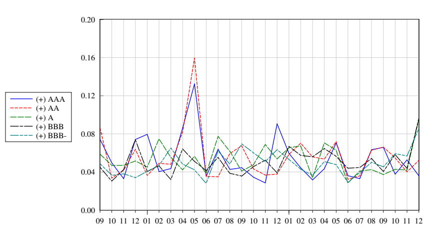
(d) Subprime crisis (-)



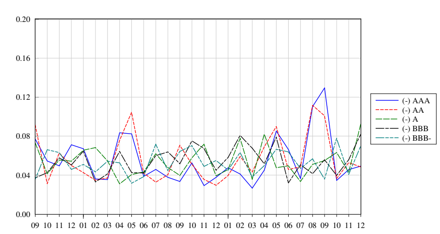
(e) Global crisis (+)



(f) Global crisis (-)



(g) Post-crisis (+)



(h) Post-crisis (-)

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Chapter 6

The Determinants of Bank Equity Risks

6.1 Introduction

In the US banking sector, anecdotal evidence shows that bank risk taking is associated with managerial shareholdings (Demsetz et al., 1997; Anderson and Fraser, 2000), the presence of capital adequacy requirements (Konishi and Yasuda, 2004), board structure and CEO power (Pathan, 2009), and franchise value (Keeley, 1990; Demsetz et al., 1997; Anderson and Fraser, 2000). While the majority of bank risk studies are motivated from a corporate governance perspective, given the relative importance of firms' fundamental characteristics in explaining equity risk[53], it is surprising that the role of fundamental variables in explaining bank risk has not yet been fully explored.[54] Given the profound changes to the US banking system and the growing importance of securitisation to banks' risk management over the past decade, the US bank risk literature requires some updating.

[53]Evidence of cross-sectional and time series relations between return volatilities and firms' characteristics has been documented; for example, return on equity (Wei and Zhang, 2006), earnings growth, institutional ownership (Xu and Makiel, 2003), and dividend yield (Pástor and Veronesi, 2003).

[54]Stiroh (2006) finds evidence that the US BHCs' operating choice and non-interest generating activities affect bank equity risks over the 1997 to 2004 period. The author (p. 245) makes it clear that the objective of his investigation is to find out 'how differences in ex ante operating choices, captured by cross-sectional differences in balance sheet and income statements, are linked to the volatility of future returns'. The objective of this study differs in two major ways. First, I study the within-bank relation between the banks' fundamental characteristics and the bank equity risks (i.e. the within-effects). Second, this chapter focuses on the changes in the impact of the fundamental characteristics on bank risks during the recent crisis. The implications in this study are mainly offered to shareholders and bondholders in the context of investment and risk management as well as bank regulators in relation to banks' exposure to funding illiquidity risks.

The recent 2007 to 2009 financial crisis highlights the tragic consequences of banks' excessive risk taking and brings to light the banks' vulnerability to systematic funding illiquidity shocks (Gorton, 2009). The understanding of the fundamental sources of bank equity risks during the recent crisis offers important policy implications to bank regulators in relation to the effectiveness of the existing tools in monitoring and regulating banks' risk, and to a range of market participants that include shareholders, bondholders, borrowers, etc. Following prior literature (see, for example, Anderson and Fraser, 2000; Stiroh, 2006; Haq and Heaney, 2012), this study utilises market-based equity risk and unravels the fundamental sources of bank risks. Specifically, I investigate the impact of bank opacity, profitability, loan portfolio asset quality and capital adequacy on various components of bank risks (market, interest rate, crisis-related, funding illiquidity, market wide default and idiosyncratic risks) and focus on their interactions during the crisis.

In the US 'shadow' banking system there is a maturity mismatch feature in that banks issue short-term ABCP to finance long-term structured finance securities via off-balance sheet conduits (see, Eichengreen, 2008; Frank et al., 2008; Brunnermeier, 2009; Acharya et al., 2013). During the recent crisis, the banks reluctantly provided contingent liquidity to the conduits via their credit line facilities and were susceptible to considerable funding illiquidity risks. I consider banks' exposure to funding illiquidity risks as a source of bank risks in my variance decomposition and study its determinants. Improved understanding of the fundamental sources of banks' funding illiquidity risks is of utmost importance to regulators in measuring banks' exposure to systemic risks and guiding the development of effective regulatory risk measurement and management tools.

As pointed out by a number of researchers (see, for example, Benmelech and Dlugosz, 2009; Brunnermeier, 2009; Gorton, 2009; Mählmann, 2013), securitised and structured finance products (e.g., the CDOs and subprime RMBS) are responsible for the intensification of the recent crisis. As downgrades of these structured securities spiked in 2007 (Benmelech and Dlugosz, 2009), the structured finance securities' prices plunged (for losses on RMBS, see, Merrill et al., 2012). The structured finance market is shown empirically to be the origin of contagion and thus represents a source of considerable risk during the crisis (Fender and Scheicher, 2009; Longstaff, 2010; see Chapter 5). Banks were essentially subject to the spillovers of shocks that constitute a formidable source of bank risk during the crisis. To this end, I depart from the prior literature and consider a crisis-related component of bank equity risks that reflects the degree of BHCs' exposure to the troubled structured finance market.[55] The evidence in this study shows that banking firms with weaker fundamentals were more vulnerable to contagion during the crisis.

An important fundamental variable I consider is the banks' asset composition. It has been

[55]The structured finance market is measured by the ABX AAA index, a benchmark index which tracks the performance of a static portfolio of subprime RMBS).

widely acknowledged that banks are more opaque than non-banks given their unique role of delegated monitoring. The main source of opacity pertains to investors' informational asymmetry in evaluating the credit quality of banks' loan assets which are not fully disclosed. Asset composition is a major determinant of bank opacity because banks' investment in opaque assets is relatively harder for analysts to value, resulting in a larger degree of disagreement in valuation amongst credit rating agencies (Morgan, 2002; Iannotta, 2006, Flannery et al., 2013). Evidence shows that investors insufficiently discount risks in banks' opaque investments, which are then rewarded with higher market valuation leading to higher systematic risk and lower idiosyncratic risk (Jones et al., 2013).[56] To my knowledge, the role of banks' opacity in explaining bank risks has not been fully examined in the literature.[57] To fill this gap, I test whether banks' exposure to opaque assets contributes positively to bank equity risks.

This chapter makes several important contributions to the existing bank risk literature. First of all, this study seeks to identify the fundamental sources of bank risks by investigating the determinants of the market-based bank equity risks using a diverse set of bank-specific fundamental characteristics that include banks' profitability (earnings and non-interest income), loan portfolio credit quality (non-performing loans)[58], Tier 1 capital ratios, loan-to-deposit ratios and various control variables. This chapter establishes empirically the link between banks' fundamental and equity risks and offers insight to investors in the context of asset valuation by highlighting the substantive relevance of fundamental analysis in evaluating bank stocks' risk and return relationship. Second, I inquire whether the recent financial crisis has had any effects on the impact of banks' fundamental variables on bank equity risks; that is, whether the relevance of some banks' fundamental characteristics have become stronger. In doing so, I provide useful implications to market users in the context of investment management during a crisis period characterised by increasing macroeconomic risks and risk aversion. Third, specific to the context of the recent crisis, I am the first to consider banks' exposure to the troubled structured finance market and the asset-backed money market (ABCP) as constituents of bank equity risks. The identification of the fundamental determinants of banks' exposure to the shocks originated from these markets has important policy implications in relation to the quantification and the regulation of banks' systemic risks. Fourth, to my knowledge, I am the first to examine directly the relation between bank opacity, as measured by the banks' asset composition, and equity risks in the US banking sector and to examine its

[56] Jones et al. (2013) argue that bank opacity hinders the effectiveness of market discipline to price risks and translates into higher risk of systemic failure.

[57] Stiroh (2006) finds evidence that banks' lending activities determine banks risks. However, the author does not explicitly test for the effects of asset opaqueness on bank risks.

[58] Non-performing loans to total assets have been studied by Stiroh (2006) as control variables for bank total risks. Haq and Heaney (2012) consider banks' credit risk, measured by the loan-loss provision to total asset and non-performing loans to total assets but do not consider non-performing loans as determinants of bank risks.

interaction during the crisis. Lastly, this study contributes to the literature on bank liquidity risk management by allowing us to test explicitly whether banks' buffer of Tier 1 capital reduces banks' exposure to market wide funding illiquidity shocks. The evidence in this study justifies the urge for higher regulatory capital requirements in limiting banks' exposure to systemic risks.

Using pooled weighted least squares (WLS) regressions with two-way fixed effects, I quantify the impact of bank opacity and banks' fundamental characteristics on the various components of bank equity risks and specifically examine their interactions during the recent crisis. I find evidence that banks' exposure to various trading and loan assets contributes significantly and positively to the banks total and idiosyncratic risks in the non-crisis subsample.[59] However, little evidence of significant differences between the impact of opaque and transparent assets on bank equity risks is documented. Asset opaqueness in general does not contribute to bank equity risks consistent with Jones et al. (2013) in that the riskiness of banks' investment in opaque assets were insufficiently discounted and inaccurately priced. The impact of asset composition on bank risks has in general become negative during the crisis, suggesting some structural changes in the perceived riskiness of banks' lending activities by the market. More importantly, my study documents reasonably strong evidence that the banks' earnings to total assets and Tier 1 capital ratios determine (negative relation) significantly bank equity risks. Banks with higher profitability and larger buffer of Tier 1 capital have significantly lower bank equity risks in both the non-crisis and crisis subsamples. In addition, while the impact of non-performing loans on the bank equity risks was insignificant during the non-crisis subsample, its impact on banks' total, market wide default and idiosyncratic risks increased by threefold. Banks' loan portfolio credit quality has become the most relevant fundamental risk factors to asset valuation when the crisis unfolded. Banks with poorer loan portfolio credit quality suffered higher return volatilities and were more exposed to the heightening market wide default risks, particularly during the crisis. From an investor's perspective, the empirical relation between banks' fundamental and equity risks highlights the important role of banks' fundamental characteristics in evaluating bank stock performance. In addition, this paper documents a strong and negative empirical relation between banks' Tier 1 capital ratios and the degree of banks' exposure to the unexpected shocks from the US structured finance market and the asset-backed money market. The evidence implies that banks' buffer of Tier 1 capital is an effective shield against the contagion-related spillovers of shocks and against the funding illiquidity risks.

This chapter relates closely to a number of papers that examine bank performance during the financial crisis. Fahlenbrach et al. (2012) compare banks' performance during the 1998 and the recent 2007 to 2009 financial crises, and find that banks with higher exposure to illiquid assets and leverage under-performed during the recent crisis. Acharya et al. (2013) study banks' issuance of

[59] Throughout the study, I use the terms residual risks, firm-specific risks and idiosyncratic risks interchangeably.

ABCP and find that banks with higher exposure to ABCP conduits had lower returns. Beltratti and Stulz (2012), based on cross-country evidence, find that large banks' under-performance during the 2007 to 2008 period is related to their reliance on short-term funds and their funding fragility in relation to capital adequacy and deposit. A number of papers present evidence that corporate governance practices played little role in explaining the under-performance of bank stocks, for example: better alignment of CEO incentives with shareholders performed worse (Fahlenbrach and Stulz, 2011), banks with more shareholder-friendly boards under-performed (Beltratti and Stulz, 2012), etc. The evidence in this study supplements the findings of these papers and further reveals that banks' under-performance during the crisis is related to banks' fundamental risks pertaining to profitability, loan portfolio asset quality, funding illiquidity risks and lending activities. The findings in this study also lend support to the fundamentalist view that banks' fundamental performance is crucial in explaining stock performance with profound implications to shareholders and bondholders. From a supervisory perspective, this study shows that one major source of bank equity risk is banks' vulnerability to funding illiquidity shocks, which is fundamentally determined by banking firms' degree of capital adequacy. The evidence in this study provides empirical support to the urge for higher regulatory capital requirement in preventing systemic failure in light of market wide funding illiquidity.

The remainder of this chapter is organised as follows. Section 2 discusses my motivation and explains my hypotheses. Section 3 explains my data and empirical framework. Section 4 reports my empirical results and Section 5 concludes.

6.2 Motivation and hypotheses

6.2.1 Bank opacity

It is commonly acknowledged in the prior literature that banks are more opaque than non-banks (Morgan, 2002). The opacity lies on the notion of informational asymmetry arising in a number of ways. First, asymmetric information arises from the relative difficulty in valuing banking firms' assets when banking firms, as the delegated monitors, have privileged knowledge on loans' credit qualities and do not fully disclose this information. In addition, the banks might understate their losses during worsening financial conditions (Gunther and Moore, 2003) or smooth their earnings (Bhat, 1996; Fonseca and González, 2008). The lack of transparency and the potential problems of moral hazard are the fundamental causes of bank opacity. Second, bank opacity arises from the opaqueness of its trading assets (Jones et al., 2013). Morgan (2002) points out that trading assets are more liquid and may be easier to 'slip' in and out of the financial statements at banks' discretion given the mark-to-market accounting treatment. As a result, the wider scope for banks to manipulate the amount of booked trading assets gives rise to the banks' relative opacity to non-banks. Third, the banks' issuance of opaque securitised financial products (e.g. ABS, collateralised mortgage obligations (CMO) and CDOs) via off-balance sheet conduits increased drastically over the past two decades (Weaver, 2008; Brunnermeier, 2009). Since the structured securities are in general hard-to-value and are nontransparent, their valuation became extremely difficult during the crisis, resulting in considerable uncertainty and opacity amongst banking firms.

Asset composition is a major determinant of bank opacity. On the empirical side, the banks' loans and financial assets are important sources of disagreement amongst bond rating agencies, with split ratings more likely for banks consistent with higher relative opacity (Morgan, 2002; Iannotta, 2006). The underlying argument pertains to the stylised fact that banks' investments in opaque assets are relatively harder for analysts or rating agencies to evaluate. Asset composition may affect bank risks in the context of bank opacity in three ways. First, Jones et al. (2013) show that the banks' investments in opaque assets are related to higher systematic risks and lower idiosyncratic risks over time as a result of inefficient market discipline in pricing risks. I put forward this contention and test explicitly the relation between asset opaqueness and bank risks. Second, some types of bank assets may be more cross-correlated and have a lower degree of diversification than other asset types. For instance, banks' trading assets (e.g. subprime related CDOs), which are shown in hindsight to be highly correlated across securitised tranches as a result of wrong actuarial assumptions (Jaffe, 2008; Weaver, 2008) and over-reliance on rating agencies (Partnoy, 2009). The banks' exposure to these assets may pose a higher risk to individual banks in terms of solvency and contribute to bank equity risks.[60] Third, during the recent crisis, banks with more investments in hard-to-value assets may be prone to receiving rating downgrades and write-offs, and are thus more subject to risks in relation to funding illiquidity and insolvency. While return volatilities are determined by public information (Jones et al., 1994) and the risks embedded in the opaque assets were not fully priced by investors before the crisis (Jones et al., 2013), the investors received wake-up calls and systematically sold from these bank stocks, resulting in tremendous downward price pressure. Bank asset opaqueness may have become increasingly relevant to investors during the crisis as an indicator of risk.

From my discussion above, I advance three hypotheses centering on the notion of bank opacity, measured by asset composition. Hypothesis 1A asserts that banks' asset composition significantly explains the bank risks. Hypothesis 1B alleges that banks' investments in more opaque assets

[60] On the other hand, a competing argument by Flannery et al. (2004) states that bank opacity may not affect return volatilities. The argument states that since the impact of changes in true values of the assets on stock returns are only available publicly on a quarterly basis, the asset price volatilities are low between information arrival dates and that asset price changes only when information reaches the market.

have a stronger positive impact on bank risks than those of the transparent assets. Hypothesis 1C contends that the impact of asset composition on bank risks differs across the non-crisis and crisis subsamples.

6.2.2 Structured finance market failure and banks' funding illiquidity risk

Brunnermeier (2009) points out that the 'shadow' banking system and the process of securitisation have both contributed to the severity of the recent crisis. Within the 'shadow' banking system, banks are incentivised to issue and underwrite excessively complex and opaque structured finance securities using off-balance sheet conduits as means of risk transfer and regulatory arbitrage (Acharya et al., 2013). The off-balance sheet SIVs carry the same maturity mismatch feature as in the traditional banking model and usually rely on the issuance of short-term ABCP to finance the purchases of longer term assets, such as ABS and CDOs (Eichengreen, 2008, and Frank et al., 2008). Since banking firms were liable for the credit lines granted to the off-balance sheet SIVs, they were exposed to considerable funding illiquidity risk as investors were unwilling to roll over the short-term money market instruments during the crisis.[61]

The banking firms' vulnerability to the shocks from the asset-backed money markets and the troubled structured finance market highlights the importance of effective and timely liquidity risk management. Cornett et al. (2011) find empirically that the four main drivers of liquidity risk in modern banks are the changes in banking firms' core deposits, liquid assets, equity capital and exposure to loan commitments. The authors show that it is the core deposits rather than total deposits that stabilise the liquidity supply and that the core deposits and originated loans increased during the time when the market liquidity of bank assets was low. Banking firms' equity capital is of importance to liquidity management since it serves as a buffer that protects depositors from liquidity shocks and helps absorb risk at large banks (Diamond and Rajan, 2000; Berger and Bouwman, 2012). Based on the evidence and theoretical arguments, I argue that banks' equity capital, core deposit and total loans contain important information that reflect the underlying fundamental risks and thus the equity risks. To this end, I include the ratios of total loan to total core deposits to gauge the banks' ability to meet funding demands, the Tier 1 capital ratio as a measure of banks' equity capital in buffering funding illiquidity shocks, and the ratio of total core deposits to total assets as a control variable for the supply of retail deposits. Hypothesis 2A asserts

[61] Acharya et al. (2013) find that the liquidity guarantees on the ABCP were concentrated in the ABCP conduits sponsored by commercial banks. The authors conclude that banks did not securitise for risk transferring but rather for regulatory arbitrage purposes (i.e. to reduce the base of risk weighted assets), especially amongst banks with less capital. The authors find that stock returns were lower for banks with higher exposure to the ABCP conduits during the recent crisis and that losses in conduits were borne by banks. The evidence suggests that banks' exposure to funding illiquidity risks was at least in part priced in the market, lending support to my conjecture.

that banks' funding ability and capital adequacy are related negatively to bank equity risks. To test whether their relevance to explaining bank equity risks might have elevated during the crisis, Hypothesis 2B asserts that their impact on bank equity risks strengthened became more negative during the crisis.

6.2.3 Profitability, loan portfolio credit quality and bank risks

Evidence in support of a negative relation between earnings and return volatilities has been documented in the literature. Wei and Zhang (2006) argue that the firms' return on equity and variances of return on equity are integral parts of their conditional volatilities and find evidence that return on equity explains stock return volatilities in both time-series and cross-sectional dimensions. Likewise, Cooper et al. (2003) examine bank stock returns and document significant return predictability in the quarterly changes of banks' earning per share, leverage, loan loss reserve and non-interest income within an asset pricing framework.

The evidence suggests that banks' profitability and loan portfolio credit quality might have contained important information with regard to banks' operating performance and fundamental risks that impact on bank stock performance and bank equity risks. Hypothesis 3A asserts that banks' profitability, measured by earnings to total assets, contributes negatively to bank risks while Hypothesis 4A contends that banks with better loan portfolio credit quality, measured by the amount of non-performing loans, have lower risks.[62] Hypotheses 3B and 4B assert that the impact of banks' profitability and loan portfolio credit quality on bank risks have increased, respectively, during the crisis.

6.3 Data and empirical approach

My sample consists of all publicly available traded US BHCs, with $500 million or more consolidated assets, that file FR Y-9C forms with the Federal Reserve quarterly over the sample period from 2006Q1 to 2011Q4. All the companies' quarterly consolidated fundamental and financial data are obtained via the Bank Regulatory database in the Wharton Research Data Services (WRDS) Database. The quarterly fundamental data are merged with the market data from the CRSP database[63] by PERMCO and RSSD ID[64] and with the linking table provided by the New York

[62] Stiroh (2006) finds evidence that non-performing loans to total assets is positively related to banks' total risks. Meeker and Gray (1987) show that the amount of non-performing loans are satisfactory measures of bank asset quality.

[63] Similar to Anderson and Fraser (2000), I include stocks with SIC codes: 6021 (National commercial banks), 6022 (State commercial banks), 6029 (Commercial banks, NEC) from CRSP.

[64] PERMCO is the CRSP unique company identifier while RSSD is the unique bank identifier on the Bank Regulatory database (the variable is RSSD9001).

Federal Reserve Bank (FRB)[65]. I screen out those quarterly observations in which there are missing or unmerged data to 227 BHC and 3447 bank-quarters. The total assets are adjusted for inflation using a seasonally-adjusted GDP deflator with a base price level of 2005.

Following Jones et al. (2013), all balance sheet variables are calculated as the quarterly averages of the beginning and ending values of quarter t while the income measures are annualised quarterly amounts. Variable names that start with "LN_" or end with "_A" refer to those variables that are log transformed or normalised by the total assets respectively. To reduce the potential bias due to outliers, all bank variables have been winsorised at the 99^{th} percentile (1% at each tail) at each cross-section. In addition, to ensure that I am capturing genuine causal relations and to lessen potential endogeneity problems, all independent variables in the regressions are lagged by one quarter.

6.3.1 The ABX indices

Evidence of contagion travelling from the US structured finance market to domestic US markets has been documented during the recent crisis (Longstaff, 2010; Chapters 4 and 5). The unexpected shock components of the structured finance market represent a source of crisis-related risk during the subprime crisis (Fender and Scheicher, 2009; Chapter 5). To account for the relative importance of the crisis-specific risks, I consider a bank equity risk component related to the innovations in the ABX index.

Since its index initialisation in 2006, the ABX index family has become an important type of stress barometer for subprime RMBS market conditions (Fender and Scheicher, 2009). The ABX indices, maintained by MARKIT, are equally-weighted and static portfolios that each reference 20 subprime RMBS deals. The indices serve as benchmarks of the structured finance market in which the securities are collateralised by subprime home loans. Five ABX indices, corresponding to the AAA, AA, A, BBB and BBB- credit ratings of the underlying RMBS deals, are maintained.[66] For the purpose of the analysis in this chapter, the ABX index of the ABX.HE.06-1 vintage, which was issued in January 2006 and has the longest historical data, is included for the variance decomposition of bank equity risks. As shown in Fig. 4-1 of Chapter 4, the prices of the five ABX indices of the ABX HE.06-1 vintage all started to fall in early 2007 and declined sharply from mid 2007 till mid 2009. The ABX AAA index outperformed the rest of the ABX indices and was the most resilient after the recent crisis. In addition, the evidence presented in Chapter 5 shows that the ABX AAA innovations were the most relevant in asset pricing compared to the remaining four ABX indices and, hence, I include the ABX AAA index in the decomposition of bank equity risks and study its

[65] The linking table can be accessed via: http://www.newyorkfed.org/research/banking_research/datasets.html
[66] For more details on the ABX indices, please refer to Section 4.3 of Chapter 4.

determinants.

6.3.2 Decomposing bank equity risks

Following the variance decomposition approach in prior literature (see, Anderson and Fraser, 2000; Pathan, 2009; Haq and Heaney, 2012), I decompose bank risks into six components, which are: market, interest rate, the crisis-related (ABX), funding illiquidity (ABCP), default spread and residual risks. I am the first to evaluate the determinants of the banks' crisis-related (ABX) risk and funding illiquidity (ABCP) risk using the banks' fundamental variables, and to investigate whether there is any impact of the recent 2007 to 2009 financial crisis on the explanatory power of fundamental variables on bank equity risks.

To this end, I estimate multifactor models for each BHC using all available daily observations of excess returns in each quarter. In particular, to separate the effects of each factor variable from each other, I apply an orthogonalisation to the model and decompose the six risk components, based on the following empirical approach:

1. Using all daily observations in each quarter, I orthogonalise the factor variables by running the following regressions in order:

$$INT_t = \alpha + \beta R_{MKT,t} + \epsilon_{INT,t} \tag{6.1}$$

$$R_{ABX,t} = \alpha + \beta R_{MKT,t} + \epsilon_{INT,t} + \epsilon_{ABX,t} \tag{6.2}$$

$$ABCP_t = \alpha + \beta R_{MKT,t} + \epsilon_{INT,t} + \epsilon_{ABX,t} + \epsilon_{ABCP,t} \tag{6.3}$$

$$DEF_t = \alpha + \beta R_{MKT,t} + \epsilon_{INT,t} + \epsilon_{ABX,t} + \epsilon_{ABCP,t} + \epsilon_{DEF,t}, \tag{6.4}$$

   where $R_{MKT,t}$ is the daily excess returns of the value-weighted CRSP market index, INT_t is the daily yield of the 3-month Treasury bills, $R_{ABX,t}$ is the daily excess returns of the ABX AAA index, $ABCP_t$ is the daily yield spreads of the one-month ABCP above the one-month Treasury bill rates, and DEF_t is the default spreads between the Moody's AAA and BAA corporate bond yields.

2. I obtain and use the factor variable innovations (ϵ), which represent the unexpected components of the factor variables (i.e. shocks) to estimate the multifactor model for the i^{th} BHC:[67]

$$R_t^i = \alpha^i + \beta^i R_{MKT,t} + \gamma_1^i \epsilon_{INT,t} + \gamma_2^i \epsilon_{ABX,t} + \gamma_3^i \epsilon_{ABCP,t} + \gamma_4^i \epsilon_{DEF,t} + \varepsilon_t^i, \tag{6.5}$$

[67] I screen out those BHCs with less than 30 daily observations in any quarters in estimating Equation 9.3.

where R_t^i is the daily excess returns of the i^{th} BHC.

3. Since the factor variables are orthogonal to each other, the variance decomposition is straightforward:

$$\sigma_i^2 = \beta_i^2 \sigma_{MKT}^2 + \gamma_{i,1}^2 \sigma_{\epsilon_{INT}}^2 + \gamma_{i,2}^2 \sigma_{\epsilon_{ABX}}^2 + \gamma_{i,3}^2 \sigma_{\epsilon_{ABCP}}^2 + \gamma_{i,4}^2 \sigma_{\epsilon_{DEF}}^2 + \sigma_{\varepsilon}^2, \tag{6.6}$$

where the σ_i^2, $\sigma_{\epsilon_{INT}}^2$, $\sigma_{\epsilon_{ABX}}^2$, $\sigma_{\epsilon_{ABCP}}^2$, $\sigma_{\epsilon_{DEF}}^2$ and σ_{ε}^2 refer to the variances[68] of the excess returns of the i^{th} BHC, market index, innovations of the US interest rate, ABX index, ABCP yield spreads, default spreads and the residuals of Equation 9.3, respectively, based on daily observations over each quarter.

4. The risk measures (quarterly equivalent) for *each BHC* and *each quarter* are then computed as:

$$\sigma_i^{TOTAL} = \sigma_i \times \sqrt{T}, \tag{6.7}$$
$$\sigma_i^{MKT} = \sqrt{\beta_i^2 \sigma_{MKT}^2} \times \sqrt{T}, \tag{6.8}$$
$$\sigma_i^{INT} = \sqrt{\gamma_{i,1}^2 \sigma_{\epsilon_{INT}}^2} \times \sqrt{T}, \tag{6.9}$$
$$\sigma_i^{ABX} = \sqrt{\gamma_{i,2}^2 \sigma_{\epsilon_{ABX}}^2} \times \sqrt{T}, \tag{6.10}$$
$$\sigma_i^{ABCP} = \sqrt{\gamma_{i,3}^2 \sigma_{\epsilon_{ABCP}}^2} \times \sqrt{T}, \tag{6.11}$$
$$\sigma_i^{DEF} = \sqrt{\gamma_{i,4}^2 \sigma_{\epsilon_{DEF}}^2} \times \sqrt{T}, \tag{6.12}$$
$$\sigma_i^{RESID} = \sigma_{\varepsilon_i} \times \sqrt{T}, \tag{6.13}$$

where T is the number of daily observations in each quarter. These are, henceforth, referred to as the total ($TOTAL$), market (MKT), interest rate (INT), crisis-related (ABX), ABCP, default spreads (DEF) and residual ($RESID$) risks.

[68] Variance is computed as:

$$\sigma_j^2 = \frac{1}{T}\sum_{t=1}^{T}(r_t^j - \bar{r}^j)^2,$$

where $j \in \{i, \mathrm{MKT}, \mathrm{INT}, \mathrm{ABX}, \mathrm{ABCP}, \mathrm{DEF}\}$, T is the total number of observations in that quarter, r_t^j is the excess returns of j on day t and $\bar{r}^j$ is the simple average daily excess returns of j in that quarter. The error variance of the i^{th} BHC is computed as:

$$\sigma_{\varepsilon_i}^2 = \frac{1}{T}\sum_{t=1}^{T}(\varepsilon_t^i - \bar{\varepsilon}^i)^2,$$

6.3.3 Bank variables

The bank variables used in this study can be grouped in six categories, which are: asset composition, profitability, fundamental risk, funding illiquidity risk, and market and other control variables.

For asset composition, I follow Jones et al. (2013) and compute the proportion of each type of bank assets to total assets, as shown in Panel A of Table 1. $TRADE\_A$ is the amount of trading assets held by the BHCs scaled by total assets. The bank loan variable ($LOAN\_A$) is broken down into three components: the commercial real estate ($COMREAL\_A$), residential real estate ($RESREAL\_A$) and all other loans ($OTHLOAN\_A$). Banks' profitability (Panel B) is measured by earnings scaled by total assets and non-interest income returns (both measures are annualised). As for the banks' fundamental risks (Panel C), loan portfolio asset quality is measured by the ratio of non-performing loans to total assets. For the banks' exposure to funding illiquidity risks, I compute the ratio of total loans to core deposits and also include the Tier 1 capital ratio in my study (Panel D). A higher loan-to-deposit ratio and lower Tier 1 capital ratio mean that the bank has lower ability to fund any unforeseen requirements and is more vulnerable to funding illiquidity risk.

As for my control variables, I include a proxy for interest rate risk exposure, computed as the absolute value of the differences between short-term assets, and short-term liabilities and equity. To measure market liquidity, the turnover ratios are computed by dividing the number of shares traded by the number of outstanding shares in each month, following Chordia et al. (2001). I average the monthly turnover ratios over the three months in each quarter and then log transform the ratios. Other control variables include Keeley's Q[69], the market to book equity ratio, and total core deposits to total assets.

[69]Keeley's Q is computed by summing market value and total liability, and then dividing the sum by book equity value. Keeley (1990) argues that the Q measure is a proxy for franchise value.

6.3.4 Empirical approach

To identify the significant determinants of bank risks, I estimate pooled WLS regressions with two-way fixed effects. The general equation for the pooled WLS regressions is written as follows:

$$
\begin{aligned}
ln(\sigma^{j}_{i,t}) =& \alpha_1(TRADE\_A)_{i,t-1} + \alpha_2(COMREAL\_A)_{i,t-1} + \alpha_3(RESREAL\_A)_{i,t-1} \\
&+ \alpha_4(OTHLOAN\_A)_{i,t-1} + \alpha_5(OTHOPAQ\_A)_{i,t-1} + \alpha_6(TRANSP\_A)_{i,t-1} \\
&+ \alpha_7(LOAN\text{-}TO\text{-}DEPOSIT)_{i,t-1} + \alpha_8(TIER1\_CAP)_{i,t-1} + \alpha_9(EBT\_A)_{i,t-1} \\
&+ \alpha_{10}(NONINT\_A)_{i,t-1} + \alpha_{11}(NPL\_A)_{i,t-1} + \alpha_{12}(INTRISK\_A)_{i,t-1} \\
&+ \alpha_{13}ln(TURN)_{i,t-1} + \alpha_{14}(KEELEY's\ Q)_{i,t-1} + \alpha_{15}(MVBVEQ)_{i,t-1} \\
&+ \alpha_{16}(COREDEP\_A)_{i,t-1} + \sum_{i=1}^{227}\gamma_i(BHC)_i \\
&+ \sum_{t=1}^{24}\psi_t(Quarter)_t + \epsilon_{i,t}, \qquad (6.14)
\end{aligned}
$$

where subscript i denotes the individual BHC ($i = 1, 2, \dots, 227$), t denotes the quarterly period ($t = 1, 2, \dots, 24$) and j denotes the risk measures ($j \in \{TOTAL, MKT, INT, ABX, ABCP, DEF, RESID\}$). α, γ and ψ are the coefficients to be estimated. BHC and $Quarter$ are the firm and time dummy variables, respectively. Practically, I use the pooled least squares dummy variables (LSDV) approach with firm and time fixed effects to estimate the regression and weight the regressions by the log market capitalisation (LN_MCAP_{t-1}). The reported robust standard errors are clustered by both firm and time dimensions following Cameron et al. (2011).[70] I suppress the intercept terms given that the asset composition variables sum up to unity at each cross-section.

To investigate whether the relevance of fundamental variables in explaining bank risks changed during the crisis, I include a crisis dummy variable into the baseline regressions, and interact it with the banks' asset composition and fundamental variables. The crisis window is defined as the 2007Q1 to 2009Q1 period, as explained in Section 2.5. By focusing on the interaction terms of the banks' earnings, non-interest income, non-performing loans, loan-to-deposit ratios and the Tier 1 capital ratios with the crisis dummy variables, this study reveals the effects of the recent crisis on the relations between fundamental variables and equity risks.

[70] My regressions contain independent variables that are likely to correlate both within firms, across time, and simultaneously across both firm and time; hence, two-way clustering of standard errors is helpful in eliminating bias (Thompson, 2011). However, the standard errors are only asymptotically correct. To ensure model consistency, I also consider alternative model specifications in which the WLS regressions are estimated with: i) two-way fixed effects and clustered standard errors by firm, ii) time fixed effects and clustered standard errors by firm, and iii) time fixed effects and clustered standard errors by firm and time. The different clustering and fixed effects options have little effect on my empirical results.

6.4 Empirical results

6.4.1 Summary statistics

Table 6.2 reports the full sample and subsample means and standard deviations of the bank variables. First, the mean (median) of inflation-adjusted total bank assets is \$51.7 (\$1.5) billion. Loan assets represent the largest proportion of bank assets averaging at 69.0% with 14.5% in commercial real estate loans, 17.0% in residential real estate loans and 37.4% in other loans. Other opaque assets, transparent assets and trade assets average at 23.7%, 6.4% and 0.7%, respectively. In comparison to Jones et al.'s (2013) study based on the 2000 to 2006 period, profound changes in the banks' loan asset composition are observed. In particular, banks have noticeably less commercial real estate loan assets on their balance sheets, from 27.6% over 2000 to 2006 (as shown in Table 1 of Jones et al. (2013)) to my full sample mean values of 14.5% over 2006 to 2011, as shown in Panel B. Because of concern over the heightening risk of mortgage default, banks have shifted from commercial real estate loans (pre-crisis level of 34.1% reduced to the crisis level of 19.8%) into other loans.[71] Total loans to assets have increased from the pre-crisis 68.6% to 71.6% during the crisis while trading assets also increased from 0.6% to 0.9%.

For the banks' profitability, the full sample mean (median) earnings to total assets is 0.1% (0.9%) while that of the non-interest income to total assets is 1.2% (1.0%). The subsample statistics show that banks' mean earnings to total assets declined from the pre-crisis level of 1.6% to 0.1% during the crisis and to -0.4% during the post-crisis subsample. In addition, banks' credit risks heightened during and after the crisis as evinced by the increases in banks' non-performing loans to total assets from the pre-crisis level of 0.4% to 1.2% during the crisis, and further to 2.9% in the post-crisis subsample. For the banks' funding ability, the mean loan-to-deposit ratio has increased from 1.42 to 1.50 while the Tier 1 capital ratio has declined from 11.5% to 10.8% in the crisis subsample suggesting that banks on average faced a more constrained funding position and had less equity capital as a buffer to liquidity shocks.

All bank equity risks increased remarkably during the crisis, as shown in the crisis subsample statistics and remained at considerably high levels in the post-crisis subsample. The banks' full sample mean (quarterly equivalent) TOTAL risk is 28.46% while the RESID risk represents the largest risk component with a mean value of 24.26%. The second largest component of equity risk refers to the MKT risk with a mean value of 10.20%. The full sample mean INT, ABX, ABCP, and DEF risks are 2.23%, 2.56%, 2.69% and 2.27%, respectively.

[71] These statistics are consistent with Cornett et al. (2011) who show that during 2008, US commercial banks received more core deposits and extended more commercial and industrial (C&I) loans.

6.4.2 Determinants of bank equity risks - full sample

Table 6.3 reports the results of the baseline regressions of Equation 6.14 when either banks' TOTAL, MKT, INT, ABX, ABCP, DEF or RESID risks are the dependent variables. The model fit of the WLS regressions is satisfactory and in general yield high R^2 values: 81% (TOTAL), 65% (MKT), 31% (INT), 31% (ABX), 32% (ABCP), 30% (DEF) and 81% (RESID). F-tests of joint significance on the right hand side variables for all six risk models are significant at the 1% significance level and are not reported.

Regarding the banks' asset composition, Hypothesis 1A is in general not supported in that banks' exposure to various types of loan assets does not explain bank equity risks. However, the coefficients on all types of loan assets except the transparent assets are significant in explaining the INT risks. Banks with more loan assets on their balance sheets were less impacted by the variations in the 3-month Treasury bill rate, possibly because the banks' ability to extend loans during a period of high macroeconomic risk reflects the banks' fundamental strength and relatively stable sources of liquidity. Hypothesis 1B, which asserts that banks with more opaque assets are more risky, is in general not supported. The F-tests of equality between the estimated parameters of the five types of opaque assets and the transparent assets reveal that the impact of opaque assets on bank equity risks are largely more negative than those of the transparent assets across all risk models except the MKT and DEF risks (despite being insignificant). Banks' investments in relatively more opaque assets translate into lower bank equity risks somewhat consistent with Jones et al. (2013) who conclude that the risks in banks' opaque investments were not priced accurately.

I document compelling evidence that banks' fundamental variables significantly determine the seven bank equity risks, lending strong support to Hypotheses 2A, 3A, and 4A. First, the estimated parameters of the banks' earnings to total assets are statistically significant and negative in the TOTAL, MKT, ABX, ABCP and RESID risk models. A one standard deviation increase in banks' earnings to total assets (3.0%) would reduce (in logarithmic) TOTAL risk by 1.25%, MKT risk by 1.44%, ABX risk by 8.65%, ABCP risk by 5.88%, and RESID risk by 1.29%, approximately.[72] The statistically significant negative relation between the banks' earnings and equity risks is informative from the perspective of an investor and of a bank regulator in that banks with lower profitability were more susceptible to the idiosyncratic shocks from the troubled structured finance market and the asset-backed money market. In addition, the coefficients of banks' non-interest income to total assets are also significant in the TOTAL and RESID risk models so that banks with more income arising from off-balance sheet activities and fee-based income (i.e. more diversified sources of income) have less total and idiosyncratic risks. With regard to banks' credit risks, as

[72]For instance, a one standard deviation increase in earnings to total assets (3.0%) would translate into $[0.030 * \frac{-1.392}{ln(28.458)} = -0.0125]$ 1.25% lower TOTAL risks.

hypothesised in Hypothesis 3A, the coefficients on the non-performing loans to total assets are highly significant and negative in the TOTAL, INT, ABX, DEF and RESID risk models. As for the economic significance, a one standard deviation increase in banks' non-performing loans to total assets (2.1%) would increase TOTAL risk by 4.04%, INT risk by 35.90%, ABX risk by 14.80%, DEF risk by 17.08%, and RESID risk by 5.05%, approximately. The evidence suggests that banks' loan portfolio credit quality significantly determines bank equity risks and are negatively associated with banks' exposure to the variations in the 3-month Treasury bills, ABX AAA innovations and market wide default risk. Likewise, the estimated parameters of the banks' Tier 1 capital ratios are highly significant and negative across all bank equity risks except the MKT risk, lending empirical support for Hypothesis 2A. A one standard deviation increase in banks' Tier 1 capital ratios (3.4%) leads to 3.44% lower TOTAL risk, 26.18% lower INT risk, 13.01% lower ABX risk, 25.41% lower ABCP risk, 22.18% lower DEF risk, and 3.99% lower RESID risk, approximately.

The evidence presented suggests that the market-based bank equity risks are related significantly to banks' sources of fundamental risks pertaining to profitability, loan portfolio credit quality and capital adequacy. I am the first paper to unravel the within-bank relations between banks' fundamental performance and equity risks and show empirically that banks with weaker fundamentals were, to a larger extent, negatively affected by the crisis-related shocks originating from the troubled structured finance market and related to the market wide default risk. The findings provide useful implications to investment management and highlight the relevance of fundamental analysis in evaluating bank stock performance during a period characterised by heightening macroeconomic risk and uncertainty. From a supervisory perspective, my analysis documents the relationship between banks' capital adequacy and equity risks, and (more importantly) demonstrates that banks with higher levels of equity capital are less affected by systematic funding illiquidity shocks as measured by the unexpected tightening in the ABCP spreads. The evidence presented leads us to conclude that proper management in the banks' regulatory capital requirement poses as an effective preventive measure against systemic failure in relation to funding illiquidity.

6.4.3 Crisis interaction effects

Table 6.4 reports the results of my crisis models, with the crisis dummy and interaction variables. The asset composition variables, earnings to total assets, non-interest income to total assets, non-performing loans, loan-to-deposit ratios and the Tier 1 capital ratios are interacted with the crisis dummy variables to allow for shift changes in the slope coefficients. Similarly, I report the results of each crisis model when either the TOTAL, MKT, INT, ABX, ABCP, DEF, and RESID risks are the dependent variables.

First, the coefficients of the crisis dummy variables are significant and positive in the TOTAL, ABCP and RESID risk models. When the crisis dummy variable equals to one, the TOTAL risk would increase (in logarithmic) by 70.84%, the ABCP risk by 625%, and the RESID risk by 91.38%. These findings show that bank equity risks increased significantly during the crisis with the impact on the ABCP risk economically stronger than on the TOTAL and RESID risks. Second, during the non-crisis period, the various types of bank assets contribute significantly and positively to the TOTAL and RESID risks, lending some support to Hypothesis 1A. However, I document no significant differences between the impact of opaque and transparent assets on the bank equity risks, which is in general inconsistent with Hypothesis 1B.[73] Factoring in the crisis interaction effects, the estimated coefficients on the interacted asset composition variables are in general negative across the bank risk models, except for the ABX risk model. That is, banks with more trading and loan assets on their financial statements are perceived by the market as less risky during the crisis and that such a negative relation as documented in the baseline model of Table 6.3 is driven by the crisis subsample. The evidence is perhaps consistent with the theoretical explanation by Gatev and Strahan (2006), who found that when market wide funding liquidity is scarce, deposit inflows lower banks' funding costs and provide banks with a hedge against funding illiquidity shocks. Nonetheless, Hypothesis 1C is not supported.

Third, during the non-crisis subperiod, the impact of banks' earnings and Tier 1 capital ratios on bank equity risks remains qualitatively similar to the baseline regression results, despite the estimated parameters on the Tier 1 capital ratios being noticeably more negative. Note that the coefficient of the earnings to total assets in the MKT risk model is positive and significant at the 5% level. A one standard deviation increase in earnings to total assets (3.0%) increases banks' MKT risk by 3.53% (in logarithmic unit). This evidence is consistent with Jones et al. (2013), who show that investments in opaque assets required higher rates of returns (higher EBT_A) and lead to higher systematic risks over 2000 to 2006. As for banks' credit risks, during the non-crisis subperiod, the coefficients on non-performing loans on the TOTAL, ABX, DEF and RESID risks are insignificant and plunged to almost one-third of those in the baseline models, except in the INT risk model, in which the coefficient of the non-performing loans remained significant at the 1% level. The significant positive relation between banks' non-performing loans and equity risks identified in the baseline model is in a large part driven by the crisis subsample, so that Hypothesis 4A does not hold unconditionally. Remarkably, the coefficients on the crisis interaction terms of the non-performing loans in the TOTAL, DEF, and RESID risk models are significant and positive in that the positive impact of the non-performing loans on the bank equity risks has largely strengthened during the crisis in support of Hypothesis 4B. The percentage changes in bank equity risks given a

[73] I estimate F-tests of coefficient tests between the opaque and transparent assets in a similar fashion as in the baseline models of Table 6.3. The F-statistics are universally insignificant across all bank risk models and, hence, the results are not reported here.

one standard deviation increase in non-performing loans rise from the non-crisis level of 1.21% to the crisis level of 4.35% (%$\triangle$ in impact $\approx$260%) for the TOTAL risk, from 6.36% to 21.52% (%$\triangle$ in impact $\approx$238%) for the DEF risk, and from 1.73% to 5.30% (%$\triangle$ in impact $\approx$206%) for the RESID risk. The evidence reveals a structural change in the market's perception about bank risk in that loan portfolio credit quality has become the most relevant fundamental risk factor among banks during the crisis. That is, banks' fundamental risks in relation to the loan portfolio credit quality are associated with the banks' exposure to the heightening market wide default risk during the crisis. With regard to the crisis interaction effects of the banks' profitability and funding related variables, the interaction terms of the banks' earnings and Tier 1 capital ratios are insignificant and thus fail to support Hypotheses 2B and 3B. Overall, both banks' earnings and Tier 1 capital ratios remain fundamentally important in determining bank equity risks, irrespective of the sample used.

Regarding the control variables, the banks' log turnover ratios explain (with positive coefficients) all bank equity risks, except the DEF risk, which is consistent with the empirical findings in the literature (for a review on the relationship between price changes and trading volume, see Karpoff (1987)). The positive relation between trading activity and the bank equity risks may arise from a possible 'flight-to-safety' phenomenon, as pointed out by Longstaff (2010). Keeley's Q is negative and significant at the 1% level across all bank equity risks except the ABCP risk, indicating that higher franchise value is associated with lower bank risks, which is consistent with prior studies in the existing bank risk literature. Lastly, I find weak evidence that banks' core deposits and market-to-book values explain bank risks.

In summary, I demonstrate that bank equity risks are in a large part attributed to its fundamental characteristics. The banks' increased vulnerability to contagion effects, the heightening risk aversion, and funding illiquidity risks during the recent crisis is attributed by their fundamental risks relating to their loan portfolio credit quality. That is, banks' fundamentals have become more relevant to asset valuation during the crisis, highlighting the importance of fundamental analysis in evaluating the bank stocks' risk and return relationship. Besides, the negative relationship between the Tier 1 capital ratio and the ABX and ABCP risks documented in this study suggest that banks with a larger buffer of Tier 1 capital were less subjected to shocks from the troubled US structured finance market (the ABX innovations) and the market wide funding illiquidity risks over 2006 to 2011. From a regulatory perspective, the findings justify the urge for a higher regulatory capital requirement to limit banks' exposure to systemic risks. Overall, while market discipline facilitates a timely measure of bank risks, banks with stronger fundamentals were perceived to be less risky.

6.5 Conclusions

Following the variance decomposition approach of Anderson and Fraser (2000), this paper decomposes BHCs' equity risks into the market systematic, interest rate, crisis-related, funding illiquidity, default spread and residual risks, and studies their major determinants using a diverse set of banks' fundamental variables that include banks' asset composition, profitability, funding ability and loan portfolio credit quality. I inquire whether banks' investment in opaque assets contributes to their equity risks and find evidence that banks' investment in loan assets contribute positively (negatively) to their risks during the non-crisis (crisis) period. However, I document no significant differences between the impact of opaque and transparent assets on bank equity risks, implying that the higher riskiness in banks' opaque investment was not accurately priced in the market. My main results show that profitability and capital ratios are crucial in explaining banks' total, interest rate, crisis-related, ABCP, default spread and residual risks throughout the whole sample while the impact of non-performing loans on bank risks was relevant only during the crisis. The increase in relevance of loan portfolio credit quality to bank risks is consistent with a 'flight-to-safety' explanation in that banks' amount of non-performing loans were important risk indicators that guided investors' investment and 'flight' decisions.

This paper presents new evidence supporting the fundamentalist view that fundamental variables are important in explaining banks' stock performance and equity risks. In particular, the relevance of banks' fundamental risks relating to loan portfolio credit quality increased significantly during the recent crisis, supplementing the findings in Fahlenbrach et al. (2012) and Acharya et al. (2013). As suggested in the prior literature, changes in unsystematic risks may disrupt the risk-return relationship of investment portfolios (Merton, 1987; Campbell et al., 2001; Goyal and Santa-Clara, 2003; Ang et al., 2006). The identification of the fundamental sources of banks' unsystematic risk components thus provides profound implications to investors in the context of asset pricing and risk management. From a regulatory viewpoint, the negative relation between banks' Tier 1 capital and their equity risks identified in this paper contributes to bank liquidity risk management and justifies the urge for higher regulatory capital requirement. While the experience of the recent crisis and the credit crunch brings to light banks' vulnerability to systematic funding illiquidity, the banks' capital adequacy has to be effectively managed to prevent any future occurrence of systemic bank failures.

Table 6.1: Variables description

This table contains a description of the bank variables used in this study. All accounting variables are computed as averages of beginning and ending quarter values, deflated using a seasonally adjusted GDP deflator with a base year of 2005.

Variables	Description
Panel A: Asset composition variables	
$TRADE\_A$	Trading assets to total assets.
$LOAN\_A$	Total loans to total assets.
$COMREAL\_A$	Commercial real estate loans to total assets.
$RESREAL\_A$	Residential real estate loans to total assets.
$OTHLOAN\_A$	All other loans to total assets.
$OTHOPAQ\_A$	All other opaque assets to total assets. All other opaque assets include available-for-sale or held-to-maturity MBS or ABS that are not guaranteed by a government entity, fixed assets, investments in unconsolidated subsidiaries and other real estate investments.
$TRANSP\_A$	All transparent assets to total assets. All transparent assets include cash, federal funds sold, securities under reselling agreement, guaranteed available-for-sale and held-to-maturity securities.
Note: $TRADE\_A + COMREAL\_A + RESREAL\_A + OTHLOAN\_A + OTHOPAQ\_A + TRANSP\_A = 1$.	
Panel B: Bank profitability	
EBT_A	The earnings before extraordinary items and taxes normalised by total assets (annualised).
$NONINT\_A$	Non-interest income to total assets (annualised).
Panel C: Bank fundamental risks	
NPL_A	Proportion of non-performing loans to total assets as a measure of credit risks.
Panel D: Bank funding variables	
LOAN-TO-DEPOSIT	Ratio of total loans to core deposits.
$TIER1\_CAP$	Tier 1 risk-based capital ratio (BHCK7206).
Panel E: Market variables	
LN_TURN	Log turnover ratios. Turnover ratio is the number of traded shares over the number of outstanding shares in a month. The ratio I use is the log transform of the monthly average of turnover ratios over the three months in each quarter.
Panel F: Other variables	
$INTRISK\_A$	The absolute value of the difference between short-term assets and short-term liabilities and equity, normalised by total asset, as a measure of banks' exposure to interest rate risk.
$KEELEY's\ Q$	The sum of market value of common equity and the book value of liabilities divided by the book value of assets. It is used as a measure of franchise value (see, Anderson and Fraser, 2000).
$MVBVEQ$	The ratio of market value to book value of equity.
$COREDEP\_A$	The amount of core deposit scaled by the total assets.
$MCAP$	The market capitalisation of a bank stock, computed as the product of its price and number of shares outstanding at the end of each quarter.
$BVEQ$	The book value of the total shareholders' equity of a banking firm.

Table 6.2: Summary statistics

This table reports the full sample, pre-crisis, crisis and post-crisis subsample means, medians and standard deviations (Stdev) of the bank variables used in this study. For a detailed description of the variables, please refer to Table 6.1. The crisis subperiod covers the period 2007Q1 to 2009Q1 as described in Section 2.5.

Variable	Full sample			Pre-crisis		Crisis		Post-crisis	
	Mean	Median	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Panel A: Bank equity risks (in %)									
σ^{TOTAL}	28.458	21.811	21.946	11.555	4.158	33.007	25.537	30.950	19.649
σ^{MKT}	10.195	6.523	11.529	4.349	3.647	13.109	15.216	9.971	8.799
σ^{INT}	2.230	1.296	3.000	1.109	1.103	2.478	3.153	2.440	3.246
σ^{ABX}	2.556	1.517	3.403	0.954	0.877	3.059	4.150	2.734	3.129
σ^{ABCP}	2.693	1.495	3.641	1.043	0.948	3.294	4.404	2.810	3.393
σ^{DEF}	2.269	1.447	2.726	0.961	0.852	2.647	3.057	2.440	2.750
σ^{RESID}	24.261	17.540	20.135	9.868	3.861	27.589	22.325	26.824	19.540
Panel B: Asset composition									
$TRADE\_A$	0.007	0.000	0.027	0.006	0.027	0.009	0.034	0.005	0.019
$LOAN\_A$	0.690	0.708	0.128	0.686	0.133	0.716	0.129	0.671	0.122
$COMREAL\_A$	0.145	0.039	0.182	0.341	0.163	0.198	0.200	0.030	0.026
$RESREAL\_A$	0.170	0.172	0.089	0.170	0.090	0.164	0.089	0.176	0.088
$OTHLOAN\_A$	0.374	0.394	0.189	0.174	0.090	0.353	0.207	0.464	0.129
$OTHOPAQ\_A$	0.237	0.228	0.110	0.248	0.120	0.225	0.113	0.244	0.103
$TRANSP\_A$	0.064	0.046	0.060	0.059	0.079	0.049	0.052	0.079	0.054
Panel C: Bank profitability									
EBT_A	0.001	0.009	0.030	0.016	0.009	0.001	0.033	−0.004	0.031
$NONINT\_A$	0.012	0.010	0.012	0.014	0.014	0.012	0.011	0.012	0.012
Panel D: Bank fundamental risks									
NPL_A	0.018	0.012	0.021	0.004	0.004	0.012	0.015	0.029	0.023
Panel E: Banks' funding position									
$LOAN\text{-}TO\text{-}DEPOSIT$	1.363	1.242	0.599	1.422	0.893	1.503	0.612	1.228	0.388
$TIER1\_CAP$	0.117	0.114	0.034	0.115	0.029	0.108	0.026	0.125	0.039
Panel F: Market variables									
LN_TURN	−0.808	−0.796	1.298	−1.151	0.991	−0.781	1.394	−0.704	1.296
RET	−3.626	−2.908	22.605	2.696	8.494	−10.480	23.858	−0.380	23.695
Panel G: Other control variables									
$INTRISK\_A$	0.150	0.124	0.114	0.162	0.111	0.144	0.105	0.151	0.122
$KEELEY's\ Q$	1.020	1.009	0.064	1.090	0.052	1.027	0.060	0.988	0.046
$MVBVEQ$	1.200	1.114	0.683	1.925	0.590	1.265	0.618	0.882	0.531
$COREDEP\_A$	0.550	0.571	0.138	0.551	0.145	0.519	0.136	0.575	0.131
ASSET \$Million	51,700	1,466	246,000	48,000	210,000	56,000	258,000	49,500	249,000
MCAP \$Million	5,504	151	24,500	8,111	32,600	5,960	26,000	4,181	19,000
BVEQ \$Million	4,503	126	20,200	4,497	18,500	4,508	1,900	4,501	21,600

Table 6.3: Determinants of bank equity risks - pooled WLS regressions with two-way fixed effects

This table reports the findings of the pooled WLS regressions of the banks' total (σ^{TOTAL}), market systematic (σ^{MKT}), interest rate (σ^{INT}), crisis-related (σ^{ABX}), ABCP (σ^{ABCP}), market wide default spread (σ^{DEF}) and residual risks (σ^{RESID}) on banking firms' asset composition, profitability, funding position, loan portfolio asset quality and other control variables. The dependent variables are the quarterly-equivalent risk measures of bank stock return volatilities as explained in Section 6.3.2. The asset composition variables include the proportion of trade assets ($TRADE\_A$), commercial loans ($COMREAL\_A$), residential loans ($RESREAL\_A$), other loans ($OTHLOAN\_A$), other opaque loans ($OTHOPAQ\_A$) and transparent assets ($TRANSP\_A$) to the quarterly average total assets ($ASSET$). The fundamental and market variables include: earnings before taxes and extraordinary items to total assets (EBT_A), non-interest income to total assets ($NONINT\_A$), non-performing loans to total assets (NPL_A), loan-to-deposit ratios ($LOAN\text{-}TO\text{-}DEPOSIT$), Tier 1 capital ratios ($TIER1\_CAP$), interest rate risk ($INTRISK\_A$), Keeley's Q, market-to-book value ratios ($MVBVEQ$), core deposits to total assets ($COREDEP\_A$) and turnover ratios (LN_TURN). Two-way firm and time fixed effects are accounted for in the WLS regressions with standard errors clustered by firm and time dimensions. The WLS regressions are weighted by log market capitalisation. The F-tests of joint significance between coefficients on asset composition variables are reported in the lower panel. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Determinants of bank equity risks														
Dependent Variables	$LN(\sigma_t^{TOTAL})$		$LN(\sigma_t^{MKT})$		$LN(\sigma_t^{INT})$		$LN(\sigma_t^{ABX})$		$LN(\sigma_t^{ABCP})$		$LN(\sigma_t^{DEF})$		$LN(\sigma_t^{RESID})$	
Model	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Asset composition:														
$TRADE\_A_{t-1}$	0.387	(0.729)	0.731	(1.128)	−5.136**	(2.530)	4.866*	(2.513)	1.632	(2.305)	3.114	(2.655)	−0.080	(0.818)
$COMREAL\_A_{t-1}$	−0.659	(0.666)	−0.179	(0.959)	−2.820**	(1.339)	1.514	(2.074)	0.013	(1.967)	−2.362**	(1.109)	−0.624	(0.696)
$RESREAL\_A_{t-1}$	−0.599	(0.829)	0.440	(1.147)	−2.905*	(1.680)	1.102	(2.041)	2.224	(2.225)	−0.825	(1.777)	−0.607	(0.867)
$OTHLOAN\_A_{t-1}$	−0.813	(0.677)	0.326	(0.981)	−4.031***	(1.444)	1.705	(2.088)	0.135	(2.105)	−2.048*	(1.120)	−0.823	(0.733)
$OTHOPAQ\_A_{t-1}$	−0.175	(0.584)	−0.131	(0.598)	−3.008**	(1.218)	1.416	(2.224)	0.386	(1.920)	−0.895	(0.905)	−0.052	(0.621)
$TRANSP\_A_{t-1}$	0.588	(0.460)	−0.090	(0.552)	−0.696	(1.300)	3.251	(2.368)	2.890	(1.774)	−1.304	(0.987)	0.716	(0.464)
Fundamental variables:														
EBT_A_{t-1}	−1.392***	(0.402)	−1.113**	(0.527)	−0.733	(1.094)	−2.705**	(1.194)	−1.943*	(1.131)	−1.716	(1.455)	−1.372***	(0.418)
$NONINT\_A_{t-1}$	−2.746**	(1.204)	−3.200	(2.196)	−4.690	(3.684)	1.043	(4.872)	0.423	(4.154)	−0.551	(2.987)	−2.750*	(1.497)
NPL_A_{t-1}	6.449***	(1.320)	−3.934	(2.839)	13.710***	(2.462)	6.615**	(3.151)	1.438	(2.956)	6.663**	(2.608)	7.666***	(1.327)
$LOAN\text{-}TO\text{-}DEPOSIT_{t-1}$	0.011	(0.021)	0.005	(0.032)	0.208***	(0.077)	−0.054	(0.135)	−0.108	(0.094)	−0.116	(0.080)	0.006	(0.023)
$TIER1\_CAP_{t-1}$	−3.386***	(0.676)	−1.756	(1.559)	−6.176***	(1.196)	−3.592**	(1.656)	−7.404***	(1.910)	−5.345***	(1.563)	−3.738***	(0.678)
Control variables:														
$INTRISK\_A_{t-1}$	−0.077	(0.167)	−0.269	(0.278)	0.131	(0.349)	0.437	(0.515)	0.105	(0.542)	−0.394	(0.443)	−0.132	(0.162)
$Keeley's\ Q_{t-1}$	−1.316**	(0.564)	0.161	(1.063)	−2.336*	(1.363)	−2.504	(1.714)	−0.112	(1.765)	−2.145	(1.330)	−1.745***	(0.570)
$MVBVEQ_{t-1}$	−0.031	(0.063)	0.144	(0.096)	−0.028	(0.146)	0.018	(0.122)	−0.209	(0.190)	0.021	(0.106)	−0.054	(0.064)
$COREDEP\_A_{t-1}$	0.171	(0.238)	−0.514	(0.534)	0.252	(0.644)	0.053	(0.866)	−0.826	(0.681)	0.271	(0.603)	0.287	(0.242)
LN_TURN_{t-1}	0.046	(0.029)	0.216***	(0.063)	0.061	(0.062)	0.155***	(0.045)	0.070	(0.055)	−0.024	(0.055)	0.028	(0.025)
N	3,153		3,153		3,153		3,153		3,153		3,153		3,153	
R^2	0.806		0.653		0.310		0.312		0.315		0.296		0.814	
F-tests														
$TRADE\_A - TRANSP\_A$	−0.201		0.821		−4.440**		1.615		−1.258		4.418*		−0.796	
$COMREAL\_A - TRANSP\_A$	−1.247***		−0.089		−2.124**		−1.737		−2.877		−1.058		−1.340***	
$RESREAL\_A - TRANSP\_A$	−1.187*		0.530		−2.209**		−2.149		−0.666		0.479		−1.323**	
$OTHLOAN\_A - TRANSP\_A$	−1.401***		0.416		−3.335***		−1.546		−2.755		−0.744		−1.539***	
$OTHOPAQ\_A - TRANSP\_A$	−0.763***		−0.041		−2.312***		−1.835**		−2.504		0.409		−0.768**	

Table 6.4: Determinants of bank equity risks with crisis dummy and interactions - pooled WLS regressions with two-way fixed effects

This table reports the findings of the pooled WLS regressions of the banks' total (σ^{TOTAL}), market systematic (σ^{MKT}), interest rate (σ^{INT}), crisis-related (σ^{ABX}), ABCP (σ^{ABCP}), market wide default spread (σ^{DEF}) and residual risks (σ^{RESID}) on banking firms' asset composition, profitability, funding position, loan portfolio asset quality and other control variables. To capture the crisis effect, I include a crisis dummy variable (crisis period: 2007Q1-2009Q1) and interact the crisis dummy variable with the banking firms' fundamental variables and asset composition variables. The dependent variables are the quarterly-equivalent risk measures of bank stock return volatilities as explained in Section 6.3.2. The asset composition variables include the proportion of trade assets ($TRADE\_A$), commercial loans ($COMREAL\_A$), residential loans ($RESREAL\_A$), other loans ($OTHLOAN\_A$), other opaque loans ($OTHOPAQ\_A$) and transparent assets ($TRANSP\_A$) to the quarterly average total assets ($ASSET$). The fundamental and market variables include: earnings before taxes and extraordinary items to total assets (EBT_A), non-interest income to total assets ($NONINT\_A$), non-performing loans to total assets (NPL_A), loan-to-deposit ratios ($LOAN\text{-}TO\text{-}DEPOSIT$), Tier 1 capital ratios ($TIER1\_CAP$), interest rate risk ($INTRISK\_A$), Keeley's Q, market-to-book value ratios ($MVBVEQ$), core deposits to total assets ($COREDEP\_A$) and turnover ratios (LN_TURN). Two-way firm and time fixed effects are accounted for in the WLS regressions with standard errors clustered by firm and time dimensions. The WLS regressions are weighted by log market capitalisation. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Determinants of bank equity risks														
Dependent Variables	$LN(\sigma_t^{TOTAL})$		$LN(\sigma_t^{MKT})$		$LN(\sigma_t^{INT})$		$LN(\sigma_t^{ABX})$		$LN(\sigma_t^{ABCP})$		$LN(\sigma_t^{DEF})$		$LN(\sigma_t^{RESID})$	
Model	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Asset composition:														
$TRADE\_A_{t-1}$	2.014	(1.263)	−0.179	(2.015)	3.344	(3.792)	3.154	(4.007)	6.044	(3.723)	4.112	(4.639)	2.798**	(1.335)
$COMREAL\_A_{t-1}$	1.120	(0.792)	−0.782	(1.746)	−2.462	(1.540)	3.269*	(1.764)	3.334	(3.032)	−0.810	(1.553)	1.843**	(0.766)
$RESREAL\_A_{t-1}$	0.448	(0.915)	−0.509	(1.657)	−2.316	(1.767)	1.293	(1.896)	3.989	(3.004)	0.121	(2.256)	1.277	(0.933)
$OTHLOAN\_A_{t-1}$	1.995***	(0.744)	1.422	(1.557)	−1.577	(1.570)	3.537*	(1.888)	4.505	(3.080)	−0.056	(1.652)	2.492***	(0.755)
$OTHOPAQ\_A_{t-1}$	1.125*	(0.587)	0.163	(0.885)	−1.918	(1.444)	1.388	(1.969)	3.325	(2.875)	−0.327	(1.596)	1.585**	(0.644)
$TRANSP\_A_{t-1}$	1.610**	(0.775)	0.211	(1.003)	−0.214	(1.756)	2.795	(2.232)	4.865*	(2.799)	−0.860	(1.861)	1.917**	(0.768)
Fundamental variables:														
EBT_A_{t-1}	−0.868	(0.719)	2.733**	(1.303)	0.677	(1.263)	−2.004	(1.470)	−2.724*	(1.450)	−2.828*	(1.578)	−1.718**	(0.705)
$NONINT\_A_{t-1}$	−3.642	(2.247)	−7.215**	(3.597)	−7.121*	(4.012)	2.019	(5.947)	0.734	(4.699)	−0.418	(4.224)	−2.542	(2.090)
NPL_A_{t-1}	1.937	(1.842)	−5.277	(3.437)	9.507***	(2.829)	4.572	(2.849)	−4.198	(3.367)	2.480	(2.806)	2.624	(1.736)
$LOAN\text{-}TO\text{-}DEPOSIT_{t-1}$	−0.084**	(0.039)	−0.109*	(0.056)	0.113	(0.077)	−0.217	(0.182)	−0.186	(0.134)	−0.182**	(0.086)	−0.082*	(0.045)
$TIER1\_CAP_{t-1}$	−3.796***	(1.241)	−1.148	(2.175)	−5.958***	(1.475)	−4.885***	(1.543)	−8.000***	(2.346)	−5.933***	(1.472)	−4.693***	(1.066)
Crisis dummy and interaction variables														
$CRISIS_t$	2.372***	(0.913)	0.612	(1.400)	2.054	(1.688)	−0.232	(2.410)	5.868*	(3.203)	1.604	(2.464)	2.914***	(0.836)
$CRISIS_t \times$														
$TRADE\_A_{t-1}$	−1.621	(1.050)	1.100	(1.239)	−7.299***	(2.777)	2.021	(3.231)	−6.556*	(3.667)	−0.782	(2.729)	−2.849***	(0.982)
$OTHLOAN\_A_{t-1}$	−2.020**	(0.935)	−0.017	(1.471)	−1.130	(1.756)	0.332	(2.456)	−5.421*	(3.170)	−1.616	(2.381)	−2.579***	(0.840)
$OTHOPAQ\_A_{t-1}$	−2.241**	(0.970)	−0.816	(1.465)	−1.579	(1.720)	0.835	(2.927)	−5.682*	(3.191)	−1.399	(2.338)	−2.777***	(0.918)
$TRANSP\_A_{t-1}$	−2.176**	(1.014)	−1.048	(1.668)	−0.842	(1.731)	1.018	(3.255)	−3.532	(3.632)	−1.748	(2.431)	−2.515***	(0.968)
$COMREAL\_A_{t-1}$	−2.823***	(1.024)	−0.396	(1.566)	−1.928	(1.713)	−0.414	(2.574)	−6.764**	(3.104)	−2.087	(2.277)	−3.408***	(0.913)
$RESREAL\_A_{t-1}$	−2.008**	(0.972)	−0.362	(1.508)	−1.818	(1.600)	1.131	(2.520)	−4.396	(3.210)	−1.691	(2.096)	−2.611***	(0.876)
EBT_A_{t-1}	−0.671	(1.147)	−5.534***	(1.830)	−2.855	(1.999)	−1.593	(1.985)	1.822	(1.983)	1.077	(1.877)	0.392	(1.035)
$NONINT\_A_{t-1}$	2.658	(2.561)	8.093**	(3.697)	1.527	(5.473)	3.050	(7.188)	−3.900	(4.912)	−0.014	(6.144)	0.717	(2.378)
NPL_A_{t-1}	5.005**	(2.114)	1.130	(4.289)	−2.049	(3.710)	3.918	(2.770)	1.868	(4.361)	5.918*	(3.374)	5.424***	(2.041)
$LOAN\text{-}TO\text{-}DEPOSIT_{t-1}$	−0.065	(0.044)	0.004	(0.075)	−0.090	(0.103)	0.095	(0.114)	−0.140	(0.105)	−0.053	(0.098)	−0.089*	(0.047)
$TIER1\_CAP_{t-1}$	0.025	(0.016)	0.015	(0.029)	0.009	(0.030)	0.004	(0.035)	0.022	(0.041)	0.041	(0.031)	0.029**	(0.013)
Control variables:														
$INTRISK\_A_{t-1}$	0.275	(0.232)	0.236	(0.315)	0.597	(0.443)	0.718	(0.593)	0.500	(0.576)	−0.303	(0.479)	0.154	(0.226)
$Keeley's\ Q_{t-1}$	−4.138***	(1.056)	−2.888*	(1.539)	−4.821***	(1.475)	−6.448***	(1.724)	−2.224	(1.770)	−4.278***	(1.348)	−4.511***	(0.948)
$MVBVEQ_{t-1}$	−0.020	(0.082)	0.126	(0.119)	0.042	(0.159)	0.034	(0.141)	−0.241	(0.200)	0.024	(0.122)	−0.026	(0.082)
$COREDEP\_A_{t-1}$	−0.493	(0.529)	−0.508	(0.913)	−0.323	(0.563)	−0.816	(0.974)	−1.305	(0.842)	−0.429	(0.630)	−0.692	(0.443)
LN_TURN_{t-1}	0.138***	(0.044)	0.326***	(0.062)	0.143**	(0.071)	0.237***	(0.054)	0.169*	(0.092)	0.060	(0.054)	0.112***	(0.041)
N	3,153		3,153		3,153		3,153		3,153		3,153		3,153	
R^2	0.669		0.576		0.267		0.282		0.270		0.259		0.721	

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Chapter 7

The Predictability of Bank Stock Returns and Its Implications for the Asset 'Fire Sales' and 'Flight-to-Safety' Phenomena

7.1 Introduction

In the literature, there is ample evidence that BHCs' stock returns can be predicted by a number of fundamental variables (see Cooper et al., 2003; Bessler et al., 2007). Recent evidence suggests that predictability in bank returns might have existed during the recent 2007 to 2009 financial crisis. Fahlenbrach et al. (2012) compare bank stock performance across the 1998 and recent 2007 to 2009 financial crises and show that the banks' exposure to illiquid assets and leverage contribute positively to their under-performance. Acharya et al. (2013) study the banks' securitisation and the issuance of ABCPs, and document a similar conclusion that banks with higher exposure to the ABCP conduits under-performed during the recent crisis. This evidence supports the fundamentalist viewpoint that fundamental variables are relevant in explaining bank stock returns. Motivated by these research, this study updates the bank return predictability literature and formulates an out-of-sample setting to test whether fundamental variables predict one-quarter ahead bank stock returns, based on a sample period that covers the recent 2007 to 2009 financial crisis and part of the ongoing European sovereign debt crisis. My main contributions to the literature are threefold. First, this study focuses on the identification of the determinants of one-quarter ahead bank stock returns over a sample period characterised by increasing risk aversion and volatilities. I demonstrate how the banking firm's characteristics reflect their fundamental risks during the crisis and highlight the relevance of fundamental analysis in evaluating bank stock performance, providing profound implications to a wide range of market users (including the retail and institutional investors, etc.) in the context of investment and risk management. Second, to my knowledge, this study is the first to document solid evidence that the bank's fundamental variables significantly predicted future trading activities in bank stocks, both during and after the crisis. My analysis uses both trading ratio and order flow measures to gauge the intensity and direction of trading. The evidence that banks with weaker fundamentals and of a smaller size were traded more intensely during the crisis and that the higher trading activity was dominated by sell pressure leads me to conclude that the bank stock return predictability pertains to investors' asset 'fire sale' and 'flight-to-safety' behaviour during the crisis. In other words, the bank's fundamentals and size were the major criteria evaluated by investors in formulating their 'flight' decision. Third, I propose and demonstrate how the banking firm's fundamental variables can guide profitable investable strategies, both during and after a crisis.

A number of previous studies have documented evidence of a 'fire sale' and of a 'flight-to-safety' from financial stocks during the recent 2007 to 2009 financial crisis. A 'fire sale' of an asset is described as a forced sale, usually at prices far below intrinsic values, that can arise for various reasons, for example: deleveraging and fund redemption requirements among hedge funds (Ben-David et al., 2012), investors' 'flight' to funds domiciled in developed markets (Jotikasthira et al., 2012), capital withdrawals by mutual fund shareholders (Coval and Stafford, 2007), and the commercial bank's funding obligations after huge losses (French et al., 2010, pp. 67), etc. Anand et al. (2013) show that buy-side institutions avoided trading illiquid stocks during the recent crisis while Longstaff (2010) notes that the financial stocks were traded more intensely during the crisis, which is consistent with portfolio rebalancing for risk management purposes and possible 'flight-to-safety' into safer and more liquid asset classes. Taken together, the phenomenon of 'fire sales' or 'flight-to-safety' from illiquid financial stocks may have a considerable impact on their returns (Coval and Stafford, 2007) and may account for the possible return predictability among bank stocks. I argue that the criteria by which investors base their 'fire sale' or 'flight' decisions pertain to the bank's fundamental variables. In other words, investors might have excessively sold bank stocks with poor fundamentals, leading to a relation between past fundamental performance and future stock returns during the recent crisis. In this study, I conjecture that those banking firms with the worst fundamentals might be more subject to the asset 'fire sales' or the 'flight-to-safety' phenomena, and have consistently under-performed.

Following the prior literature of the bank's fundamental variables, I consider include those variables relating to the bank's return volatilities (Anderson and Fraser, 2000; Ang et al., 2006, 2009), earnings (Basu, 1983; Cooper et al., 2003), loan portfolio credit quality (Thakor, 1987;

Wahlen, 1994; Meeker and Gray, 1997; Jones et al., 2013)[74], exposure to funding illiquidity risks (Fahlenbrach et al., 2012; Acharya et al., 2013), non-interest income (Cooper et al., 2003; Bessler et al., 2007), size (Banz, 1981; Gandhi and Lustig, 2011) and turnover ratios (Chordia et al., 2001). There are a couple of distinct features specific to this study, as follows. First, in the context of the recent crisis, banking firms' exposure to the structured finance market (measured by the ABX AAA index, a benchmark index for the US structured finance market) may affect bank stock returns, evidence of contagion from the structured finance market to the US financial stocks has been documented (Longstaff, 2010). The banks' exposure to the structured finance market may stem from their holding of trade assets, which include the subprime related structured securities (Jones et al., 2013), and this represents a considerable source of fundamental risks. To this end, a component of return volatilities relating to the variations of the ABX AAA index (denoted hereafter as the ABX risk) is considered, following the variance decomposition approach of Anderson and Fraser (2000). The evidence in this study shows that the banks' ABX risk possess significant predictive power over future bank stock returns. Second, prior studies suggest that banking firms' exposure to funding illiquidity risks has a considerable impact on bank stock returns during the crisis (Fahlenbrach et al., 2012; Acharya et al., 2013). The main source of banks' vulnerability to funding illiquidity risks commonly points to the maturity mismatch feature in the 'shadow' banking system in which banks issue structured finance securities via off-balance sheet conduits (Brunnermeier, 2009). These conduits issue short-term ABCP to fund their purchases of longer-term structured finance securities; for example, ABSs, RMBSs and CDOs. Banking firms were responsible for providing contingent funding to the conduits via credit line facilities and were, therefore, subject to tremendous funding illiquidity risks during the crisis. Given the unique nature of the banks' off-balance sheet activities and liquidity risk relating to their credit line commitments, to my knowledge, this is one of the first papers that empirically examines the relationship between banking firms' exposure to funding illiquidity risks and future stock returns within the context of asset pricing.

To anticipate some of my findings, the banks' earnings, non-performing loans, loan-to-deposit ratios, Tier 1 capital ratios, bank size, idiosyncratic and ABX risks are univariately important in explaining the cross-section of one-quarter ahead bank stock returns. Banking firms with lower profitability, more non-performing loans, lower Tier 1 capital ratios, higher loan-to-deposit ratios, smaller market capitalisation, higher idiosyncratic and ABX risks have significantly lower simple and risk-adjusted returns in the next quarter. The multivariate analysis based on the Fama and Macbeth (1973) and the fixed effects panel regressions confirm the importance of banks' earnings,

[74] Jones et al. (2013) find that non-performing loans to total assets is negatively related to excess market equity value above book value while Meeker and Gray (1997) show that the amount of non-performing loans are a satisfactory measure of bank asset quality.

non-performing loans, ABX risk and Tier 1 capital ratios in determining the one-quarter ahead bank stock returns. Since a size effect is prominent, I conduct a two-way sort portfolio analysis to disentangle the size effect from the predictability of other bank variables. I find that the predictive power of the banks' fundamental variables is evident within the small (0-30%) and mid (31%-70%) cap size portfolios. The one-quarter ahead returns decrease monotonically towards the portfolios of the weakest fundamentals and highest equity risks. Nonetheless, size does not fully account for the predictability because the combined portfolio (P5-P1) one-quarter ahead returns of the size adjusted portfolios sorted by earnings, non-performing loans, loan-to-deposit ratios, and Tier 1 capital ratios are still significantly different than zero.

To relate the findings to the asset 'fire sale' and 'flight-to-safety' phenomena, I apply the same two-way sort portfolio analysis sorted on size and fundamental variables and report the average one-quarter ahead turnover ratios. The turnover ratios increase monotonically towards the portfolios of the lowest earnings, highest non-performing loans, highest loan-to-deposit ratios and lowest Tier 1 capital ratios among the mid and small-sized portfolios while their combined portfolio (P5-P1) turnover ratios are significantly different than zero. Taken together with the evidence that the portfolios of the poorest fundamentals under-performed, I argue that investors might have switched from the bank stocks with weak fundamentals at 'fire sale' prices to other stocks. To gauge the relative strength of the buy-sell pressure among bank stocks, I follow the market microstructure literature and construct an order flow variable based on the daily price changes. Based on the same two-way sort portfolio analysis, I report the average one-quarter ahead order flows and observe that the order flows decrease monotonically towards the portfolios of the lowest earnings, highest non-performing loans and the lowest Tier 1 capital ratios among the small bank stocks. Their combined portfolio (P5-P1) order flows are significantly different from zero, suggesting that bank stocks with weaker fundamentals experienced relatively larger sell pressure, on average. Collectively, banks with lower profitability, loan portfolio credit quality or a smaller buffer of Tier 1 capital have lower average one-quarter ahead returns, higher trading intensity, and received relatively stronger sell pressure, providing strong support to my 'fire sale' or 'flight-to-safety' hypothesis. Said in a different way, the concentration of sell pressure on bank stocks with weak fundamentals is consistent with the asset 'fire sale' or 'flight-to-safety' phenomena, and this lead me to conclude that banks' fundamental performance is the most relevant criteria used by investors in formulating their 'flight' decisions on bank stocks. These results are robust to a multivariate setting that controls for the firm and time fixed effects. In the Fama and Macbeth (1973) and fixed effects panel regressions, I document evidence that the banks' non-performing loans, Tier 1 capital ratios, and size predict significantly the one-quarter ahead turnover ratios with the turnover predictability increasing with declining bank size.

I organise the remainder of this study as follows. Section 2 develops my hypotheses and introduces the banks' fundamental variables. Section 3 explains the construction of my database, the sample selection and the empirical approach. Section 4 reports the empirical findings and Section 5 concludes.

7.2 Motivation and Hypotheses

7.2.1 The 'Fire Sale' or 'Flight-to-Safety' Hypothesis

The 'fire sale' of assets has been a widely discussed issue of the recent crisis. Shleifer and Vishny (2011) point out that a 'fire sale' is broadly defined as a forced sale of assets at dislocated prices when the seller could not repay the creditors unless the assets are liquidated. Asset 'fire sales' are made at disrupted prices far below the best use values because the specialist buyers within the same industry might also be financially constrained and unable to bid for the assets, given some adverse common shocks to the industry. Therefore, the non-specialist buyers, who have less expertise with the assets, are able to acquire the assets at discounted prices (Shleifer and Vishny, 1992). A common mechanism in which asset 'fire sale' takes place is through collateralised debt financing. Upon an adverse industry-wide common shock, a large number of financial constrained borrowers defaulted and forfeited their collateral to the lender, who then sold the assets at 'fire sale' prices.

A 'fire sale' of financial assets could have more profound and systemic consequences to financial stability than in other assets since a number of investors finance their investments with funds that can be withdrawn at short notice (Shleifer and Vishny, 2011). For instance, hedge funds and mutual funds, with heavily leveraged positions, invest with the investors' subscribed capital, which are withdrawn systematically during times of financial distress. Another example refers to the maturity mismatch feature in the traditional banking model in which the banks' long-term loan assets are financed by the combination of short-term demand deposits and commercial papers. A 'fire sale' of assets becomes inevitable when these hedge funds face surging demand of fund redemption by investors and when the banks face strong demand for deposit withdrawal or even runs. As the US banking sector gradually moved into a 'shadow' banking system, financial institutions were incentivised to issue excessively structured finance securities, collateralised with subprime mortgage loan assets or other subprime related structured securities and financed with the issuance of short-term ABCP via off-balance sheet conduits. At the onset of the crisis, the market for the subprime related structured securities plummeted. Rating downgrades in these securities spiked (Benmelech and Dlugosz, 2009) and the funding liquidity dried as investors were unwilling to renew the ABCP. As asset prices fell amidst the heightening uncertainty regarding the collateral values of the structured securities, the funding and market illiquidity reinforced each other in a spiral, as proposed by Brunnermeier and Pedersen (2009). In their model, increases in margin requirements (funding illiquidity) as a result of security price declines force arbitrageurs to sell their securities in a 'fire sale' to meet the margin call. Asset prices decline and diverge further from the fundamental values (market illiquidity) and the spiral starts again. The cascades of illiquidity, the distressed equity market and the sluggish economy during and after the recent financial crisis highlight the broad and profound impact of 'fire sale' on financial stability and its contribution to systemic risk.

On the empirical side, evidence of 'fire sales' in financial assets includes the hedge funds' withdrawal of equity holding for deleveraging and fund redemption purposes (Ben-David et al., 2012), investors' 'flight' to funds domiciled in developed markets (Jotikasthira et al., 2012), capital withdrawals by mutual funds' shareholders (Coval and Stafford, 2007), commercial banks' selling of assets at 'fire sale' prices after mark-to-market losses or balance sheet shocks (French et al., 2010, pp. 67), and liquidity purposes (Adrian and Shin, 2010; Anand et al., 2013). In addition, Longstaff (2010) finds that the trading activities amongst US financial stocks intensified during the subprime crisis, which is consistent with portfolio rebalancing and 'flight-to-safety' phenomena. A natural question stemming from this evidence arises. What criteria were used by investors to formulate their 'flight' or investment decisions? This chapter relates the evidence of return predictability in bank stocks to the 'fire sale' and 'flight-to-safety' phenomena and conjectures that the banks' fundamental characteristics are important criteria considered by investors when they are forced to sell bank stocks in a 'fire sale' or when they have decided to 'fly' to other assets. Specifically, disproportionately large selling pressure might have been concentrated on banks that are more fundamentally risky (i.e. with weaker fundamentals), facilitating the significant return predictability in banks' fundamental variables over future stock returns during the recent crisis. This conjecture is denoted as the 'fire sale' or 'flight-to-safety' hypothesis.

7.2.2 Hypotheses in Relation to the Banks' Fundamental Variables

I construct four types of bank-specific fundamental variables that reflect the banks' fundamental risks. The first type of variable pertains to the banking firms' profitability. Earnings (or earning yield) have been extensively researched and have been shown to demonstrate a positive relationship with absolute risk-adjusted stock returns (see, for example, Basu, 1975, 1983; Lamont, 1998). As pointed out by Cooper et al. (2003), firms' earnings have been monitored closely by investors as a major indicator of a firms' fundamental performance. Likewise, the post-earnings announcement literature documents evidence that previously announced earnings predict subsequent estimated abnormal returns (Bernard and Thomas, 1990). More pertinently, Cooper et al. (2003) find that changes in earnings per share significantly predict bank stock returns. Motivated from this evidence, I update the return predictability literature by testing the first hypothesis, as follows:

Hypothesis 1: Banks with lower profitability, as measured by earnings and non-interest incomes to total assets, have significantly lower one-quarter ahead stock returns.

I construct my bank profitability variables following Jones et al. (2013) and use earnings before tax and extraordinary items scaled by total assets.[75] In addition, the sources of income for banking firms have become more diversified as commercial banks have become increasingly involved in off-balance sheet activities for risk management and regulatory arbitrage (Grammatikos et al., 1986; Brunnermeier, 2009; Acharya et al., 2013). Non-interest income has increased relative to interest income in traditional banking models and the major elements of non-interest income include brokerage and underwriting of derivatives, letters of credit that generates fee income, foreign exchange and foreign transaction income, and trading account gains and losses (Rogers and Sinkey, 1999). I include the annualised non-interest income scaled by total assets as a measure of bank earnings arising from nontraditional banking activities.

The second type of fundamental variable measures the quality of bank loan portfolios. Commercial banks typically have a large pool of loan assets relative to equity and, hence, the loan asset quality may impact on stock performance. The three widely used measures of bank loan portfolio quality are non-performing loans, loan-loss reserve, and loan charge-offs, which are shown empirically to affect future stock returns and cash-flows (Wahlen, 1994). Meeker and Gray (1987) analysed the banks' non-performing loans and show that non-performing loans are a good measure of bank asset quality. Non-performing loans also explain the banking firms' excess market value above book value over 2000 to 2006 (Jones et al., 2013). I include banking firms' non-performing loans to total assets and study its relation with bank stock returns. Hence, the second testable hypothesis is as follows:

Hypothesis 2: Banks with lower loan portfolio credit quality, as measured by non-performing loans to total assets, have significantly lower one-quarter ahead stock returns.

As for the third type of bank-specific variable, I consider two measures of banks' exposure to funding illiquidity risks, notably the Tier 1 capital ratios and the loan-to-deposit ratios. Both measures reflect the banking firm's abilities to fulfil funding requirements and provide contingent liquidity. Banks' exposure to funding illiquidity risks arise mainly from their exposure to illiquid assets and their funding obligations relating to off-balance sheet conduits. Hence, the third hypothesis is as follows:

[75] My variable construction is similar in spirit to various asset pricing studies that use fundamental variables (see, for example, Basu, 1983; Fama and French, 1992).

Hypothesis 3: Banks with lower funding ability and a smaller buffer of Tier 1 capital, as measured by loan-to-deposit ratios and Tier 1 capital ratios, have significantly lower one-quarter ahead stock returns.

The fourth type of banking variable refers to banks' equity risks (return volatilities). A number of studies have shown that stocks' return volatilities explain the cross-section of stock returns (see, for example, French et al., 1987; Ang et al., 2006). I follow the approach of Anderson and Fraser (2000) and decompose the bank stock return volatilities into three components: market, crisis-related and idiosyncratic risks. Just as market systematic risks are to some extent significant in explaining expected stock returns (Fama and French, 1992), a number of recent papers revisit the importance of idiosyncratic risks and find strong predictability in realised (Goyal and Santa-Clara, 2003; Ang et al., 2006, 2009) and expected idiosyncratic volatilities (Fu, 2009). The underlying argument for the importance of idiosyncratic risks is that investors may not always be able to fully diversify their portfolios, a feature that is supported by empirical evidence with regard to individual investors' portfolio holdings (Barber and Odean, 2000) and mutual funds' holdings (Falkenstein, 1996). The recent literature documents an anomaly in which there is a strong negative relationship between idiosyncratic risks and stock returns. In addition, the crisis-related risk reflects the banks' exposure to the unexpected shocks from the US structured finance market. Longstaff (2010) documents evidence of contagion travelling from the US structured finance market to various US domestic markets during the crisis while Fender and Scheicher (2009) find evidence that the declines in the structured finance market indices, the ABX indices, reflected substantial market illiquidity risks and increasing risk aversion. I will test whether bank market risk, ABX risk and idiosyncratic risk relate negatively with future bank stock returns, as follows:

Hypothesis 4: A bank's equity risks, including market risk, ABX risk and idiosyncratic risk, significantly predict their one-quarter ahead stock returns.

7.3 Data and Summary Statistics

My data sample covers the banking firms' quarterly observations that lie between 2006Q1 and 2011Q4. My sample period is selected based on three considerations. First, the financial sector was among one of the most severely impaired markets in the US during the recent crisis. I exploit the fact that bank stocks suffered huge losses and seek to specifically quantify the impact of banks' fundamental risks on their under-performance during the recent crisis. An improved understanding of the banks' fundamental risks is useful for portfolio management and risk management perspectives. Second, one main contribution of this study is to reveal the main drivers of future trading activity during the recent crisis. There is evidence that suggests possible asset 'fire sales' and 'flight-to-safety' from financial stocks during this sample period. Taken together with the fact that bank stocks consistently under-performed during this period, the main fundamental determinants of future trading activity identified can be reasonably interpreted as the main criteria used by investors to formulate their 'fire sale' or 'flight' decisions. Third, this chapter considers banks' exposure to the structured finance market as a source of fundamental risk and studies its impact on future bank stock returns. Since the ABX AAA index is available from its introduction in January 2006, I follow Longstaff (2010) and select the start of my sample period as 2006Q1.

I include publicly traded US BHCs that file FR Y-9C forms quarterly over the 2006Q1 to 2011Q4 period. The FR Y-9C form collects consolidated financial data in the form of a balance sheet, an income statement and supporting schedules of the US BHCs, which have more than $500 million total assets. I obtain the BHCs' financial data from the Bank Regulatory database accessed via the WRDS database. The quarterly accounting data is then merged with the market data from the CRSP database.[76] The merger is based on a linking table provided by the New York FRB[77] that matches each company (identified by the CRSP unique company identification number, PERMCO) to a unique RSSD ID assigned by the Federal Reserve Board to each unique bank in the Bank Regulatory database. I screen out those quarterly observations in which there are missing or unmerged data and adjust the banks' total assets for inflation using a seasonally-adjusted GDP deflator. The sample consists of 227 BHCs and 3001 firm-quarter observations. Following Jones et al. (2013), the banks' balance sheet variables at quarter t are calculated as the beginning and ending quarterly average values. For both earnings and non-interest income variables which are recorded at calendar year-to-date (i.e. stock data), I divide the values of the first quarter and the quarterly changes of the second, third and fourth quarters of each calendar year by the corresponding quarterly averaged total assets and then annualise the income measures. Bank variables with natural log transformation or scaled by the average total assets are denoted as 'LN_' and '_A' respectively. The fundamental variables are winsorised at a 99^{th} percentile (1% at each tail) at each cross-section to lessen the problem of outliers.

According to the submission instruction manual of the Board of Governors of the Federal Reserve System (Section GEN-3), BHCs are required to submit their completed FR Y-9C reports to the Federal Reserve System within 40 calendar days after the end date of each calender quarter.[78] [79] To ensure that the banks' quarterly fundamental information are available to investors, all

[76]As the focus of my investigation is on the US banking firms that are publicly traded, I follow Anderson and Fraser (2000) and only include stocks with the following SIC codes in my sample: 6021 (National commercial banks), 6022 (State commercial banks), and 6029 (Commercial banks, NEC).

[77]The linking table can be accessed via: http://www.newyorkfed.org/research/banking_research/datasets.html

[78]For the fourth quarter ending in December, the submission deadline for BHCs is 45 calendar days.

[79]The manual can be accessed online via: http://www.federalreserve.gov/reportforms/forms/FR_Y-9C20130331_i.pdf

bank fundamental variables are lagged by one quarter; that is, quarter t variables in this chapter represent banks' fundamental performance in quarter $t-1$. For the purpose of my analysis, while I use quarter t accounting variables to predict quarter $t+1$ stock returns, I am effectively mapping quarter $t+1$ stock returns with banks' fundamental performance in quarter $t-1$, which are assumed to be known only at the end of quarter t.[80]

7.3.1 Summary Statistics

Table 7.1 describes the four main types of bank fundamental variables while the summary statistics are reported in Table 7.2. For the profitability measures in Panel A, the banks' earnings to total assets has a mean (median) of 0.1% (0.9%) while the mean (median) non-interest income to total assets is 1.2% (1.0%) and has a smaller standard deviation. For banks' fundamental risks in Panel B, the banks' non-performing loans to total assets averages at 1.8% (median=1.2%) and exhibits positive skewness. In addition, I also include a control variable that measures banks' exposure to interest rate risk, following Jones et al. (2013), computed as the absolute value of the differences between short-term assets and short-term liabilities and equity, scaled by the total assets. To measure the banks' funding ability and exposure to the funding illiquidity risks, I compute the loan-to-deposit ratios as the banks' total loan assets to total core deposits and the Tier 1 capital ratios as the total Tier 1 core capital to total risk-weighted assets. A bank with a lower loan-to-deposit ratio and a higher capital ratio has more funding reserves to meet funding demands and are less exposed to funding shocks. While the regulatory requirement of Tier 1 capital ratio is 6%, the mean (median) ratio in my sample is 11.7% (11.4%) while the mean (median) loan-to-deposit ratio is 1.36 (1.24), as shown in Panel C of Table 7.2. As for the bank equity risks in Panel D, I consider three components of bank equity risks following the variance decomposition approach of Anderson and Fraser (2000), notably the market systematic, the crisis-related and the residual risks. The crisis-related risk reflects the banking firms' exposure to the unexpected shocks from the ABX AAA index, which is a benchmark index for the structured finance market and tracks a static portfolio of AAA-rated subprime RMBSs.[81] The details of the construction of the bank risk variables are provided in Appendix A.2. All three components of bank risk are positively skewed while the idiosyncratic risk constitutes the largest proportion of the bank stock total return volatilities.

I follow Chordia et al. (2001) and compute a turnover ratio to gauge the level of trading activity at the firm level. First, I construct the monthly turnover ratio as the ratio of the total number

[80] I also replicate my analysis without lagging the quarterly variables. The findings of predictability are to a large extent stronger and more significant. I report the results based on the lagged quarterly variables consistently throughout the paper.

[81] For details about the ABX index family, please refer to Section 4.3 of Chapter 4.

of shares traded in a month to the end of month number of outstanding shares from the CRSP database. I then average the monthly turnover ratios within each quarter and log transform the average turnover ratio.[82] As shown in Panel E, the mean (median) log turnover ratio is -0.81 (-0.80) with a standard deviation of 1.30. My bank stock returns are quarterly returns, computed as the cumulative returns over the three months in each quarter, with a mean (median) of -3.63% (-2.91%) and a standard deviation of 22.61%. The banking firm's size is measured by its market capitalisation, computed as the product of its share price and the number of outstanding shares at the end of each quarter. I also include a measure of a firm's current valuation relative to book value using the ratio of market capitalisation to book value of total shareholders' equity.

7.4 Empirical Results

7.4.1 Univariate Portfolio Analysis

Table 7.3 presents a cross-sectional analysis of one-quarter bank stock returns and the banking firms' fundamental variables based on one-way sort portfolios. At the end of quarter t, I sort the bank stocks into quintile portfolios according to the quarter t fundamental variables[83] and report the equally-weighted average quarter $t+1$ simple returns, risk-adjusted returns, log turnover ratios and log market capitalisation, as shown in Panels A - D of Table 7.3, respectively. A number of interesting results emerge.

First, I find that banking firms' earnings, non-interest income, non-performing loans, loan-to-deposit ratios, Tier 1 capital ratios, size, ABX and idiosyncratic risks are univariately important in explaining the cross-section of bank stock returns, as shown in Panel A and Panel B. The combined (P5-P1) portfolio returns are significant and most considerable in the portfolios sorted by variables relating to non-performing loans (-8.89%), earnings (8.79%), Tier 1 capital ratios (7.47%), idiosyncratic risks (-7.28%) and loan-to-deposit ratios (-6.97%). I find little evidence that the return predictability is attributed to the differential in risks, as shown by the qualitatively and quantitatively similar results in the risk-adjusted returns of the Fama and French (1993) three-factor model (FF-3) in Panel B. All of my hypotheses are supported in that banking firms with lower earnings (H1), higher non-performing loans (H2), lower Tier 1 capital ratios, higher loan-to-deposit ratios (H3) and higher ABX and idiosyncratic risks (H4) have significantly lower one-quarter ahead returns. This evidence is in line with my prediction that banking firms with weaker fundamen-

[82] I also use an alternative turnover ratio, computed as the quarterly total number of shares traded divided by the end of quarter number of outstanding shares, in my analysis. The two measures of turnover are qualitatively similar and have negligible effect on my findings (untabulated).

[83] As aforementioned, the fundamental variables at the end of quarter t represents those variables of quarter $t-1$. This is to ensure that the publicly available accounting information is available to investors. The bank stock return volatilities and market values are not lagged.

tal performance consistently under-performed during and after the recent crisis, highlighting the relevance of banks' fundamental characteristics in valuing assets.

Second, Panel C evaluates the cross-sectional relationship between the banking firms' fundamental variables and the log turnover ratios in the cross-section. I have identified significant cross-sectional differences in log turnover ratios between Portfolios 5 and 1, sorted by all banking variables except the non-performing loans. The turnover ratios increase monotonically with the bank stocks' market systematic and idiosyncratic risks. The combined portfolio (5-1) turnover ratios are the largest in portfolios sorted by past firm size and market systematic risk. At a first approximation, the banking firms' profitability, non-performing loans, exposure to funding illiquidity, size, market risk and past turnover ratios are positively related to future turnover ratios while the ABX and residual risks have a negative relationship with future turnover ratios. So far, the univariate test results suggest that return predictability may be in part attributed by the patterns of trading activities in bank stocks and is possibly related to the 'fire sale' and 'flight-to-quality' phenomena suggested in prior studies.

Third, I find strong evidence of size effects, as shown in Panel D. Banking firms with higher earnings, non-interest income, lower Tier 1 capital ratios, higher turnover ratios, higher market risk, lower ABX and residual risks have on average higher market capitalisation.

While the findings are univariately valid, I proceed to test the determinants of the banks' one-quarter ahead returns within a multivariate setting to further control for various firm characteristics as well as the unobserved heterogeneity across firms and time.

7.4.2 Multivariate Analysis

I study the determinants of one-quarter ahead bank stock returns based on the following baseline model specification:

$$\begin{aligned} R_{i,t+1} =& \beta_1 LN(\sigma^{RESID})_{i,t} + \beta_2 LN(\sigma^{ABX})_{i,t} + \beta_3 LN(\sigma^{MKT})_{i,t} + \beta_4 EBT\_A_{i,t} + \beta_5 NONINT\_A_{i,t} \\ &+ \beta_6 NPL\_A_{i,t} + \beta_7 LOAN\text{-}TO\text{-}DEPOSIT_{i,t} + \beta_8 TIER1\_CAP_{i,t} + \beta_9 LN\_MCAP_{i,t} \\ &+ \beta_{10} INTRISK_{i,t} + \beta_{11} MVBVEQ_{i,t} + \beta_{12} LN\_TURN_{i,t} + \alpha_i + \upsilon_t + \epsilon_{i,t}, \end{aligned} \tag{7.1}$$

where $i = 1, \ldots, 227$ and $t = 1, \ldots, 24$. $R_{i,t+1}$ is the quarterly return of the i^{th} BHC in quarter $t+1$ and $\epsilon_{i,t}$ is the error term. α_i and υ_t are the unobserved firm and time fixed effects, to be estimated using firm and quarterly dummy variables.

I use two approaches to estimate Equation 7.1, namely the Fama and Macbeth (1973) two-stage regression and the pooled regression with two-way fixed effects (least squares dummy variable (LSDV) approach). In the first stage of the Fama and Macbeth (1973) procedure, cross-sectional regressions are estimated at each quarter. Then, in the second-stage, I report the time series average coefficients over the sample period and the t-statistics based on the Newey-West (1987) robust standard errors with 4 lags.[84] The Fama and Macbeth (1973) regression adjusts for correlation across firms but may understate standard errors if dependent variables are auto-correlated, especially over longer-horizons (Fama and French, 1988), as in this quarterly data frequency study. To check the robustness, I also estimate a pooled regression with two-way firm and time fixed effects. I include firm and quarterly dummy variables to the regression and report the robust standard errors clustered by both firm and time following Cameron et al. (2011).[85]

Table 7.4 reports the results of the multivariate regressions. First, the significant positive coefficients in the banks' earnings to total assets in both regressions lend support to Hypothesis 1 in that a one per cent increase in the banks' earnings to total assets would increase the bank stock returns by approximately 0.47% in the next quarter, as shown in the fixed effects model. Second, the non-performing loans are significant at the 1% level of significance and are negatively related to banks' one-quarter ahead returns in support of Hypothesis 2. Precisely, a one per cent increase in the non-performing loans to total assets on banks' balance sheet translates into 1.92% lower one-quarter ahead returns, as shown in the results of the fixed effects regression. Third, banks with higher Tier 1 capital ratios have significantly higher one-quarter ahead bank stock returns, which lends support to Hypothesis 3 and the argument that banks with a larger buffer of Tier 1 capital were less susceptible to systematic shocks in funding illiquidity (Fahlenbrach et al., 2012; Acharya et al., 2013). A one per cent increase in the Tier 1 capital ratios lead to 0.57% higher one-quarter ahead returns, which is robust to both the Fama and Macbeth (1973) and fixed effects panel regression methods used. Besides, evidence of the predictability of the ABX risks and in the market-to-book ratios over future stock returns is also documented, lending some support to Hypothesis 4.

In summary, my multivariate analysis confirms my univariate findings of significant predictive ability in banks' fundamental variables over future bank stock returns. The results from the univariate analysis suggest the existence of possible size effects among the sorted portfolios. To disentangle the size effects from the predictability of fundamental variables, I follow Cooper et al. (2003) and report the results of the two-way sort portfolio analysis in the next section.

[84] I also estimate the Newey-West (1987) standard errors using 1 and 2 lags, respectively. The choice of lag lengths (i.e. 1, 2, or 4) has little effect on my findings.

[85] As pointed out by Thompson (2011), since my regressors vary considerably across firms, both over time and simultaneously, clustering by both firm and time dimensions would be the most appropriate method and would result in less bias. In addition, since the standard errors based on the multi-way clustering are only correct asymptotically, I also estimate the regression using one-way firm clustering since my time dimension consists only of 24 quarters. Nonetheless, the results of the one-way clustering are similar and, hence, my findings are robust.

7.4.3 Controlling for Firm Size

Table 7.5 reports the results of the two-way sort portfolios on firm size and banks' fundamental variables. At the end of quarter t, I first sort the bank stocks into three portfolios (breakpoints at 30% and 70%) based on log firm size. Then, within each return portfolio, I further sort the stocks into five portfolios by banks' earnings, non-performing loans, loan-to-deposit ratios, Tier 1 capital ratios, ABX and residual risks, in which significant predictability has been identified in the previous tests. The equally-weighted quarter $t+1$ returns are then reported. I average the three size portfolios at each quintile portfolio dimension so that the size-adjusted quintile portfolios have comparable bank size. The combined portfolio (P5-P1) returns are reported and the statistical tests refer to the two-sample t-tests assuming unequal variances.

There are three main findings. First, in the two-way sort portfolios, the combined portfolio returns of the size-adjusted portfolios are significant for the banks' earnings, non-performing loans, loan-to-deposit ratios and Tier 1 capital ratios sorted portfolios while those of the crisis-related and residual risks are insignificant. The combined portfolio returns of the size-adjusted portfolios are the largest for the non-performing loans (Panel B, -9.13%), earnings (Panel A, 8.71%) and Tier 1 capital ratios (Panel D, 8.68%) and are significant at the 5% level. Size alone does not fully account for the return predictability in the banks' fundamentals. Second, marginally significant size effects are present in the corner portfolios of the poorest fundamentals; that is, P1 of earnings, P5 of non-performing loans, P1 of Tier 1 capital ratios, and P5 of residual risks. In these bank portfolios, the small cap stocks under-performed the mid and large cap stocks. Third, I find that the significant return spreads across the quintile portfolios in all six banks' fundamental variables mostly intersect with the mid and small cap return portfolios. The predictability in the banks' fundamental variables over the one-quarter ahead bank stock returns concentrates on the mid and small cap bank stocks. Despite the finding that larger banks tending to have higher absolute turnover (as shown in my univariate analysis), the return predictability in small and mid cap stocks are in general consistent with a 'fire sale' or 'flight-to-safety' phenomenon in which size and fundamental variables are the major criteria used by investors to formulate their 'flight' or portfolio rebalancing decisions.

7.4.4 'Fire Sale' or 'Flight-to-Safety' Argument

My 'fire sale' or 'flight-to-safety' hypotheses conjectures that a banking firm's fundamental performance and a firm's size are the major factors investors consider when formulating their trading strategies and investment decisions over my sample period. To validate my conjecture, I use the same two-way sort portfolios on firm size and fundamental variables as in the previous section, but instead report the quarter $t+1$ log turnover ratios and the combined portfolio (P5-P1) turnover ratios in Table 7.6. I will then examine the cross-sectional portfolio spreads of turnover ratios among the sorted portfolios.

In the two-way sort portfolio analysis, I find strong evidence in support of my 'fire sale' hypothesis. The turnover ratios of the combined portfolio (P5-P1) sorted by all six fundamental variables are highly significant at the 1% significance level amongst the mid and small cap bank stocks. In the mid and small cap return portfolios, the one-quarter ahead log turnover ratios increase monotonically towards the portfolios of the poorest fundamental performance; that is, towards P1 of earnings, P5 of the non-performing loans, P5 of the loan-to-deposit ratios and P1 of the Tier 1 capital ratios. More precisely, bank stocks of smaller firm size and with weaker fundamentals in the previous quarter were traded more intensely and under-performed consistent with the 'fire sales' and 'flight-to-safety' phenomena.

To reveal how the impact of the banking firms' fundamentals on future trading activities changed over my sample period, I plot the quarterly combined portfolio log turnover ratios (CPT) of the large and small cap bank stocks based on the two-way sort portfolio analysis of size and the four banks' fundamental variables, which include the earnings, non-performing loans, loan-to-deposit ratios and Tier 1 capital ratios, in Fig. 7-1 - 7-4. Each combined portfolio is computed as the corner portfolio of the weaker fundamentals minus the corner portfolio of the stronger fundamentals so that a positive CPT refers to higher turnover conditional on a weaker fundamental performance. For instance, the earning combined portfolio is computed as Portfolio (1) of the lowest earnings minus the Portfolio (5) of the highest earnings. I also plot the differences of the CPT between the groups of large and small cap stocks to gauge the magnitude of size effects on the turnover ratios.

For the size and earnings sorted portfolios, as shown in Fig. 7-1, the CPT (P1-P5) of the small cap stocks have become positive from 2007Q1 onwards and have increased noticeably from 2008Q4 onwards and peaked in 2009Q3 (2.0) and in 2010Q2 (2.2). A differential in predictive power due to size is evident as the CPT (P1-P5) of the small cap stocks are considerably higher than those of the large cap stocks as shown by the upward trending bar chart. As for the non-performing loans and size sorted portfolios, as shown in Fig. 7-2, the CPT (P5-P1) of the small cap stocks have become positive in 2008Q1 (0.3) and have risen to 1.6 in 2009Q4 after the collapse of Lehman Brothers, and to as high as 2.1 in 2010Q1. Throughout the sample, the differences of the CPT between the small and large cap stocks are positive and have increased remarkably during the recent crisis. In Fig. 7-3 of the loan-to-deposit ratios and size sorted portfolio analysis, I observe that the CPT (P5-P1) of the small cap stocks were in general positive, except during the 2010Q1-2010Q2 period.[86] A

[86]The sudden dip in the CPT of the small cap stocks during the 2010Q1-2010Q2 period might be in part attributed to the Quantitative Easing by the Fed Reserve that exogenously affected the US banking firms' supply of deposits and ability to extend loans. Since both the numerator and denominator of the loan-to-deposit ratio are both impacted by the monetary policy, I am uncertain as to the underlying reason for the the sudden change in the trading patterns.

large size spread (i.e. the differential in predictive power between large and small bank stocks) in the CPT between the small and large cap stocks is present in the first half of the sample period and the spread has largely reversed after 2009Q4. As for the Tier 1 capital ratios and size sorted portfolios, the findings are qualitatively similar to those of the non-performing loans of Fig. 7-2 in that the size effect has become more prominent when the crisis unfolded.

The graphical analysis yields the following main implications. First, among the mid and small cap bank stocks, trading activity is concentrated on the bank stocks with weaker fundamentals and its intensity becomes stronger when the market conditions deteriorated during the crisis. Second, the predictive power of banking firms' fundamental variables over future trading intensity is considerably stronger among smaller stocks. Third, the differential in predictive power of fundamental variables between big and small stocks is more pronounced among the combined portfolios sorted by non-performing loans and Tier 1 capital ratios with the strength increased over the sample period. Fourth, the predictability largely persisted during and even after the recent crisis. Overall, the stronger size effects and the larger portfolio spreads of one-quarter ahead turnover ratios during the crisis provide additional evidence in support of the 'fire sale' and 'flight-to-safety' phenomena. In other words, the evidence in this study reveals that investors excessively sold small bank stocks with weaker fundamentals during and after the crisis.

I have checked the robustness of my results by running a Fama and Macbeth (1973) regression and a two-way fixed effects pooled regression (LSDV approach) using the one-quarter ahead log turnover ratios as dependent variables, with similar choices of standard errors as in Section 7.4.2. To show how the fundamental variables' contribution to future trading activities interacts with bank size, I interact the bank variables with the log firm size and report the results in Table 7.7.

First of all, banks' non-performing loans contribute positively to future trading activities in general and that when firm size is smaller, the positive relation is relatively stronger in magnitude. In other words, a smaller firm with higher non-performing loans is traded more intensely. Second, Tier 1 capital ratios are also highly significant and relate negatively to one-quarter ahead turnover ratios. The positive interaction term of Tier 1 capital ratios suggests that when bank size decreases, the negative impact of Tier 1 capital ratios on future turnover ratios becomes stronger; that is, banks with smaller buffers of Tier 1 capital are traded more intensely. Third, the coefficients of the residual and ABX risks are also significant; however, the findings are in general inconsistent with the two-way sort portfolios.

In summary, my multivariate findings confirm my two-way sort portfolio results on turnover ratios and show reasonably strong evidence that banking firms' loan portfolio asset quality, exposure to funding illiquidity risks and firm size are the main determinants of bank stocks' trading intensity.

Nonetheless, this observation has little effects on my conclusions.

The main implication is that bank stock return predictability is related closely to the 'fire sale' and 'flight-to-safety' phenomena in which banking firms' fundamental variables are the major criteria used by investors to guide their investment decisions.

7.4.5 Direction of Trading - Daily Order Flow Measures

The major caveat of the quarterly turnover ratios is that it does not distinguish between the buy and sell orders; that is, the higher turnover ratios may be dominated by buyer or seller-initiated orders. To validate my conjecture that the higher quarterly turnover ratios among banking firms of small size and weak fundamentals are consistent with the asset 'fire sale' or 'flight-to-safety' phenomena, additional evidence that the higher trading activity was dominated by sell side pressure is required. In addition, the analysis so far has been based on the premise that the substantively lower one-quarter ahead returns and higher turnover ratios can be collectively taken as evidence of the dominance of sell pressure among the bank stocks. I am aware that the lower quarterly returns might be disproportionately driven by large declines in a relatively small number of trading days and does not necessarily imply the presence of the asset 'fire sale' or 'flight-to-safety' phenomena.

To address these two issues, I follow the market microstructure literature and construct a proxy measure of daily order flows based on the daily closing prices of the bank stocks. The daily order flow measure is based on the assumption that a buy (sell) order today is approximated by observing that the closing price today closed at higher (lower) prices than the closing price yesterday. I construct a buy-sell order indicator variable that takes the value of 1 when it is a buy order today, -1 for a sell order and 0 otherwise. I gauge the quarterly relative strength of a bank stocks' buy-sell pressure by summing its buy-sell order variable over each quarter and divide the sum by its total number of available trading days in the quarter, as follows:[87]

$$ORDER\_FLOW_{i,t} = \frac{\sum_{j=1}^{N_{i,t}} I_{i,j}}{N_{i,t}} \tag{7.2}$$

where $I_{i,j}$ is the buy-sell order indicator variable of the i^{th} BHC on the j day in quarter t while $N_{i,t}$ is the total number of available daily price observations of the i^{th} BHC in quarter t. A positive (negative) $ORDER\_FLOW$ can be interpreted as a relative strength in buy (sell) pressure and means that there are relatively more (fewer) positive daily price changes than negative price changes in a quarter.

After obtaining the bank-level order flow variable, I apply two-way sort portfolio analysis sorted on size and the six bank fundamental variables as in Section 7.4.3 and report the one-quarter ahead

[87] I screen out bank-quarters in which a bank has less than 60 daily closing price data available in any quarter to ensure that the order flow variable is consistent and comparable across banks and quarters.

order flows. I test whether the one-quarter ahead order flows are significantly lower amongst the portfolios of weaker fundamentals and report the results in Table 7.8. The results based on the order flow variable are remarkably consistent with my previous results, based on the quarterly turnover ratios, and lend strong support to my asset 'fire sale' or 'flight-to-quality' hypothesis. First, the order flow variables decrease monotonically towards the portfolios of weaker fundamentals, that is, P1 of the earnings to total assets, P5 of non-performing loans, and P1 of the Tier 1 capital ratios, intersecting with the small cap portfolios ($< 30\%$). Second, the combined portfolio one-quarter ahead order flows (CPOF) (P5-P1) are significantly different than zero at the 1% level for the earnings (Panel A) and non-performing loans (Panel B) sorted portfolios and at the 5% level for the Tier 1 capital ratios (Panel C) sorted portfolios among the small cap stocks. More precisely, a small cap portfolio of the lowest earnings or highest non-performing loans has on average approximately 5% lower order flows (stronger sell pressure) while a small cap portfolio of the lowest Tier 1 capital ratios has about 4% lower order flows. In other words, the evidence shows that the small cap bank stocks of lower earnings, Tier 1 capital ratios or higher non-performing loans have significantly lower future one-quarter ahead returns, higher trading activity and stronger sell side pressure over 2006 to 2011, a result that is consistent with my conjecture that banks' fundamental variables are the major criteria that guided investors' investment and 'flight' decisions during the recent crisis.

In Figures 7-5 to 7-7, I plot the quarterly CPOF of the small and large cap bank stocks sorted by the banks' earnings, non-performing loans, and Tier 1 capital ratios, in which significant CPOF are identified. I also plot the differences in the CPOF between the groups of small and large bank stocks to reveal the size effects. In Figure 7-5 of the earnings sorted portfolios, the CPOF (P1-P5, lowest minus highest EBT_A) of the small cap stocks are largely below zero throughout the sample period (over 2007Q2-Q3 and 2008Q2-2011Q4), that is, small bank stocks with lower earnings had experienced relatively stronger sell pressure. The CPOF of the small bank stocks dipped noticeably after the Lehman Brothers' collapse in 2008Q4, and tumbled in 2009Q2 after the stock market downturn in the US. The (small minus large) size spreads between the CPOFs widened from 2008 onwards and remained wide after the crisis. As for the non-performing loans sorted portfolios in Figure 7-6, the CPOF (P5-P1, highest minus lowest NPL_A) have become negative during 2008Q3, 2009Q2, and from 2009Q4 until the end of the sample. Some size effects exist during and after the recent crisis in that the relatively higher sell pressure in bank stocks of poorer loan portfolio credit quality is more prominent amongst the small cap stocks. Fig. 7-7 plots the CPOF (P1-P5, lowest minus highest $TIER1\_CAP$) of the Tier 1 capital ratios sorted portfolios and shows that the CPOF of the small cap bank stocks have become negative during (2007Q3-4) and after the crisis (from 2009Q2 to the end of the sample). Note that the CPOF of the large cap stocks with lower capital ratios also experienced relatively stronger sell pressure over the period 2007Q4 to 2008Q2.

Overall, the graphical analysis reveals that the small cap stocks of lower earnings, Tier 1 capital ratios or higher non-performing loans experienced relatively larger sell pressure, as shown by the lower CPOF, during and after the recent crisis, more notably after the Lehman Brothers bankruptcy (2008Q3) and the stock market crash in the US in 2009Q1. Taken together with the evidence of significant turnover and return predictability, I conclude that banks' size and fundamental characteristics pertaining to profitability, loan portfolio credit quality and capital adequacy, were the most important criteria used by investors in formulating their asset 'fire sale' and 'flight-to-safety' decisions.

7.4.6 Ex-ante Investable Strategies

In this section, I evaluate the economic significance of the bank stock return predictability by examining the cumulative returns of the one-way sort portfolios, sorted by the bank variables over the period 2006Q2 to 2011Q4. I formulate my ex ante investable strategies assuming that investors have prior information that these bank variables are relevant in predicting the future stock returns. With an initial investment of $100 on the combined portfolios at the end of 2006Q2, I rebalance and reinvest the proceeds in new combined portfolio sorted at the end of the next quarter, assuming no transaction costs. I include three benchmark strategies based on the S&P 500 composite index, the 3-month t-bills and the bank industry portfolio from the Fama and French 49 industry portfolios.[88] The details and results of the investable strategies are reported in Table 7.9.

My investable strategies are highly profitable and outperformed substantially the three benchmark strategies. In general, the strategies that short the portfolios with the worse fundamentals and lend at the risk-free rate outperformed the zero-cost portfolios. The highly profitable strategies refer to the portfolios sorted by banks' earnings ($743), non-performing loans ($832), Tier 1 capital ratios ($606), and idiosyncratic risks ($644). My findings show that the bank stock predictability is economically significant and that investors can make substantively higher profit than the benchmark strategies. Note that the economic significance remains profound after taking into account the risks as shown in the FF-3 α in Panel B of Table 7.3.

7.5 Conclusions

This chapter has investigated quarterly bank stock return predictability over a sample period that covers the recent 2007 to 2009 financial crisis. I document new evidence that bank fundamental

[88]I have obtained the bank industry portfolio monthly returns from Kenneth R. French's web site. I thank French for making the data available to the public.

variables pertaining to profitability, loan portfolio credit quality, funding ability and capital ratios, and equity risks contain important information that significantly predicted one-quarter ahead bank stock returns during and after the recent crisis within an out-of-sample setting. In my univariate analysis, banks with lower earnings, more non-performing loans, higher loan-to-deposit ratios, lower Tier 1 capital ratios, higher idiosyncratic and crisis-related (ABX) risks have significantly lower one-quarter ahead bank stock returns. My multivariate tests based on the Fama and Macbeth (1973) regression and the fixed effects panel regressions find consistent results that the banks' earnings, non-performing loans, ABX risk and Tier 1 capital ratios are significant determinants of future bank stock returns, controlling for firm and time fixed effects. The return predictability of banks' fundemental characteristics over the one-quarter ahead returns is significant among the mid and small-sized portfolios. However, size cannot fully account for the return predictability, as evinced by the significant combined portfolio returns of the size-adjusted portfolios sorted by the banks' fundamental variables. The evidence in this chapter reveals how banks' fundamental characteristics affect the risk-return relationship in the stock market and highlights the relevance of fundamental analysis in evaluating bank stock performance during a sample period of contagion and increasing macroeconomic risks.

In the literature, a number of studies document evidence of asset 'fire sales' and 'flight-to-safety' from financial stocks to safer assets during the recent crisis. I advance my 'fire sale' or 'flight-to-safety' hypothesis in which banks with higher fundamental risks experienced relatively higher sell pressure due to the 'fire sale' of assets and for 'flight-to-safety' reasons. To my knowledge, I am the first to demonstrate that the return predictability in banks' fundamental variables relates closely to the investors' asset 'fire sale' or 'flight-to-safety' phenomena. In particular, I address an important research question: what were the major criteria considered by investors in formulating their portfolio rebalancing or 'flight' decisions during the crisis? Based on a two-way sort portfolio analysis, I discover that banks' earnings, non-performing loans and Tier 1 capital ratios significantly predict the one-quarter ahead bank stocks' turnover ratios among the small and mid cap bank stocks. Banks with weaker fundamentals were traded more intensely and had consistently lower returns in the next quarter. By constructing a bank-level order flow variable based on daily price changes, I provide additional evidence that the higher trading intensity concentrated on the small cap stocks with weaker fundamentals were dominated by relatively stronger sell pressure. The main contribution is that mid and small bank stocks with weaker fundamentals were excessively sold and had significantly lower returns in the next quarter, which is consistent with my 'fire sale' or 'flight-to-safety' hypothesis. More importantly, the evidence in this study reveals that banks' fundamental characteristics and size are the two most important criteria considered by investors with regard to their 'fire sale' and 'flight' strategy during the crisis.

Table 7.1: Description of the bank variables

This table contains the description of the bank variables used in this study. The four types of bank variables are as follows: banks' profitability (Panel A), fundamental risks (Panel B), funding illiquidity risks (Panel C), and market variables (Panel D).

Variables	Description (all accounting variables are averages of beginning and ending quarter values, deflated using a seasonally adjusted GDP deflator)
Panel A: Banks' profitability	
EBT_A	This variable measures banks' profitability computed as the earnings before extraordinary items and taxes to total assets (annualised).
NONINT_A	This variable is a measure of banks' income from nontraditional banking activities, computed as non-interest income to total assets (annualised).
Panel B: Banks' fundamental risks	
NPL_A	This is the proportion of non-performing loans to total assets. It is a proxy for banks' loan portfolio asset quality.
INTRISK_A	This variable measures the degree of banks' exposure to interest rate risk. It is computed as the absolute value of the difference between short-term assets and short-term liabilities and equity, normalised by total asset.
Panel C: Banks' funding illiquidity risks	
LOAN-TO-DEPOSIT	This variable is the proportion of total loans to total core deposits. It measures the degree of banks' exposure to funding illiquidity risk.
TIER1_CAP	This is the Tier 1 risk-based capital ratio, computed as the total Tier 1 capital divided by the risk-adjusted assets.
Panel D: Market variables	
LN_TURN	This variable gauges the degree of trading activities at the firm level. Following Chordia et al. (2001), I compute the turnover ratio as the number of traded shares over the number of outstanding shares at the end of each month. As I am matching the turnover ratios with quarterly returns, the turnover ratios I use is the monthly average of turnover ratios over the three months in each quarter.
RET	This variable is the quarterly compounded monthly returns over the three months in each quarter.
LN_MCAP	This is the log market capitalisation, computed as the natural log of the product of price and number of shares outstanding at the end of each quarter. I obtain the stock price and number of shares outstanding from CRSP.
MVBVEQ	This is the ratio of market value to book value of total shareholders' equity.

Table 7.2: Summary statistics

This table reports the means, standard deviations and percentile statistics of the bank variables used in this study. Please refer to Table 7.1 for a description of each bank variable.

Variable	Mean	Stdev	Percentiles				
			5%	25%	Median	75%	95%
Panel A: Banks' profitability							
EBT_A	0.001	0.030	−0.055	0.000	0.009	0.016	0.024
NONINT_A	0.012	0.012	0.001	0.006	0.010	0.016	0.033
Panel B: Banks' fundamental risks							
NPL_A	0.018	0.021	0.001	0.004	0.012	0.025	0.059
INTRISK_A	0.150	0.114	0.017	0.060	0.124	0.216	0.375
Panel C: Banks' funding and capital adequacy							
LOAN-TO-DEPOSIT	1.363	0.599	0.811	1.060	1.242	1.500	2.239
TIER1_CAP	0.117	0.034	0.074	0.098	0.114	0.134	0.176
Panel D: Bank equity risks							
σ^{MKT}	10.195	11.527	0.389	2.570	6.523	13.426	34.071
σ^{ABX}	2.583	3.346	0.117	0.645	1.507	3.272	8.522
σ^{RESID}	24.822	20.580	6.322	11.751	17.984	31.597	63.965
Panel E: Market variables							
LN_TURN	−0.808	1.298	−2.830	−1.840	−0.796	0.208	1.316
RET	−3.626	22.605	−42.407	−14.808	−2.908	6.472	32.297
Panel F: Other variables							
MVBVEQ	1.200	0.683	0.297	0.697	1.114	1.631	2.423
ASSET ($*Million*)	51,700	246,000	497	761	1466	5687	149,000
MCAP ($*Million*)	5,504	24,500	17	56	151	587	21,900
BVEQ ($*Million*)	4,503	20,200	32	64	126	518	16,900

Table 7.3: Univariate sort portfolios

This table reports the equally-weighted characteristics of the portfolios sorted by the banking firms' fundamental variables. At the end of quarter t, I sort the bank stocks into quintile portfolios according to the banks' quarter t fundamental variables and report the average quarter $t+1$ simple returns (Panel A), risk-adjusted returns (α from the Fama and French (1993) three-factor model, as in Panel B), turnover ratios (Panel C) and firm size (Panel D). The combined portfolio (5-1) returns are reported with superscripts ***, ** and * denoting statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: RET_{t+1}	Low				High		
Portfolios sorted by:	1	2	3	4	5	5-1	p-value
EBT_A_t	−10.07	−3.93	−3.08	−2.13	−1.28	8.79**	0.046
$NONINT\_A_t$	−8.03	−2.87	−4.35	−3.29	−2.04	5.99	0.122
NPL_A_t	−1.49	−1.86	−2.81	−4.51	−10.38	−8.89**	0.012
$INTRISK\_A_t$	−3.97	−4.10	−4.29	−3.87	−4.38	−0.41	0.917
$LOAN\text{-}TO\text{-}DEPOSIT_t$	−0.58	−3.34	−3.38	−5.47	−7.55	−6.97*	0.054
$TIER1\_CAP_t$	−8.76	−3.51	−3.81	−3.41	−1.28	7.47**	0.038
LN_MCAP_t	−7.26	−4.62	−4.53	−2.16	−1.87	5.38	0.209
$MVBVEQ_t$	−5.28	−5.48	−4.27	−2.91	−2.70	2.57	0.560
LN_TURN_t	−4.29	−4.68	−5.04	−4.12	−2.55	1.74	0.720
$LN(\sigma_t^{MKT})$	−5.08	−5.17	−4.49	−3.01	−2.92	2.15	0.661
$LN(\sigma_t^{ABX})$	−1.47	−3.14	−4.86	−3.67	−7.27	−5.80	0.126
$LN(\sigma_t^{RESID})$	−1.76	−2.79	−3.50	−3.21	−9.04	−7.28**	0.047

Panel B: FF-3 α							
Portfolios sorted by:	1	2	3	4	5	5-1	p-value
EBT_A_t	−10.49	−4.54	−3.54	−2.61	−1.82	8.67**	0.037
$NONINT\_A_t$	−8.65	−3.41	−4.81	−3.73	−2.50	6.15	0.114
NPL_A_t	−2.45	−2.66	−2.67	−4.88	−10.70	−8.25**	0.003
$INTRISK\_A_t$	−4.15	−4.77	−4.53	−4.40	−5.02	−0.87	0.753
$LOAN\text{-}TO\text{-}DEPOSIT_t$	−1.33	−3.51	−3.72	−5.90	−8.10	−6.77***	0.005
$TIER1\_CAP_t$	−9.03	−3.99	−4.23	−3.80	−1.91	7.12***	0.004
LN_MCAP_t	−7.70	−4.99	−4.85	−2.80	−2.47	5.23*	0.066
$MVBVEQ_t$	−5.72	−5.72	−4.66	−3.57	−3.29	2.43	0.442
LN_TURN_t	−4.66	−5.21	−5.24	−4.46	−3.33	1.34	0.614
$LN(\sigma_t^{MKT})$	−5.46	−5.49	−5.01	−3.51	−3.47	1.99	0.521
$LN(\sigma_t^{ABX})$	−2.21	−3.74	−5.05	−4.03	−7.72	−5.51**	0.038
$LN(\sigma_t^{RESID})$	−2.17	−3.47	−3.92	−3.71	−9.35	−7.18***	0.005

Panel C: LN_TURN_{t+1}							
Portfolios sorted by:	1	2	3	4	5	5-1	p-value
EBT_A_t	−0.65	−0.91	−1.02	−0.78	−0.37	0.27**	0.033
$NONINT\_A_t$	−0.95	−1.04	−1.00	−0.79	0.03	0.98***	0.000
NPL_A_t	−0.80	−0.96	−0.67	−0.72	−0.65	0.15	0.154
$INTRISK\_A_t$	−1.16	−0.86	−0.87	−0.77	−0.14	1.02***	0.000
$LOAN\text{-}TO\text{-}DEPOSIT_t$	−0.90	−0.92	−0.58	−0.70	−0.68	0.22***	0.007
$TIER1\_CAP_t$	−0.44	−0.62	−0.83	−0.79	−1.11	−0.67***	0.000
LN_MCAP_t	−1.71	−1.85	−0.90	−0.12	0.76	2.46***	0.000
$MVBVEQ_t$	−0.96	−0.98	−0.84	−0.66	−0.40	0.56***	0.000
LN_TURN_t	−2.34	−1.63	−0.87	0.11	0.88	3.21***	0.000
$LN(\sigma_t^{MKT})$	−1.82	−1.64	−0.66	0.13	0.15	1.98**	0.000
$LN(\sigma_t^{ABX})$	−0.69	−0.69	−0.74	−0.72	−1.01	−0.32**	0.010
$LN(\sigma_t^{RESID})$	−0.21	−0.53	−0.84	−1.09	−1.15	−0.94***	0.000

Panel D: LN_MCAP_{t+1}							
Portfolios sorted by:	1	2	3	4	5	5-1	p-value
EBT_A_t	6.86	7.27	7.61	8.14	8.95	2.09***	0.000
$NONINT\_A_t$	6.72	7.12	7.18	7.81	9.99	3.27***	0.000
NPL_A_t	7.93	7.62	8.16	8.02	7.04	−0.89***	0.000
$INTRISK\_A_t$	7.24	7.45	7.59	7.71	8.81	1.57***	0.000
$LOAN\text{-}TO\text{-}DEPOSIT_t$	7.94	7.52	8.23	7.76	7.34	−0.60***	0.004
$TIER1\_CAP_t$	8.23	7.77	7.65	7.64	7.47	−0.76*	0.082
LN_MCAP_t	5.56	6.48	7.23	8.28	11.16	5.60***	0.000
$MVBVEQ_t$	6.39	7.32	7.97	8.25	8.74	2.35***	0.000
LN_TURN_t	6.27	6.42	7.27	8.70	10.04	3.77***	0.000
$LN(\sigma_t^{MKT})$	6.30	6.49	8.01	9.10	8.78	2.48***	0.000
$LN(\sigma_t^{ABX})$	8.25	8.14	7.80	7.65	6.84	−1.40***	0.000
$LN(\sigma_t^{RESID})$	9.54	8.32	7.60	6.97	6.29	−3.25***	0.000

Table 7.4: Determinants of future bank stock returns

This table reports the results of the Fama and Macbeth (1973) two-pass regression and the two-way fixed effects pooled regressions (LSDV approach). The dependent variable is the one-quarter ahead $(t+1)$ bank stock returns. The quarter t independent variables include: average turnover ratios ($TURN$), market to book value ratios ($MVBVEQ$), earnings before taxes and extraordinary items to total assets (EBT_A), non-performing loans to total assets (NPL_A), non-interest income to total assets ($NONINT\_A$), interest rate risk ($INTRISK\_A$), log market capitalisation (LN_MCAP). I also include the quarterly-equivalent bank risks (the market systematic risk (σ^{MKT}), crisis-related risk (σ^{ABX}) and residual risk (σ^{RESID})) following the approach of Anderson and Fraser (2000) (please refer to Appendix A.1 for more details on the variance decomposition approach). The standard errors for the Fama and Macbeth (1973) regressions are adjusted following Newey-West (1987) using 4 lags (equivalent to a year). Both firm and time fixed effects are accounted for in the pooled regression with robust standard errors clustered by firm and time following Cameron et al. (2011). Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Determinants of one-quarter ahead bank stock returns				
	Fama-Macbeth		LSDV Regressions	
Model	Coef	S.E.	Coef	S.E.
Bank risks:				
$LN(\sigma_t^{MKT})$	0.484	(0.439)	0.095	(0.361)
$LN(\sigma_t^{ABX})$	−0.393	(0.363)	−0.697**	(0.332)
$LN(\sigma_t^{RESID})$	−0.347	(1.590)	−0.185	(1.147)
Banks' fundamental variables:				
EBT_A_t	74.959*	(41.520)	46.903**	(22.740)
$NONINT\_A_t$	23.938	(50.702)	42.020	(25.998)
NPL_A_t	−248.572***	(43.577)	−191.505***	(40.028)
$LOAN\text{-}TO\text{-}DEPOSIT\_t$	−0.598	(0.970)	−0.759	(0.578)
$TIER1\_CAP_t$	55.878***	(16.614)	56.980***	(12.956)
Control variables:				
$INTRISK\_A_t$	−1.281	(5.728)	−0.180	(3.551)
$MVBVEQ_t$	−1.061	(1.718)	−1.349**	(0.668)
LN_MCAP_t	−0.133	(0.343)	0.039	(0.362)
LN_TURN_t	0.453	(0.806)	0.690	(0.488)
$INTERCEPT$	−4.946	(8.188)	9.466	(5.901)
Firm dummy	N		Y	
Quarterly dummy	N		Y	
N	2,930		2,930	
R^2	0.240		0.301	

Table 7.5: Two-way sort portfolios - controlling for firm size

This table reports the results of the two-way sort portfolios. I first sort the bank stocks into three portfolios (breakpoints at 30% and 70%: small, mid and large) based on the banks' log market capitalisation at quarter t and then sort the stocks into five portfolios based on the banking firms' quarter t characteristics. I then report the equally-weighted average quarter $t+1$ returns (RET_{t+1}). The differences across the quintile portfolios and the size portfolios are computed with statistical inference based on two-sample t-tests assuming unequal variances. I also average the size portfolios at each quintile portfolio level so that each size-adjusted quintile portfolio has comparable average firm size and report the portfolio return spreads. The six banking firms' fundamental characteristics include the earnings to total assets (EBT_A), non-performing loans to total assets (NPL_A), loan-to-deposit ratios ($LOAN\text{-}TO\text{-}DEPOSIT$), Tier 1 capital ratios ($TIER1\_CAP$), residual risks (σ^{RESID}) and crisis related risks (σ^{ABX}). Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: EBT_A	1	2	3	4	5	5-1	**Panel B:** NPL_A	1	2	3	4	5	5-1
L	−5.48	−1.84	−0.92	0.61	−2.28	3.21	L	−0.17	−1.56	−0.37	−2.67	−4.62	−4.45
M	−8.09	−4.39	−4.05	−4.14	−1.52	6.57	M	−1.65	−2.42	−3.35	−4.86	−10.52	−8.87**
S	−17.39	−4.93	−4.66	−1.62	−1.02	16.37***	S	−1.86	−3.00	−3.55	−6.21	−15.92	−14.06***
S-L	−11.91*	−3.09	−3.74	−2.23	1.26		S-L	−1.69	−1.44	−3.19	−3.54	−11.31**	
Average	−10.32	−3.72	−3.21	−1.72	−1.61	8.71**	Average	−1.23	−2.33	−2.42	−4.58	−10.35	−9.13**

Panel C: $LOAN\text{-}TO\text{-}DEPOSIT$	1	2	3	4	5	5-1	**Panel D:** $TIER1\_CAP$	1	2	3	4	5	5-1
L	1.17	−2.13	−0.99	−4.52	−3.01	−4.18	L	−3.51	−3.14	−2.15	0.61	−0.83	2.67
M	−1.78	−2.54	−4.88	−4.41	−9.12	−7.34*	M	−8.62	−4.44	−4.60	−5.00	0.28	8.90**
S	−3.05	−5.32	−7.05	−5.79	−10.17	−7.12**	S	−14.57	−5.38	−3.82	−5.56	−0.09	14.470***
S-L	−4.22	−3.19	−6.06	−1.28	−7.16		S-L	−11.06**	−2.25	−1.67	−6.17	0.74	
Average	−1.22	−3.33	−4.31	−4.91	−7.43	−6.21*	Average	−8.90	−4.32	−3.52	−3.31	−0.22	8.68**

Panel E: $LN(\sigma^{RESID})$	1	2	3	4	5	5-1	**Panel F:** $LN(\sigma^{ABX})$	1	2	3	4	5	5-1
L	−1.15	−0.66	−1.62	−2.75	−2.16	−1.01	L	−0.68	0.22	−0.55	−1.89	−3.03	−2.35
M	−2.51	−3.57	−3.78	−4.18	−8.34	−5.83	M	−2.47	−4.03	−5.17	−5.07	−5.94	−3.47
S	−3.53	−2.92	−4.14	−5.85	−13.02	−9.50**	S	−2.49	−7.59	−4.55	−4.48	−10.41	−7.92**
S-L	−2.38	−2.26	−2.52	−3.09	−10.87*		S-L	−1.81	−7.82	−4.00	−2.59	−7.38	
Average	−2.39	−2.38	−3.18	−4.26	−7.84	−5.45	Average	−1.88	−3.80	−3.42	−3.82	−6.46	−4.58

Table 7.6: Two-way sort portfolios - controlling for firm size and reporting LN_TURN_{t+1}

This table reports the quarter $t+1$ average turnover ratios based on the two-way sort portfolios. I first sort the bank stocks into three portfolios (breakpoints at 30% and 70%) based on banks' log market capitalisation at quarter t and then sort the stocks into five portfolios based on the banking firms' quarter t characteristics. I then report the equally-weighted average quarter $t+1$ log turnover ratios (LN_TURN_{t+1}). The differences across the quintile portfolios and the size portfolios are computed with statistical inference based on two-sample t-tests assuming unequal variances. The six banking firms' fundamental characteristics include the earnings to total assets (EBT_A), non-performing loans to total assets (NPL_A), loan-to-deposit ratios ($LOAN$-TO-$DEPOSIT$), Tier 1 capital ratios ($TIER1\_CAP$), residual risks (σ^{RESID}) and crisis related risks (σ^{ABX}). Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: EBT_A	1	2	3	4	5	5-1	**Panel B:** NPL_A	1	2	3	4	5	5-1
L	0.67	0.62	0.44	0.49	0.45	−0.22	L	0.42	0.37	0.62	0.71	0.46	0.03
M	−0.49	−0.99	−1.06	−1.27	−0.94	−0.45***	M	−0.98	−1.22	−1.06	−1.03	−0.49	0.48***
S	−1.16	−1.72	−1.86	−1.98	−2.08	−0.93***	S	−2.03	−1.99	−1.89	−1.63	−1.24	0.79***
Panel C: $LOAN$-TO-$DEPOSIT$	1	2	3	4	5	5-1	**Panel D:** $TIER1\_CAP$	1	2	3	4	5	5-1
L	0.47	0.44	0.54	0.59	0.55	0.08	L	0.63	0.58	0.54	0.48	0.41	−0.22
M	−1.37	−1.08	−0.96	−0.89	−0.55	0.81***	M	−0.72	−1.02	−0.94	−0.90	−1.35	−0.63***
S	−2.00	−1.86	−1.67	−1.66	−1.60	0.41***	S	−1.30	−1.65	−1.88	−1.89	−2.06	−0.75***
Panel E: $LN(\sigma^{RESID})$	1	2	3	4	5	5-1	**Panel F:** $LN(\sigma^{ABX})$	1	2	3	4	5	5-1
L	0.39	0.44	0.52	0.57	0.56	0.18	L	0.50	0.50	0.47	0.50	0.48	−0.02
M	−1.08	−1.02	−1.12	−0.99	−0.75	0.33***	M	−1.18	−0.99	−0.94	−0.95	−0.79	0.39***
S	−1.96	−1.89	−1.90	−1.70	−1.48	0.48***	S	−1.83	−1.84	−1.71	−1.99	−1.61	0.21*

Table 7.7: Determinants of future turnover ratios (LN_TURN_{t+1})

This table reports the results of the Fama and Macbeth (1973) and the two-way fixed effects pooled regressions (LSDV approach) using one-quarter ahead log turnover ratios as dependent variables. The banking variables include: residual risks (σ_{RESID}), crisis-related risks (σ_{ABX}), earnings to total assets (EBT_A), non-performing loans to total assets (NPL_A), loan-to-deposit ratios ($LOAN\text{-}TO\text{-}DEPOSIT$), Tier 1 capital ratios ($TIER1\_CAP$) and firm size (LN_MCAP). The interaction terms of the banking variables with firm size are also included. I use the Newey and West (1987) adjusted robust standard errors with 4 lags for the Fama and Macbeth (1973) regression and the two-way clustered standard errors for the fixed effects pooled regression following Cameron et al. (2011). Superscripts '***', '**' and '*' denote statistical significance at the 1%, 5% and 10% level, respectively.

Determinants of one-quarter ahead turnover ratios				
	Fama-Macbeth		LSDV Regression	
Model	Coef	S.E.	Coef	S.E.
Banks' risks				
$LN(\sigma_t^{ABX})$	0.075	(0.082)	-0.056^{*}	(0.030)
$LN(\sigma_t^{RESID})$	-1.744^{***}	(0.369)	-0.853^{***}	(0.105)
Banks' fundamental variables				
EBT_A_t	-8.779^{*}	(4.828)	0.351	(1.863)
NPL_A_t	24.495	(14.593)	24.682^{***}	(5.667)
$LOAN\text{-}TO\text{-}DEPOSIT_t$	0.746^{***}	(0.110)	0.087	(0.106)
$TIER1\_CAP_t$	-31.161^{***}	(4.118)	-11.659^{***}	(3.816)
Firm size and interaction terms				
LN_MCAP_t	-0.324^{*}	(0.156)	-0.365^{***}	(0.098)
$\mathbf{LN\_MCAP_t}\times$				
$LN(\sigma_t^{ABX})$	-0.006	(0.009)	0.008^{**}	(0.003)
$LN(\sigma_t^{RESID})$	0.240^{***}	(0.048)	0.126^{***}	(0.011)
EBT_A_t	-0.002	(0.531)	-0.067	(0.249)
NPL_A_t	-3.310^{**}	(1.505)	-3.220^{***}	(0.707)
$LOAN\text{-}TO\text{-}DEPOSIT_t$	-0.074^{***}	(0.013)	-0.002	(0.009)
$TIER1\_CAP_t$	3.888^{***}	(0.497)	1.058^{**}	(0.431)
$INTERCEPT$	1.302	(1.198)	2.007^{**}	(0.884)
Firm dummies	N		Y	
Quarterly dummies	N		Y	
N	2,930		2,930	
R^2	0.641		0.860	

Table 7.8: Two-way sort portfolios - controlling for firm size and reporting the order flow variable ($ORDER\_FLOW_{t+1}$)

This table reports the quarter $t+1$ average order flow variables based on the two-way sort portfolios. I first sort the bank stocks into three portfolios (breakpoints at 30% and 70%) based on banks' log market capitalisation at quarter t and then sort the stocks into five portfolios based on the banking firms' quarter t characteristics. I then report the equally-weighted average quarter $t+1$ order flow measures ($ORDER\_FLOW_{t+1}$). The differences across the quintile portfolios and the size portfolios are computed with statistical inference based on two-sample t-tests assuming unequal variances. The six banking firms' fundamental characteristics include the earnings to total assets (EBT_A), non-performing loans to total assets (NPL_A), loan-to-deposit ratios ($LOAN$-TO-$DEPOSIT$), Tier 1 capital ratios ($TIER1\_CAP$), residual risks (σ^{RESID}) and crisis related risks (σ^{ABX}). Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: EBT_A							**Panel B:** NPL_A						
	1	2	3	4	5	5-1		1	2	3	4	5	5-1
L	−0.042	−0.021	−0.019	−0.017	−0.024	0.018	L	−0.023	−0.031	−0.013	−0.022	−0.036	−0.012
M	−0.060	−0.030	−0.037	−0.037	−0.028	0.032*	M	−0.034	−0.036	−0.026	−0.037	−0.065	−0.031*
S	−0.071	−0.037	−0.034	−0.030	−0.021	0.051***	S	−0.024	−0.026	−0.030	−0.043	−0.076	−0.052***
Panel C: $LOAN$-TO-$DEPOSIT$							**Panel D:** $TIER1\_CAP$						
	1	2	3	4	5	5-1		1	2	3	4	5	5-1
L	−0.015	−0.025	−0.028	−0.028	−0.030	−0.014	L	−0.024	−0.021	−0.037	−0.027	−0.026	−0.001
M	−0.029	−0.029	−0.039	−0.040	−0.056	−0.027	M	−0.054	−0.024	−0.042	−0.040	−0.031	0.023
S	−0.032	−0.044	−0.044	−0.040	−0.047	−0.015	S	−0.067	−0.043	−0.034	−0.031	−0.024	0.043**
Panel E: σ^{RESID}							**Panel F:** σ^{ABX}						
	1	2	3	4	5	5-1		1	2	3	4	5	5-1
L	−0.028	−0.009	−0.020	−0.034	−0.029	−0.001	L	−0.010	−0.020	−0.016	−0.036	−0.036	−0.026
M	−0.028	−0.036	−0.041	−0.040	−0.051	−0.023	M	−0.035	−0.038	−0.045	−0.030	−0.047	−0.013
S	−0.031	−0.033	−0.032	−0.039	−0.060	−0.030*	S	−0.043	−0.044	−0.029	−0.030	−0.050	−0.007

Table 7.9: Ex ante investable strategies

This table reports my proposed investable strategies based on one-way sort portfolios on the bank variables, including the earnings to total assets (EBT_A), non-performing loans to assets (NPL_A), loan-to-deposit ratios ($LOAN\text{-}TO\text{-}DEPOSIT$), Tier 1 capital ratios ($TIER1\_CAP$), market risk (σ_{MKT}), ABX risk (σ_{ABX}), and residual risk (σ_{RESID}). At the end of quarter t, I sort my bank stocks into five portfolios based on quarter t bank variables and invest in the zero-cost combined portfolios as described in columns (3) and (4). I then rebalance and reinvest the proceeds into new combined portfolio at the end of quarter $t+1$. With an assumption of no transaction costs, my initial investment is $100 at the beginning (2006Q2). The ending balances as at 2011Q4 are reported in the last column. Three benchmark strategies are reported. Benchmark 1 refers to a long position in the S&P 500 composite index financed with borrowing at the risk-free rate (3 month T-bills) while Benchmark 2 takes opposite positions. Benchmark 3 involves shorting the US Bank portfolios in the Fama and French 49-industry portfolios obtained from Kenneth R. French's web site and investing the proceeds in T-bills.

Investable Strategies, based on one-way sort portfolios on quarter t banking firms' fundamental variables					
Strategies	Characteristics	Description		Begin	End
Benchmark (1)	S&P & T-bills	Long S&P	Short T-bills	$100	$90.51
Benchmark (2)	S&P & T-bills	Short S&P	Long T-bills	$100	$88.65
Benchmark (3)	FF Bank Portfolio & T-bills	Short FF Bank Portfolio	Long T-bills	$100	$179.46
(1)	EBT_A	Long (5)	Short (1)	$100	$582.80
(2)	EBT_A	Long T-bills	Short (1)	$100	$743.19
(3)	NPL_A	Long (1)	Short (5)	$100	$602.38
(4)	NPL_A	Long T-bills	Short (5)	$100	$832.06
(5)	$NONINT$	Long (5)	Short (1)	$100	$333.58
(6)	$NONINT$	Long T-bills	Short (1)	$100	$515.82
(7)	$LOAN\text{-}TO\text{-}DEPOSIT$	Long (1)	Short (5)	$100	$422.17
(8)	$LOAN\text{-}TO\text{-}DEPOSIT$	Long T-bills	Short (5)	$100	$456.78
(9)	$TIER1\_CAP$	Long (5)	Short (1)	$100	$465.42
(10)	$TIER1\_CAP$	Long T-bills	Short (1)	$100	$605.63
(11)	LN_MCAP	Long (5)	Short (1)	$100	$255.72
(12)	LN_MCAP	Long T-bills	Short (1)	$100	$450.42
(13)	$LN(\sigma^{MKT})$	Long (5)	Short (1)	$100	$137.04
(14)	$LN(\sigma^{MKT})$	Long T-bills	Short (1)	$100	$290.33
(15)	$LN(\sigma^{ABX})$	Long (1)	Short (5)	$100	$332.76
(16)	$LN(\sigma^{ABX})$	Long T-bills	Short (5)	$100	$438.54
(17)	$LN(\sigma^{RESID})$	Long (1)	Short (5)	$100	$440.61
(18)	$LN(\sigma^{RESID})$	Long T-bills	Short (5)	$100	$643.97

Figure 7-1: Combined portfolio turnover ratios of the small and large cap bank stocks - based on the two-way sort portfolios of size and earnings

This figure plots the time-varying portfolio spreads in log turnover ratios based on the two-way sort portfolio by size and earnings to total assets (EBT_A). At the end of quarter t, I sort the bank stocks into three portfolios based on the market capitalisation at quarter t (breakpoints at 30% and 70%), then sort the bank stocks within each return portfolio into quintile portfolios by the banking firms' earnings at quarter t, and report the log turnover ratios at quarter $t+1$. I plot the quarterly quintile portfolio spreads (P1-P5, Portfolio (1) of the lowest earnings minus Portfolio (5) of the highest earnings) of log turnover ratios of the small and large cap stocks and also the differences in turnover ratios between the two portfolio spread measures due to size. The right-axis measures the portfolio differences in log turnover ratios while the left-axis measures the difference between the spreads due to size.

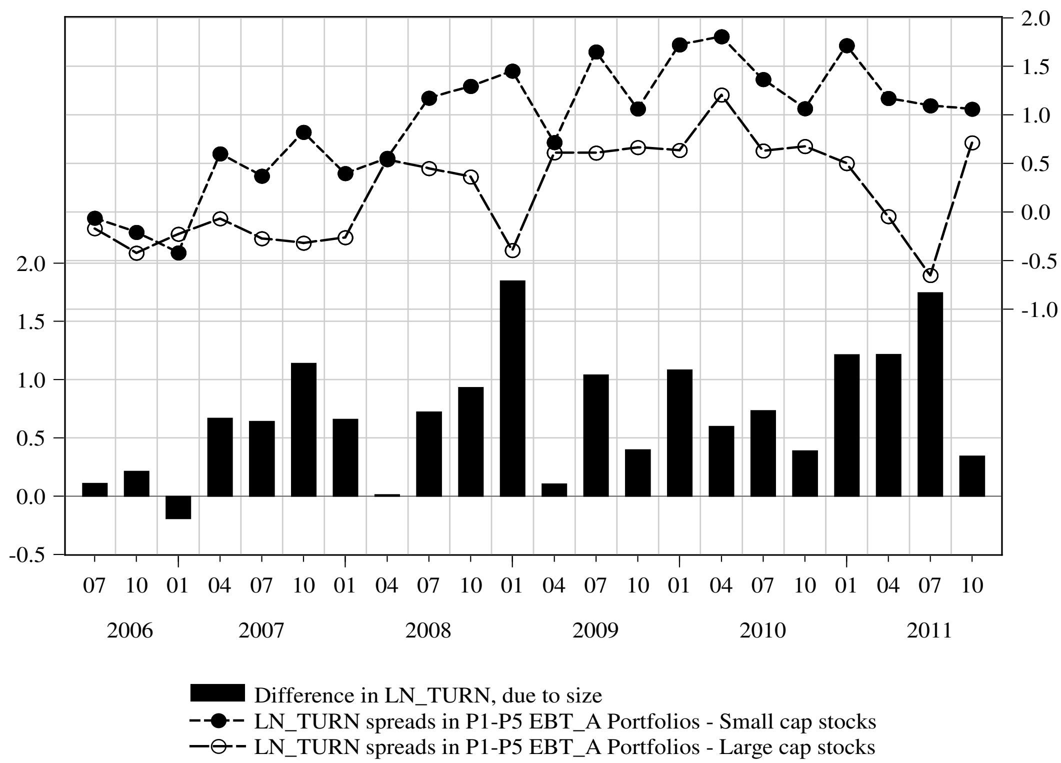


Figure 7-2: Combined portfolio turnover ratios of the small and large cap bank stocks - based on the two-way sort portfolios of size and non-performing loans

This figure plots the time-varying portfolio spreads in log turnover ratios based on the two-way sort portfolio by size and non-performing loans to total assets (NPL_A). At the end of quarter t, I sort the bank stocks into three portfolios based on the market capitalisation at quarter t (breakpoints at 30% and 70%), then sort the bank stocks within return portfolio into quintile portfolios by the banking firms' non-performing loans at quarter t, and report the log turnover ratios at quarter $t + 1$. I plot the quarterly quintile portfolio spreads (P5-P1, Portfolio (5) of the worst loan asset quality minus Portfolio (1) of the best loan asset quality) of log turnover ratios of the small and large cap stocks and also the differences in turnover ratios between the two portfolio spread measures due to size. The right-axis measures the portfolio differences in log turnover ratios while the left-axis measures the difference between the spreads due to size.

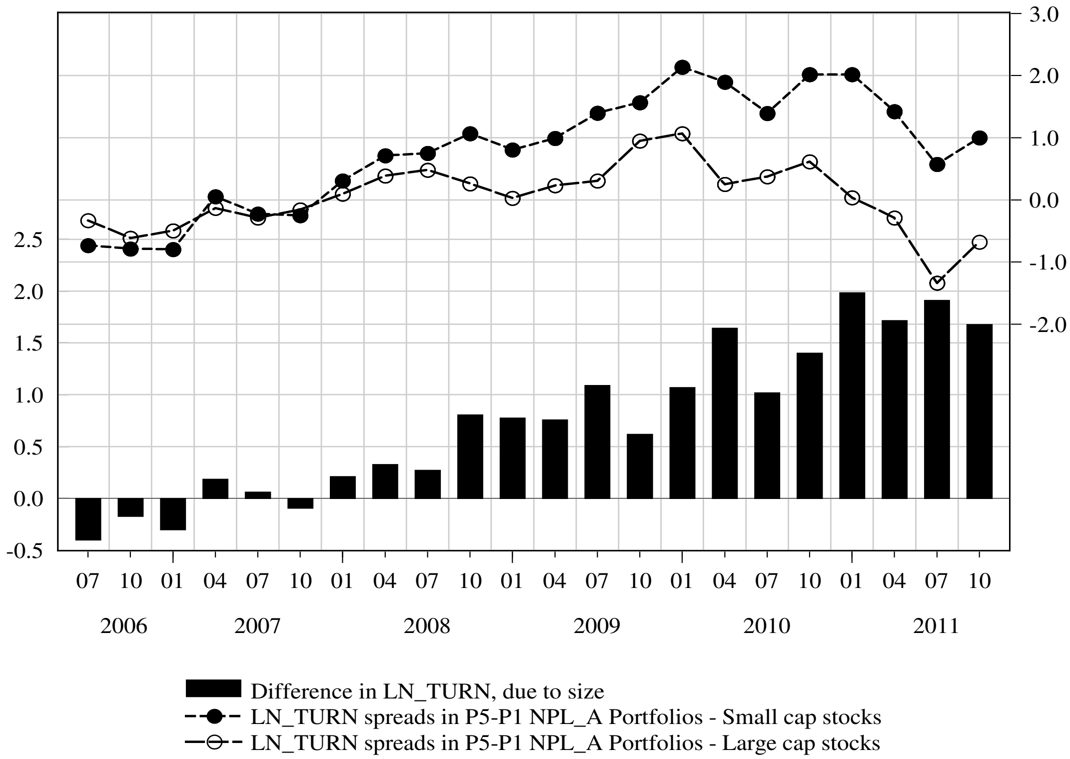


Figure 7-3: Combined portfolio turnover ratios of the small and large cap bank stocks - based on the two-way sort portfolios of size and loan-to-deposit ratios

This figure plots the time-varying portfolio spreads in log turnover ratios based on the two-way sort portfolio by size and loan-to-deposit ratios (*LOAN-TO-DEPOSIT*). At the end of quarter t, I sort the bank stocks into three portfolios based on the market capitalisation at quarter t (breakpoints at 30% and 70%), then sort the bank stocks within each return portfolio into quintile portfolios by the banking firms' loan-to-deposit ratios at quarter t, and report the log turnover ratios at quarter $t + 1$. I plot the quarterly quintile portfolio spreads (P5-P1, Portfolio (5) of the highest loan-to-deposit ratios minus Portfolio (1) of the lowest loan-to-deposit ratios) of log turnover ratios of the small and large cap stocks and also the differences in turnover ratios between the two portfolio spread measures due to size. The right-axis measures the portfolio differences in log turnover ratios while the left-axis measures the difference between the spreads due to size.

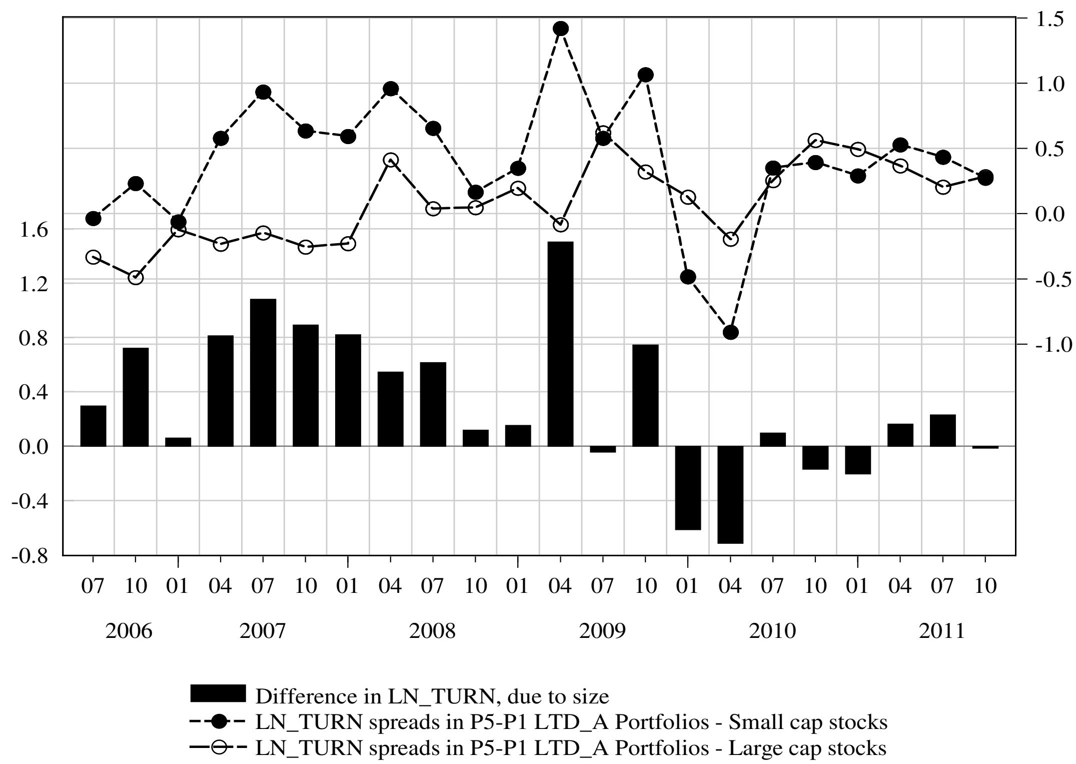


Figure 7-4: Combined portfolio turnover ratios of the small and large cap bank stocks - based on the two-way sort portfolios of size and Tier 1 capital ratios

This figure plots the time-varying portfolio spreads in log turnover ratios based on the two-way sort portfolio by size and Tier 1 capital ratios ($TIER1\_CAP$). At the end of quarter t, I sort the bank stocks into three portfolios based on the market capitalisation at quarter t (breakpoints at 30% and 70%), then sort the bank stocks within each return portfolio into quintile portfolios by the banking firms' Tier 1 capital ratios at quarter t, and report the log turnover ratios at quarter $t + 1$. I plot the quarterly quintile portfolio spreads (P1-P5, Portfolio (1) of the lowest capital adequacy minus Portfolio (5) of the lowest capital adequacy) of log turnover ratios of the small and large cap stocks and also the differences in turnover ratios between the two portfolio spread measures due to size. The right-axis measures the portfolio differences in log turnover ratios while the left-axis measures the difference between the spreads due to size.

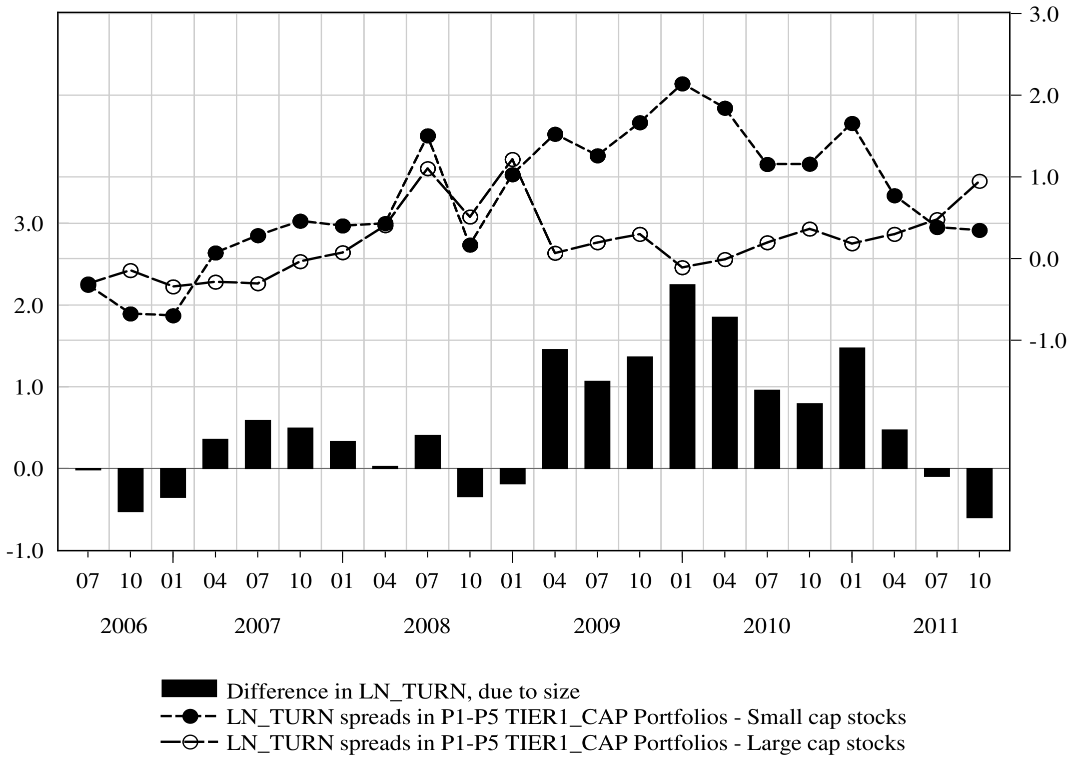


Figure 7-5: Combined portfolio order flows of the small and large cap bank stocks - based on the two-way sort portfolios of size and earnings

This figure plots the quarterly combined portfolio order flows based on the two-way sort portfolio by size and earnings to total assets (EBT_A). At the end of quarter t, I sort the bank stocks into three portfolios based on the market capitalisation at quarter t (breakpoints at 30% and 70%), then sort the bank stocks within each return portfolio into quintile portfolios by the banking firms' earnings at quarter t, and report the equally-weighted average order flows at quarter $t+1$. I plot the quarterly P1-P5 combined portfolio order flows (i.e. Portfolio (1) of the lowest earnings minus Portfolio (5) of the highest earnings) of the small and large cap stocks and also the differences in order flows between the two combined portfolio order flows due to size. The right-axis measures the order flows while the left-axis measures the size spreads.

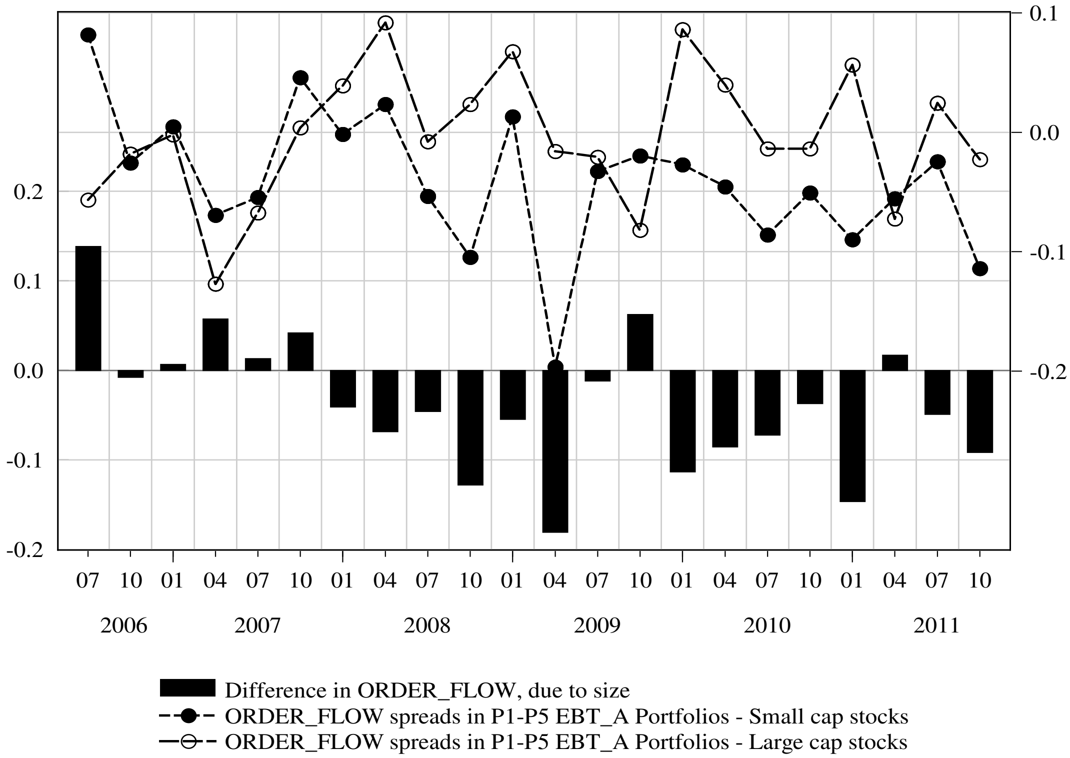


Figure 7-6: Combined portfolio order flows of the small and large cap bank stocks - based on the two-way sort portfolios of size and non-performing loans

This figure plots the quarterly combined portfolio order flows based on the two-way sort portfolio by size and non-performing loans to total assets (NPL_A). At the end of quarter t, I sort the bank stocks into three portfolios based on the market capitalisation at quarter t (breakpoints at 30% and 70%), then sort the bank stocks within each return portfolio into quintile portfolios by the banking firms' NPL_A at quarter t, and report the equally-weighted average order flows at quarter $t+1$. I plot the quarterly P5-P1 combined portfolio order flows (i.e. Portfolio (5) of the highest NPL_A minus Portfolio (1) of the lowest NPL_A) of the small and large cap stocks and also the differences in order flows between the two combined portfolio order flows due to size. The right-axis measures the order flows while the left-axis measures the size spreads.

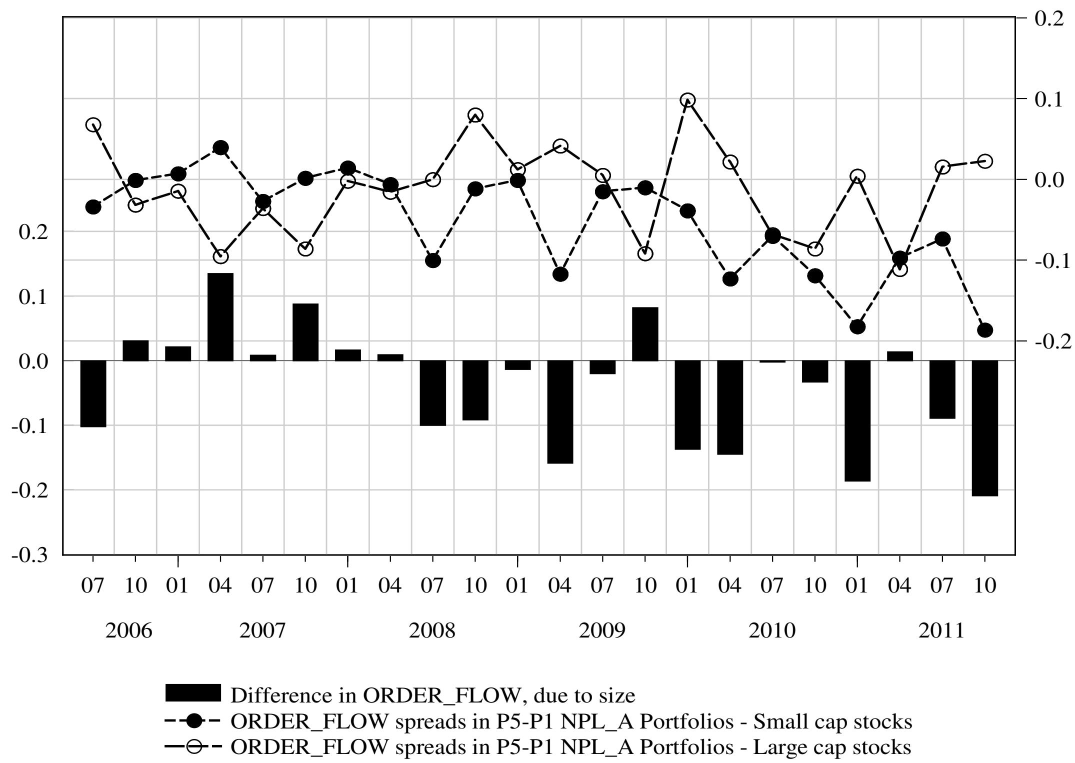
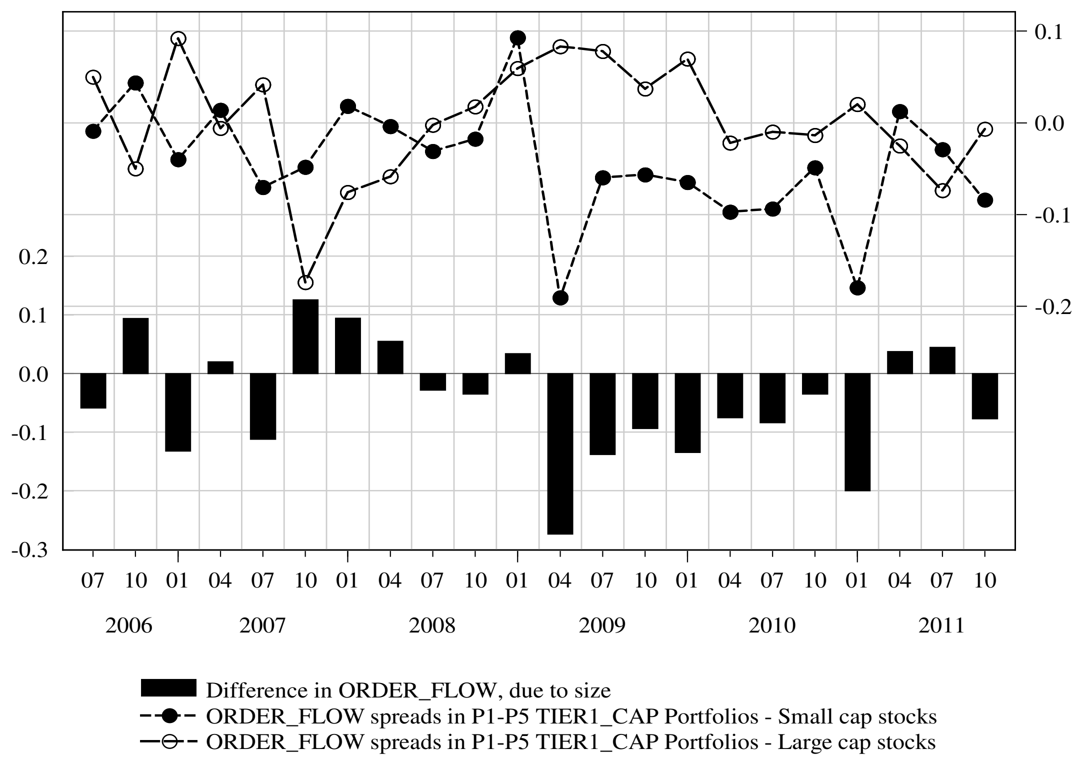


Figure 7-7: Combined portfolio order flows of the small and large cap bank stocks - based on the two-way sort portfolios of size and Tier 1 capital ratios

This figure plots the quarterly combined portfolio order flows based on the two-way sort portfolio by size and Tier 1 capital ratios ($TIER1\_CAP$). At the end of quarter t, I sort the bank stocks into three portfolios based on the market capitalisation at quarter t (breakpoints at 30% and 70%), then sort the bank stocks within each return portfolio into quintile portfolios by the banking firms' $TIER1\_CAP$ at quarter t, and report the equally-weighted average order flows at quarter $t+1$. I plot the quarterly P1-P5 combined portfolio order flows (i.e. Portfolio (1) of the lowest $TIER1\_CAP$ minus Portfolio (5) of the highest $TIER1\_CAP$) of the small and large cap stocks and also the differences in order flows between the two combined portfolio order flows due to size. The right-axis measures the order flows while the left-axis measures the size spreads.



Chapter 8

Conclusions

8.1 Introduction

The recent 2007 to 2009 financial crisis presents an ideal opportunity to study contagion for a number of reasons. First, it has clear-cut origins; that is, the subprime mortgage market and the structured finance market. Second, the recent financial crisis differs from previous crisis events in that it was characterised by significant financial innovations and by securitisation. An update in the empirical literature is essential for an understanding of the topical issues in today's financial world. Third, it is observed that financial stocks were traded more intensely during the recent crisis, which is consistent with a possible 'flight-to-safety' phenomenon (Longstaff, 2010). The recent crisis allows us to closely examine the trading patterns and stock performance in relation to the 'flight-to-safety' phenomenon, and reveals how investors made their investment or 'flight' decisions during the crisis. Fourth, it is widely-acknowledged that the recent financial crisis was characterised by severe funding and market illiquidity. This presents ideal conditions for testing the relation between funding and market illiquidity as proposed in the seminal work by Brunnermeier and Pedersen (2009). It also presents ideal conditions for studying the role of illiquidity in contagion transmission.

In this thesis, I have provided a detailed overview of the subprime and the subsequent global financial crises in relation to the ending of the US housing bubble, the securitisation process, the reinforcing liquidity spiral between funding and market illiquidity, and the failure of the structured finance market. I have then reviewed the contagion literature and addressed a few important issues, including the widespread disagreement of working definitions, the causes of contagion and the empirical methodologies, followed by a summary of the empirical evidence.

Over the past decade, the structured finance market has grown substantially and it has become one of the largest fixed income markets in the US. Despite its increasing importance to financial stability, little empirical work has been done to examine the role of the structured finance market in the context of contagion in the recent financial crisis. I fill this gap by offering a comprehensive empirical investigation of the spillovers of shocks from the structured finance market indices to a number of international markets. More importantly, I formulate my contagion tests within an asset pricing framework and test formally for any significant increase in the linkages between individual stocks and the ABX innovations during the crisis, thus contributing to both the contagion and asset pricing literature. I then examine closely the role played by the US BHCs in the recent crisis and identify the determinants of banks' equity risks and future stock returns using a set of bank-specific asset composition and fundamental variables. In addition, I contribute to the literature by discovering the link between bank stock return predictability and investors' 'fire sale' or 'flight-to-safety' phenomena during the recent crisis.

8.2 Synthesis of my empirical findings

First, I extend Longstaff's (2010) investigation to an international market perspective and test for contagion from the US structured finance market to the G5 international markets. Using weekly frequency data, my analysis shows that the shocks from the structured finance market translated into subsequent declines in the international markets, which is consistent with contagion. I find strong support for the contagion transmission via the funding liquidity and risk premia channels in that the negative shocks from the ABX indices led to subsequent higher trading intensity among financial stocks (in the US, UK, and France) relative to the market, widening of interest rate swap spreads (in all G5 countries) and heightened comovements between domestic equity and government bond market index returns (in all G5 countries except Germany). In addition, the evidence suggests possible 'flight-to-safety' from domestic equity to government bond markets, as evinced by the negative conditional correlations throughout the subprime and global crises. I check the robustness of my findings by estimating VAR models using daily data and document strong evidence of 'short-lived' contagion (as defined by Kaminsky et al. (2003)) travelling from the ABX indices into the international markets during both the subprime and global crises. The main implication is that shocks might have been transmitted via the arrival of market news, which is consistent with the information transmission channel and is in contrast to the conclusion of Longstaff (2010).

To control for the possible simultaneous contagion from the other US markets to the G5 international markets, I augment the set of exogenous regressors with a number of major US market variables in addition to the ABX indices and re-estimate the daily VAR models. Qualitatively similar evidence of contagion from the ABX indices is documented during the subprime crisis while the lagged US S&P 500 composite index returns and US government bond index returns have been found to possess significant predictive ability over the international market returns. I also find that the US lagged ABCP yield spreads, which represented shocks related to funding illiquidity and the performance of the structured securities market in the US, predicted significantly the international market returns during the global crisis. The evidence again suggests the importance of funding illiquidity in shock propagation across the international markets during the recent crisis.

In summary, the evidence presented supports the conventional view that the family of ABX indices was an important class of risk barometer during the recent crisis. The significant predictability of the ABX indices over the international market returns can alternatively be interpreted as evidence that investors had actively traded on the past performance of the ABX indices while the price discovery in general takes days rather than weeks. In addition, my results also highlight the important role of US markets in predicting the international market returns in that traders might be able to exploit the US market information to guide their investment strategies.

Second, I formulate a two-factor pricing model that is composed of the market and the ABX risk factors (ABX innovations), and estimate pooled regressions using all available individual stocks from the three major US Exchanges over the sample period 2006 to 2011. The pricing models allows me to shift changes in the intercepts and factor loadings through the interaction with the subprime and global crisis dummy variables. I document significant increases in the ABX AAA factor loadings during the subprime crisis and lower ABX AAA factor loadings during the global crisis. In other words, the individual stocks' exposure to the ABX AAA innovations has increased significantly during the subprime crisis and the the ABX AAA innovations represented a source of significant crisis-related risk during the subprime crisis. I proceed to test explicitly whether the ABX factors explain the cross-section of expected returns using a two-pass regression approach. I find that the Carhart (1997) four-factor model augmented with the ABX AAA factor holds with insignificant pricing errors only during the subprime crisis subperiod. The evidence of cross-sectional explanatory power in the ABX factor lends support to the conjecture that the impact of the unexpected shocks from the ABX AAA index on individual stock returns was considerably systematic. My findings offer strong empirical support to Fender and Scheicher (2009), who conclude that pricing models without considering the risks inherent in the ABX indices are inappropriate. Note also that most of the significant results refer to the ABX AAA innovations but not to the lower-rated ABX indices. A possible explanation is that the investment grade RMBSs, as referenced by the ABX AAA index, have similar credit quality to those securities held in investors' portfolios, thus being more relevant to asset valuation. Future research is required to validate this claim.

To reveal the evolution of the US equity market's exposure to the ABX innovations over time, I estimate a two-factor asset pricing model (with three model specifications) for each available individual stock from all US Exchanges using all daily observations in each month to gauge the stocks' sensitivity to the ABX innovations. I then compute the proportion of stocks with significant ABX factor loadings to the total number of stocks in my sample at each month to obtain a monthly series of exposures to the ABX innovations, denoted by $\kappa_{ABX,t}$. I observe strong time variation in the ABX exposure. I also observe that the exposure spiked occasionally during the subprime and global crisis subperiods, which is consistent with contagion documented by Longstaff (2010) and in Chapter 4. To examine the determinants of the time variation in the exposure series, I estimate a VAR(1) model using the ABX AAA exposure series and a few widely-acknowledged crisis variables. The Granger-causality test results show that the US stock market's exposure to the ABX AAA innovations was driven by the market illiquidity, funding illiquidity and average idiosyncratic volatilities consistent with the contagion transmission via the funding illiquidity and risk premia channels. Moreover, I seek to identify the firm-specific characteristics that determine the individual stocks' exposure to the ABX innovations using a set of logistic and multivariate cross-sectional regressions. My results show that idiosyncratic volatilities, total risks, market risks, turnover ratios and book-to-market ratios significantly explain individual stocks' exposure to the ABX innovations; however, I find little evidence of explanatory power in the firm-specific fundamental variables over the exposure. The implication is that risk-averse investors might rebalance their portfolios and tilt towards stocks with lower market risk, turnover ratios, book-to-market ratios and idiosyncratic risks to reduce their exposure to the troubled structured finance market during the recent crisis.

Third, in Chapter 6, I examine the role of the US BHCs in the recent financial crisis and specifically test for the determinants of bank equity risks using a set of bank-specific fundamental characteristics. While the empirical literature on bank risks is filled with studies motivated from a corporate governance perspective, the main contribution of my study is that, to the best of my knowledge, I am one of the first to establish the empirical linkage between banks' fundamental and equity risks and specifically unravel how the fundamental sources of bank equity risks changed during the recent crisis via examining the crisis interaction effects. Besides, I depart from prior studies and consider various sources of bank equity risks that reflect the banks' exposure to the innovations of the ABX indices, the ABCP yield spreads and the Moody's default spreads. I show empirically that an increase in the banks' buffer of Tier 1 capital decrease all components of bank equity risks. I provide direct empirical evidence that banks' management in Tier 1 capital is an effective tool to limit banks' exposure to the systematic shocks of funding illiquidity, thus justifying the urge for higher regulatory capital requirement.

Fourth, Chapter 7 uses the same sample of US BHCs and investigates quarterly bank stock return predictability using variables pertaining to banks' profitability, loan portfolio credit quality, capital ratios and equity risks over the 2006 to 2011 period. Using both univariate and multivariate tests, my analysis shows that banks' earnings, non-performing loans, Tier 1 capital ratios and the crisis-related ABX risks predicted significantly one-quarter ahead bank stock returns. Based on a two-way sort portfolio analysis, a significant size effect is evident in that the return predictability of banks' fundamental variables was largely concentrated on the mid and small cap bank stocks; however, size does not fully account for the predictability. To further unravel the relation between the significant return predictability and the asset 'fire sale' and 'flight-to-safety' phenomena, I examine the bank-level turnover ratios and order flows within a two-way sort portfolio analysis to reveal that smaller banks with weaker fundamentals were traded more intensely while the higher trading activity was largely driven by sell pressure. This study provides reasonably strong evidence that the banks' fundamental characteristics relating to profitability, loan portfolio credit quality and capital adequacy were the most important criteria considered by investors in formulating their 'fire sale' or 'flight' decisions during the recent crisis. In addition, I propose various investable strategies that investors could follow to achieve significant economic profits. These profits demonstrate the economic significance of the previous results.

8.3 Future research directions

My empirical investigation shows that the ABX indices were important leading indicators during the recent financial crisis and predicted international market returns within trading days and weeks. In addition, this study also reveals that the US equity market was systematically affected by the negative shocks from the ABX indices during the subprime crisis, as shown in the asset pricing tests of Chapter 5. A potential future research direction in relation to the ABX indices is to evaluate how the significant predictability of the ABX indices may help in portfolio management during times of considerable volatility. The formulation of a general framework in which sample-specific market information (crisis subsample) can be incorporated into a portfolio optimisation problem is useful in the context of investment and risk management. The investigation also inquires whether asset pricing models augmented with the crisis-related factors may have better out-of-sample inference that contributes to the standard mean-variance portfolio optimisation framework.

A potential research direction in relation to the current work is to examine the market performance of structured finance securities using disaggregated security-level data during the recent crisis rather than using the aggregated market indices. The use of security-level data of structured finance securities allows us to examine the return and risk relationship of various types of structured finance securities. The examination of the trading patterns and investors' behaviours in this opaque and nontransparent market provides implications to a range of market participants, such as policymakers, investors, banking institutions, underwriters, etc., in the context of investment and risk management. Given the recent failure in the structured finance market and its increasing importance to financial stability, in September 2012, the Federal Reserve announced the third round of Quantitative Easing (QE3), launching an open-ended bond purchasing programme to buy $40 billion agency MBSs each month. This was an attempt to remove the systemic risk exposure to the US housing debt market in the banking and financial sectors. Little is known in relation to the impact of the QE3 on the structured finance market and on the other major financial markets. An event study type of research may be suitable in this regard to examine whether the liquidity injection via the QE3 stabilised the markets and reduced the risk exposure in the banking and financial sectors. The quantification of the impact provides useful implications to regulators and guides future policy directions. Another important issue with regard to the QE3 refers to its impact on the effectiveness of the US monetary policy; that is, to investigate how the reduction in banking firms' exposure to systemic risk affects the effectiveness of monetary policy and in what channels the effects took place.

The third research direction is to investigate spillovers of volatilities during the ongoing European sovereign debt crisis following the empirical approach of Engle et al. (1990), Ng (2000) and In (2007). Ng (2000) studies how return volatilities in the six Pacific-Basin countries were explained by the world and regional factors and provides implications to the effectiveness of global hedging, as well as to the regulatory development on international capital flows. In (2007) studies the spillovers of volatilities between the international swap markets in the US, UK and Japan using a multivariate VAR-EGARCH model. An extension to the existing approach may be to impose additional deterministic terms on the conditional volatility equations. For instance, one can test whether the spillovers of volatilities were driven by the arrival of macroeconomic news through the introduction of various types of macroeconomic news dummy variables and their interaction terms with other market variables on the equations at a high frequency. In addition, variance decomposition may allow us to quantify the magnitude of influence of each country-specific variables on the conditional volatilities following Ng (2000) and Bekaert et al. (2005).

The fourth research direction is to test whether the banks' macroeconomic risk exposure explains the cross-section of bank stock expected returns. In Chapter 7, I find strong evidence of return predictability in banks' fundamental variables over one-quarter ahead bank stock returns, thus updating the bank stock return predictability literature (see also Cooper et al., 2003). A potential research lead is to examine the relations between banks' macroeconomic risk exposure and expected stock returns following Petkova (2006). We can then investigate whether banks' fundamental characteristics contribute significantly to their macroeconomic risk exposure, controlling for size and other pricing anomalies. The research objective is to establish a linkage between the banks' fundamentals and their respective exposure to the various sources of macroeconomic risks. Lastly, we may also examine whether the return predictability of fundamentals can be applied to other types of financial institutions or firms in other industry sectors.

8.4 Concluding remarks

In this thesis, I have shown that the US structured finance market was the origin of contagion and played an important role in asset valuation during the recent 2007 to 2009 financial crisis. In particular, I find consistent evidence of significant cross-market shock transmission and increases in comovements between the structured finance market and the international markets, which is consistent with contagion being transmitted via the funding liquidity and credit risk channels. I have learnt that the impact of contagion from the ABX indices on the US equity market had been reasonably systematic and can explain the cross-section of expected returns during the subprime crisis subsample. I find that the US stocks' exposure to the ABX innovations increased significantly during the subprime crisis and that stocks with higher market risks, idiosyncratic risks, turnover ratios and book-to-market ratios are more likely to be exposed to unexpected shocks from the ABX indices. My findings present strong evidence of possible 'flights' between domestic equity and government bond markets in the G5 international markets. In addition, focusing on the US BHCs' role in the recent crisis, I establish the link between banks' fundamental and equity risks and discover that the investors relied primarily on banks' fundamental characteristics and size in formulating their 'flight' decisions among bank stocks, both during and after the recent crisis. By motivating the contagion tests within an asset pricing perspective, I contribute to both the contagion and asset pricing literature and provide useful implications to investment and risk management during the crisis.

Lastly, I acknowledge a few limitations in my empirical investigation and discuss how future research can address these issues. First, the ABX indices used in this study refer to the ABX HE.06-1 vintage series, which are the longest available series since index inception. Every half a year, the indices are reconstituted and new vintages are initalised, tracking 20 RMBSs issued in the six months prior to the index issuance. Therefore, there is uncertainty about whether the 20 RMBSs tracked by the ABX HE.06-1 vintages accurately represent the true performance of the US structured finance market. In addition, the 20 RMBSs deals in each ABX index represent only a tiny fraction of the overall issuances of RMBSs over the years and, hence, the poor coverage of the ABX indices may make my findings less credible. Nonetheless, the first issue may not be severe because the prices and returns of the ABX HE.06-1 vintages are qualitatively similar to those used in Longstaff (2010), who uses the on-the-run ABX indices created by using the observations of the newly issued ABX vintages each time they were issued. Future research may provide further empirical examination as to how the vintages of ABX indices relate to each other and to other structured finance market indices, such as the MARKIT ITRAXX CDS indices. Second, there are no exact dates that best define the crisis outbreak. Consequently, I have relied on historical events, market performance and evidence from empirical studies that applied statistical structural break tests to guide my selection. Nonetheless, a certain degree of subjectivity remains.

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Chapter 9

Appendix

A.1 Details on monthly contagion variables

The TED spreads are the yield differentials between the US three-month T-bills and the three-month LIBOR while the Moody's BAA yield spreads are computed by subtracting the 10-year constant maturity Treasury bond yields from the Moody's BAA corporate bond yields. Both variables are commonly used as measures of credit risk, counterparty risk and the costs associated with borrowing in financial systems (see e.g. Boyson et al., 2010; Longstaff et al., 2005; Taylor and Williams, 2009).

The ABCP spreads are the yield differentials between the one-month ABCP and the US one-month T-bills, and reflect the level of stress in both the money and structured finance markets. Brunnermeier (2009) and Frank et al. (2008) point out that financial institutions' exposure to the structured ABS is often via off-balance sheet entities, such as SIVs, which borrow money by issuing ABCP and then lend that money by buying various longer maturity structured products. During the subprime crisis, investors were unwilling to roll over the ABCP that funded the SIVs amidst the rising uncertainty with regard to the valuation of the MBS. This then led to surging funding illiquidity in the structured finance market and increasing pressure in banking institutions to absorb these entities onto their balance sheets. Hence, the ABCP spreads reflect the stress level and risk in the structured product and money markets.

For the measure of average market illiquidity, I follow the intuition of Amihud (2002) and use the illiquidity measure by Acharya and Pedersen (2005), and define market illiquidity as daily price impact of order flow:

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R_{i,t,d}|}{VOLD_{i,t,d}} \tag{9.1}$$

where $D_{i,t}$ is the number of days available in month t, $R_{i,t,d}$ is the return of stock i on day d in month t, and $VOLD_{i,t,d}$ is the dollar trading volume (in millions) of stock i on day d in month t. I define and use the average market illiquidity in my time series regressions as follows:

$$AILLIQ_t = \frac{1}{N_t} \sum_{i=1}^{N_t} ILLIQ_{i,t} \tag{9.2}$$

where N_t refers to the number of available US stocks at month t.

The monthly LIBOR-OIS spread is computed by subtracting the three-month Overnight Indexed Swap (OIS) yield from the three-month LIBOR rate. The three-month LIBOR is the rate at which banks are willing to lend to other banks in which the loan has a three-month maturity. The Overnight Indexed Swap (OIS) is a fixed-for-floating interest rate derivative in which the counterparty (a bank) accepts a fixed rate and agrees to the daily overnight rate at the end of the contract term. The difference in fixed and floating rates is calculated and settled at maturity. As the OIS does not involve the exchange of the principal and hence bears very little default risk. The spread between the LIBOR and OIS reflects what banks believe is the insolvency risk of lending to other banks. (See the report from the Federal Reserve Bank of St. Louis at http://research.stlouisfed.org/publications/es/09/ES0924.pdf for more descriptive details. See Taylor and Williams, 2009; and see also Olson et al., 2012, for recent empirical evidence on international LIBOR-OIS spreads).

The value-weighted idiosyncratic volatilities series are computed as the value-weighted averages of the individual stocks' idiosyncratic volatilities of the augmented four-factor model as shown in Equation 5.24 (Model 3 of the ABX AAA model) estimated at the end of each month.

A.2 Construction of the quarterly equivalent bank risks

Following the approach of Anderson and Fraser (2000), I decompose the BHCs' return volatilities into three components: market risk, crisis-related (ABX) risk and residual risk. I estimate a market model augmented with an orthogonalised ABX factor (i.e. the ABX AAA index) for each BHC using all daily observations of excess returns in each quarter. There are two main reasons for the orthogonalisation of the ABX factor. First, this process allows me to separate the effect of the ABX index from that of the market index on banks' returns. In other words, the decomposed ABX risk represents the bank stocks' return variations in relation to the structured finance market unexplained by the market index. Second, this process simplifies my variance decomposition in that the covariance terms in the market model are negligible. I use the decomposed bank risk measures as independent variables in my regressions.

First, for each quarter, I orthogonalise the excess daily returns of the ABX AAA index ($R_{ABX,t}$) to the market excess returns by running the following regression:

$$R_{ABX,t} = \alpha + \beta R_{MKT,t} + \epsilon_{ABX,t}$$

where $R_{MKT,t}$ is the daily excess returns of the value-weighted CRSP market index. I then augment and estimate the market model with the ABX innovations ($\epsilon_{ABX,t}$) for the i^{th} BHC in each quarter:[89]

$$R_t^i = \alpha^i + \beta^i R_{MKT,t} + \gamma^i \epsilon_{ABX,t} + \varepsilon_t^i$$

where R_t^i is the daily excess returns of the i^{th} BHC. The variance decomposition is as follows:

$$\sigma_i^2 = \beta_i^2 \sigma_{MKT}^2 + \gamma_i^2 \sigma_{\epsilon_{ABX}}^2 + \sigma_{\varepsilon_i}^2$$

where σ_i^2, σ_{MKT}^2, $\sigma_{\epsilon_{ABX}}^2$ and $\sigma_{\varepsilon_i}^2$ refer to the variances[90] of the excess daily returns of the i^{th} BHC, the market index, the ABX innovations and the residuals of Equation 9.3 in each quarter, respectively. I then transform the decomposed equity risks into quarterly equivalent measures by

[89] I do not estimate the market model if the BHC has less than 30 daily return observations available in that quarter.

[90] The variance is computed as:

$$\sigma_j^2 = \frac{1}{T}\sum_{t=1}^{T}(r_t^j - \bar{r}^j)^2$$

where $j \in \{i, \mathrm{MKT}, \mathrm{ABX}\}$, T is the total number of observations in that quarter, r_t^j is the excess return of j on day multiplying the decomposed standard deviations by the square root of the total number of days in each quarter, as follows:

$$\begin{aligned}
\sigma_i^{TOTAL} &= \sigma_i \times \sqrt{T} \\
\sigma_i^{MKT} &= \sqrt{\beta_i^2 \sigma_{MKT}^2} \times \sqrt{T} \\
\sigma_i^{ABX} &= \sqrt{\gamma_i^2 \sigma_{\epsilon_{ABX}}^2} \times \sqrt{T} \\
\sigma_i^{RESID} &= \sigma_{\varepsilon_i} \times \sqrt{T}
\end{aligned}$$

where T is the number of daily observations in each quarter. Banks' total, market systematic, crisis-related (ABX), and residual risks are denoted as σ^{TOTAL}, σ^{MKT}, σ^{ABX}, and σ^{RESID} respectively.

t and $\bar{r}^j$ is the simple average daily excess returns of j in that quarter. The error variance of BHC i is computed as:

$$\sigma_{\varepsilon_i}^2 = \frac{1}{T} \sum_{t=1}^{T} (\varepsilon_t^i - \bar{\varepsilon}^i)^2$$

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