An empirical investigation of credit risk markets during financial crisis

by

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Abstract

This thesis addresses several issues in credit risk modelling through an empirical investigation of the two main markets where this risk is traded, namely corporate bond market and CDS market.

In the first part, we investigate the main determinants of credit spreads in US and UK corporate bond markets between 2003 and 2011. We explore the effect of various factors predicted by structural form models on corporate bond yield spreads. In addition, we extend our investigation to credit spreads in the corresponding corporate CDS markets. Our analysis sheds light on interdependency between corporate bond and equity markets, and on power of contingent-claim models in determining credit spreads of corporate debt. In our study, we employ a variety of econometric techniques such as pooled OLS, fixed and random panel approach, non-linear interaction effects and random sub-sampling. Our analysis shows that factors suggested by structural models explain almost half of changes of the corporate yield spread for relatively stable period of economy and more than half for the total period including the recession. The two main factors identified were equity volatility and investor confidence as measured by TED spread.

The second part is dedicated to a comparison of credit risk pricing in bond and CDS markets. In particular, we focus on the anomaly of negative CDS-Bond Basis during the recent financial crisis. Based on a no-arbitrage argument, we identify the factors that can explain the persistence of negative basis. We employ pooled OLS, panel regressions and Fama-MacBeth regression in our empirical analysis. The analysis identifies funding cost, collateral quality, liquidity risk, counterparty risk and basis volatility as the key factors driving the basis. We investigate the dynamic relation between the factors and the basis over the period covering the financial crisis. In addition, we identify and discuss the difference in dynamics of the basis for financial vs non-financial sectors, and investment grade vs high yield rating categories.

Overall, the aim of the thesis is to contribute to a limited but growing literature on empirical issues in credit risk modelling during the recent financial crisis.

Acknowledgement

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CHAPTER 1
INTRODUCTION

OUTLINE OF THE THESIS

This thesis addresses several issues in credit risk modelling through an empirical investigation of the two main markets where this risk is traded, namely corporate bond market and CDS market.

We begin in Chapter 2 with a historical overview of theoretical and empirical literature on modelling credit risk. We discuss the two main theoretical approaches (structural approach and reduced-form approach) for modelling credit risk, their comparison, extensions and empirical testing.

Following this introductory review, we proceed in Chapter 3 to an empirical investigation of the main determinants of credit spread. We work in the framework of a structural form model. In particular we explore the effect of equity volatility on corporate bond yield spreads, as measure of credit risk, in US corporate bond market between 2003 and 2011. This analysis sheds light on the questions of how integrated are the corporate bond and equity markets and how well the current contingent-claim models predict the behaviour of corporate debt. For the purpose of this analysis we use a unique panel dataset of daily observations of 602 US companies, containing their yield spreads, accounting data, equity prices and macro variables. For our analysis, we employ a variety of econometric techniques and models such as pooled OLS, fixed and random panel approach, non-linear interaction effects and random sub-sampling approach. We analyze the difference in response to determinants for investment grade versus high yield rating groups of bonds as well as financial versus non-financial. We also analyzed the data for different time periods, covering the period before, during and after the financial crisis, in particular focusing on the analysis of the sensitivity of credit spreads to determinants in response to Lehman Collapse. Our analysis shows that factors suggested by structural models of credit risk explain almost half of changes of the corporate yield spread for relatively stable period of US economy (2003 to 2007) and more than half (0.62) for the total period including the recession. We have shown that volatility is an important determinant of the corporate bond spreads, but the size of the coefficients is 3 times smaller than reported in previous literature. We find that equity volatility is not the only important factor driving the spreads up, and has at least the same effect as negative investor's confidence as measured by TED spread. However, equity volatility does have a stronger effect on change in corporate yield spreads than credit rating. Our results show some evidence that credit rating lost its power of determining credit spread variation during financial crisis and explains no more variation in spread than accounting variables. In addition to analysis of credit risk using corporate bond yield spread measure we also investigate alternative measures of credit risk using measures from the CDS market. We use CDS spreads for analysis of the same set of determinants. We find a fall in explanatory power for CDS market in comparison with corporate bond market.

Following the analysis of the US corporate credit markets, in Chapter 4, we investigate the determinants of credit spreads in UK corporate bond. The UK corporate bond market is significantly smaller than the US market. Our work is one of the first to compare and contrast the two different corporate bond markets during the period of the financial crisis. The main motivation was to test the assumptions of structural model using an alternative dataset and see how additional regulations and restrictions affect performance of credit market in UK as compared with the US. For our purpose, we used daily panel dataset for more than 100 UK companies between 2003 and 2012. In general, we conclude that contingent claim model determinants consistently explain more than half of credit spread variations for UK and US markets. However, sensitivity of credit spreads to TED spread is significantly higher in UK market. In addition, in the same fashion as in US analysis, we compare credit risk priced in UK corporate bond market with UK CDS market.

The study of credit risks using data from the two markets (corporate bond market and CDS markets) naturally leads to the final theme of our investigation, namely the comparison of credit risk priced in these two markets. We focus on this topic in Chapter

5. As a specific issue in this context, that is raising considerable interest within academia and industry, we investigate the anomaly of negative CDS-Bond basis during the recent financial crisis. The CDS-Bond basis is the difference between the CDS spread and the corresponding corporate bond spread. In a simplified setting, no-arbitrage arguments lead to a conclusion that this basis should be zero. However, historical data show that the basis has been significantly negative during the financial crisis. Using a large and unique dataset of CDS-Bond basis covering period between 2005 and 2011, we proceed to study the main determinants that could explain negative basis dynamics. Based on no-arbitrage arguments we build a negative basis trade strategy to analyze the profit opportunities for an arbitrageur. We proceed to test the consequences of the no-arbitrage argument using our empirical data set. In our analysis, we employed a variety of econometric models such as Pooled OLS, Panel approach and Fama-MacBeth style regression. We show that factors such as funding cost, collateral quality, liquidity risk, counterparty risk and volatility of basis can explain the persistence of a negative CDS-Bond basis. We uncover quite different dynamic in CDS-Bond basis movements for investments grade and high yield groups of bonds. We also show significant difference between explanatory power for financial and non-financial sectors. We conclude that during the crisis the negative basis was mainly explained by funding costs, counterparty risk and collateral quality and in smaller portion by illiquidity in bond market and volatility of basis. We show that following Lehman collapse explanatory power of collateral quality, funding cost and bond illiquidity factors significantly increased, while counterparty risk and basis volatility lost their explanatory power.

The present thesis covers a broad range of empirical issues concerning corporate credit risk. Our investigation covered a matrix spanning over several geographical locations (US, UK), markets (corporate bond market, CDS market), segments (investment-grade/high-yield, financial/non-financial) as well as different time periods (before crisis, during crisis, post-crisis). Where possible, we have tried to compare the results and investigate the reasons for the differences.

In the remainder of this chapter we give a general introduction to credit risk and financial instruments containing credit risk, as well as provide an overview of the markets where these instruments are traded.

INTRODUCTION TO CREDIT RISK

Credit risk is the risk of a financial loss due to a reduction in the credit quality of a debtor (Meissner, 2005), (Sundaresan, 2009), (Hagenstein, Mertz, & Seifert, 2004). This definition includes two related but distinct types of risks: default risk and credit deterioration risk. Default risk is the risk that the debtor may fail to pay back his dues. Credit deterioration risk refers to the risk of losses associated with the decrease in the credit quality of the debtor. It is quite common in literature to use credit risk and default risk interchangeably, however in the current work we will consider credit risk in the broader context, including the credit deterioration risk.

In the present thesis, we will be restricting our analysis to a study of credit risk in the context of corporate entities, and will not look at the interesting and large world of retail credit risk. In the context of corporate credit risk, the two of the most important instruments that are used to buy and sell credit risk exposure are corporate bonds and credit default swaps (CDSs). In what follows we look at these instruments in more detail, and introduce concepts that will be necessary for the analysis in later chapters.

CORPORATE BONDS

Bonds are interest-bearing securities which obligate their issuers to pay the lenders sum of money at specified intervals and to repay the amount lent at a pre-specified date (Benzschawel, 2012). In the present thesis we shall primarily focus on bonds issued by corporate entities. A key feature, distinguishing a corporate bond from a government bond is presence of default risk. For this reason, the price of a corporate bond is typically smaller than the price of a government bond with equivalent cash flows, to compensate the holder for bearing the risk of issuer default.

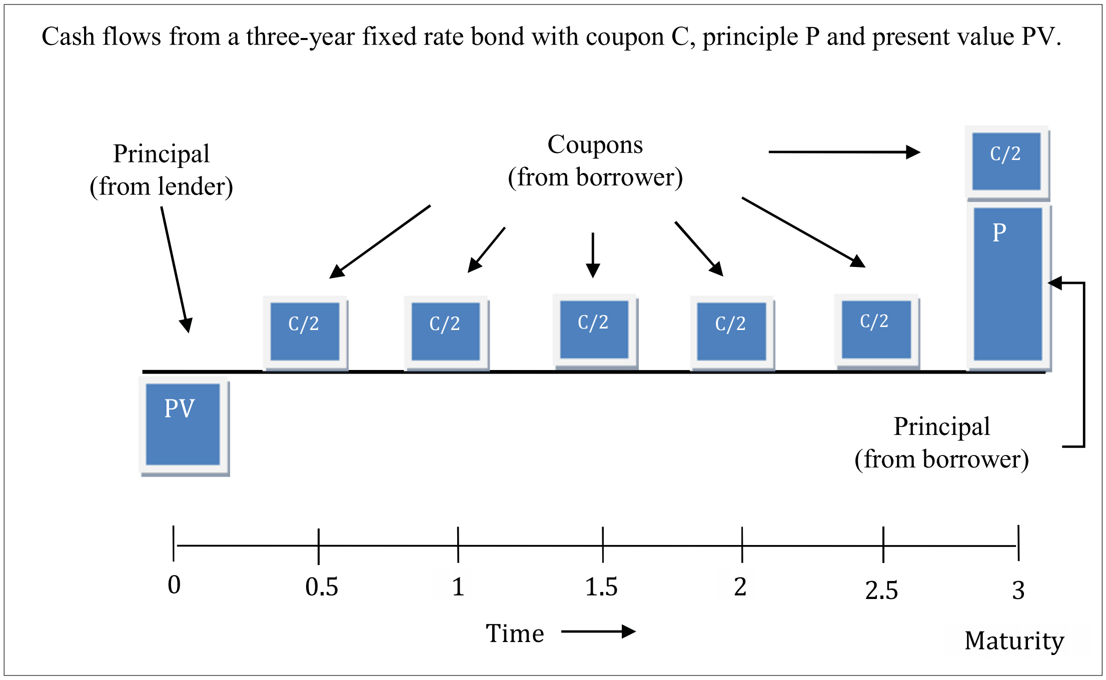
The cashflows associated with a corporate bond are shown in the Figure 1. A typical corporate bond will pay the holder a semi-annual coupons $C/2$ at regular half-yearly intervals, and have a final principal payment Par at the bond's maturity. In the event of default, the bond holder will receive a recovery payment equal to $R \cdot P\text{ar}$, where R is the recovery rate. A convenient and practically used measure of bond value is the yield on the bond. This measure is defined using the relation

$$PV = \sum_{n=1}^{2T} \frac{C/2}{(1+y/2)^n} + \frac{Par}{(1+y/2)^{2T}}$$

where *PV* is the present value of the bond, i.e. its price. *Par* and *C* are the corresponding par value and coupons associated with bond. The quantity y is the yield of the bond. In the expression above, we assume that a bond pays coupons semi-annually. The yield provides a measure of the bonds return till maturity and is particularly suited to compare different bonds. For example, when comparing yield of a corporate bond with yield of an equivalent government bond, one would typically see that the yield of a corporate bond is higher. This observation is just another way of stating that the price of a corporate bond is lower than that of an equivalent government bond. We shall use the above definition of yield in our analysis in Chapters 2 and 3.

A crucial property of corporate bonds that distinguishes it from other forms of corporate borrowing, and makes it attractive for both borrowers and lenders, is the existence of huge secondary market. The bond markets play a crucial role in the global financial system, providing a venue for the effective channelling of funds between borrowers and savers, be they sovereigns, corporate or even individuals. It is a massive market, with an outstanding global notional that totalled $95 trillion in 2010 (see Figure 2). In fact, it is significantly larger than the global equity market, which had a market capitalization of around $55 trillion at the end of 2010. The bond market has also been a growing market, with market rising to 130% of the global GDP by end of 2010 from 80% a decade before (Maslakovic, 2011). The ratio of the overall bond market to GDP is highest in the most developed markets, namely US, Japan, Europe and the UK. A large portion of the bond market corresponds to sovereign debt and various asset backed securities. However, a sizable portion of the market does belong to corporate debt. According to Tendulkar & Hancock (2014) the total amount of notional outstanding in global corporate bonds grew to a staggering $49 trillion by 2013, with two-thirds corresponding to financial sector and a third to non-financial sector.

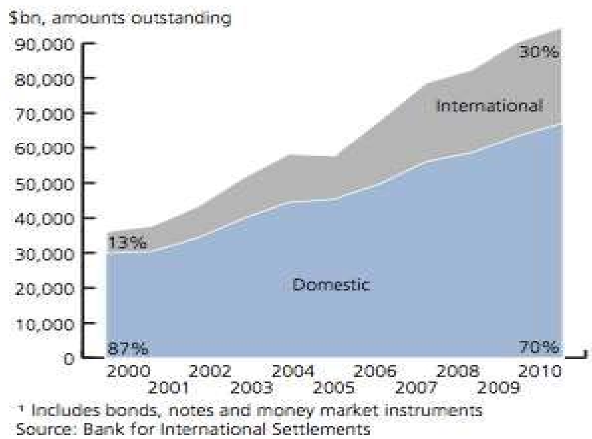
Figure 1
Cash flow diagram for corporate bond



Source: (Benzschawel, 2012).

The US bond market is by far the largest debt market in the world, follow by Japanese and European bond markets. The value outstanding on the US debt market touched $35 trillion in notional in 2010. The US bond market is divided between four major sectors: government treasury bonds ($8.8 trillion), mortgage-backed bonds ($8.5 trillion), corporate bonds ($7.5 trillion), with municipal bonds covering the remainder (Maslakovic, 2011). The daily trading volume in the (secondary) US corporate market was up to $16 billion by 2010. The market mostly operates without a central exchange, and trades over-the-counter (OTC) with hundreds of dealers playing the role of market makers. In addition, corporate bonds are also sometimes listed and traded on exchanges. In contrast, the UK corporate bond market, which will be the focus of Chapter 4, is significantly smaller. The outstanding notional on bonds for non-financial sector in the UK reached approximately 25% of the GDP (Farrant, Inkinen, Rutkowska, & Theodoridis, 2013), corresponding to approximately $600 billion.

Figure 2
World bond market



CREDIT DEFAULT SWAPS

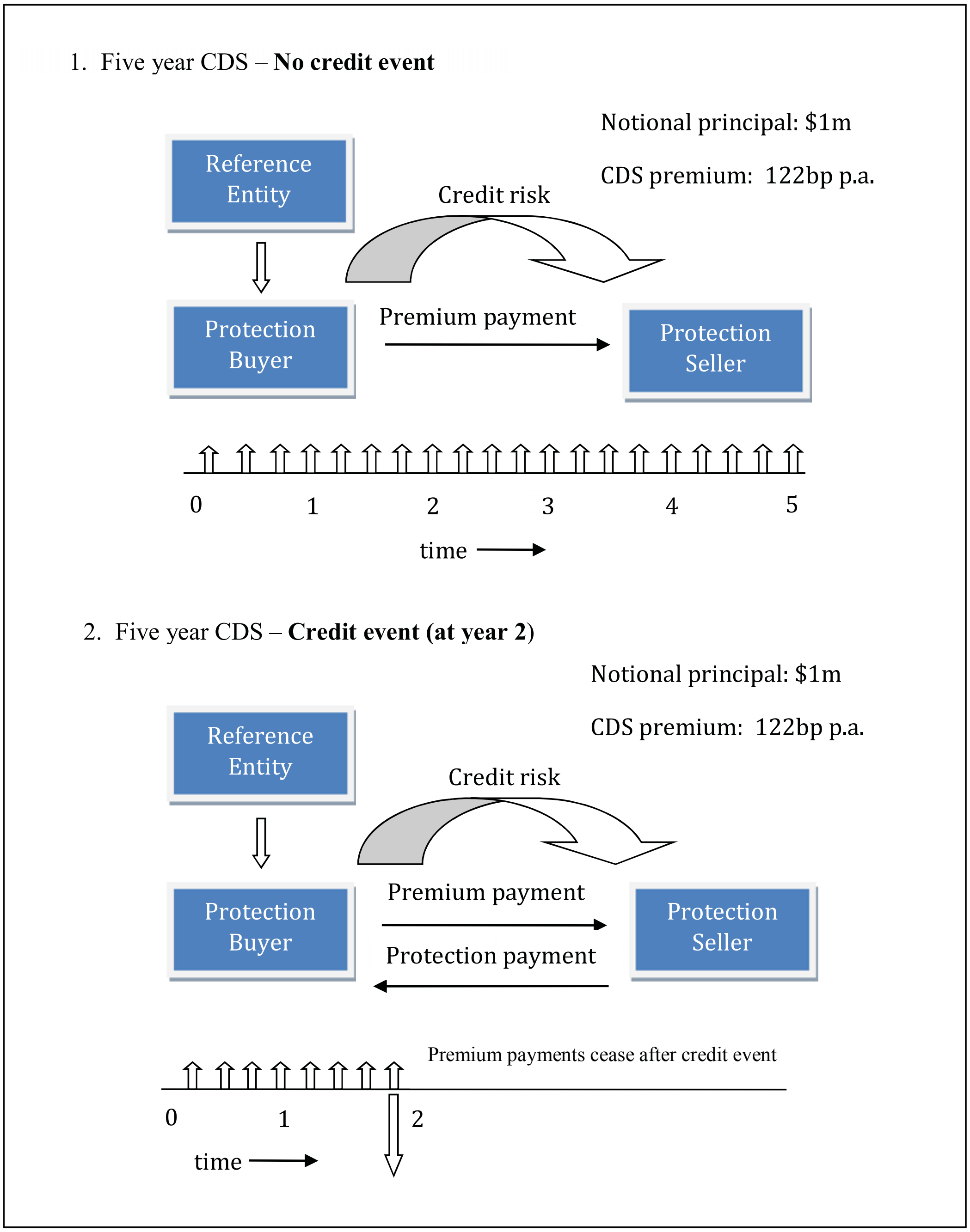
The credit default swaps are the most important and widely used product in the credit derivatives market. A single name Credit default swap is a bilateral over the counter agreement, whereby the seller of the CDS protection promises to pay the buyer of the CDS protection the loss on par, in case of credit default of a particular third party reference entity. In return, the CDS protection buyer pays a regular protection premium to the CDS seller (Galitz, 2013). The third party reference entity can be a corporation, financial institution or sovereign. In this work, we shall restrict our analysis to single name corporate CDSs that refer corporate entities.

Although, the CDS contracts are in many ways similar to insurance policies, there are some important differences. Firstly, CDS contracts are not regulated in a way similar to insurance agreements. Secondly, CDS contracts are typically marked to the market, and have values that change with market conditions. Thirdly, protection buyer does not necessary need to own reference bonds in order to buy protection. These features make CDS market unique and distinct from the insurance market (Galitz, 2013).

CDS contracts are typically traded over the counter, and are negotiated between the two counterparties who can custom tailor the terms of the bilateral contracts in the way, which suits them. The most liquid CDS contracts usually correspond to 5 years to maturity, however CDS can cover any period from 3 months to 30 years. The mechanics of a CDS contract is show in the Figure 3. The protection premium on a CDS contract is typically chosen in a way so as to make the initial value of the CDS equal zero. However, as time passes, due to the changing market conditions the value of the CDS contract will drift away from zero.

The development of the credit derivatives market has started in the early 1990s. JP Morgan is recognized as first financial institution that developed and executed a credit derivative transaction (Galitz, 2013). From the initial trades in 1990s, the credit derivatives market grew exponentially, reaching around $600 billion in notional principle outstanding by the end of 90s, and a peak value of $60 trillion by 2007. The value fell significantly in the aftermath of the financial crisis, but is still at a significant level of approximately $30 trillion in notional. According to ISDA (International swaps and derivatives association), the credit derivative market significantly exceeds the underlying corporate bond market, and attributed this to both, the popularity of credit derivatives and a slowdown in the corporate bond issuance.

Figure 3
Workings of a standard CDS contract



There are several different types of participants in the credit derivatives market. On the side of buyers of protection, the largest players are correspondingly, banks (59%), hedge funds (28%), insurers (6%), pension funds (2%), mutual funds (2%) and corporates (2%). On the sell side, the major players are, banks (44%), hedge funds (32%), insurers (17%), pension funds (4%), mutual funds (2%) and corporates (1%) (British Banker's Association, Credit Derivatives Report 2006).

Some of the main advantages of CDS that have made them popular with market participants are as follows. CDSs make it relatively easy to go short on the credit risk of an underlying. The CDS allows an investor to trade and evaluate the credit risk in an isolated manner. Another attractive aspect of CDS, is that they are an unfunded instrument, which means that, unlike a bond, a CDS requires no initial payment. This makes CDSs a natural choice for investors who face considerable funding costs. The CDS market allows have a high liquidity, making it relatively cheap to use it for hedging and speculating purposes (Hagenstein, Mertz, & Seifert, 2004), (Benzschawel, 2012), (O'Kane, 2008).

A detailed exposition on CDSs, including details about their mechanics and valuation, as well as broader issues about credit derivative markets can be found in the various credit derivatives handbooks written by major investment banks (Kakodkar, Galiani, Jonsson, & Gallo, 2006), (Beinstein & Scott, 2006), (Elisade, Doctor, & Saltuk, 2009), (Mahadevan, Musfeldt, & Naraparaju, 2011).

PAR ASSET SWAP

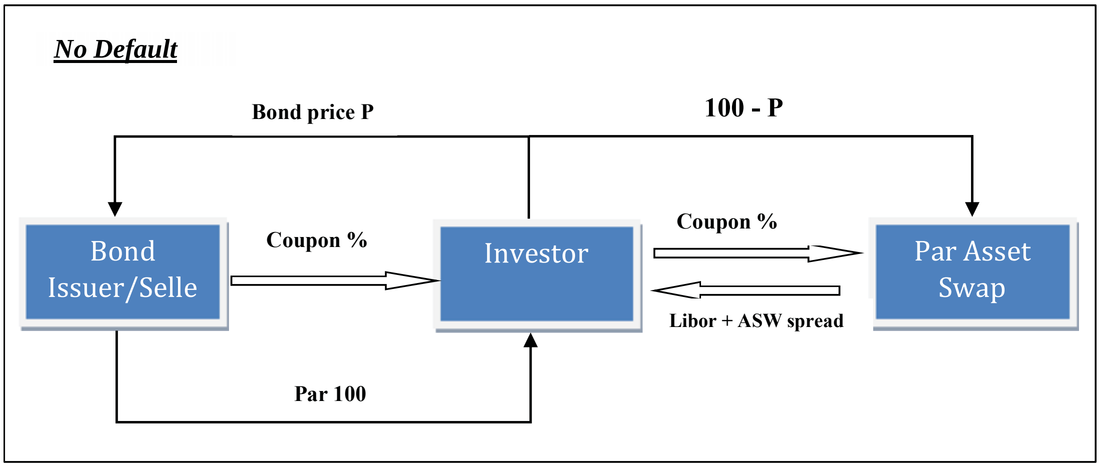
Alongside corporate bonds and credit default swaps, a common instrument used by market participants in order to get exposure to on corporate credit risk is a par asset swap. A par asset swap is an OTC derivative contract, which allows an investor to transform the fixed coupon payments from a corporate bond into a stream of floating rate payments. This allows an investor to effectively remove the interest rate risk inherent in a corporate bond, while maintaining exposure to credit risk. We shall use the concept of an asset swap in Chapter 5, where we consider a negative basis arbitrage trade. For this reason, below we look at the mechanics of par asset swap in detail.

The mechanics of a par asset swap is given in the Figure 4 (O'Kane, 2008). The diagram shows the cash flows associated with an investor entering into a par asset swap with a derivatives counterparty and a simultaneous purchase of the underlying bond by the investor. At the inception, the investor pays par to the asset swap counterparty and receives a corporate bond. At bond coupon dates, the investor pays the counterparty the coupon payments received on the bond, in return for a payment of coupon corresponding to a floating rate $LIBOR + S_{ASW}$. The asset swap typically expires with the maturity of the underlying bond, when assuming the underlying bond did not default the investor receives back the par amount from the bond. On the other hand, if at any time during before the maturity of the contract the bond defaults, the investor will receive a recovery amount from the bond issuer, but will continue to be obliged to make payments on the asset swap contract. This is an important feature of the asset swap spread, in that the swap does not extinguish in the event of bond default. This makes an asset swaps slightly different to CDSs. We shall look at the effect of this difference in Chapter 5, when considering negative basis arbitrage trades.

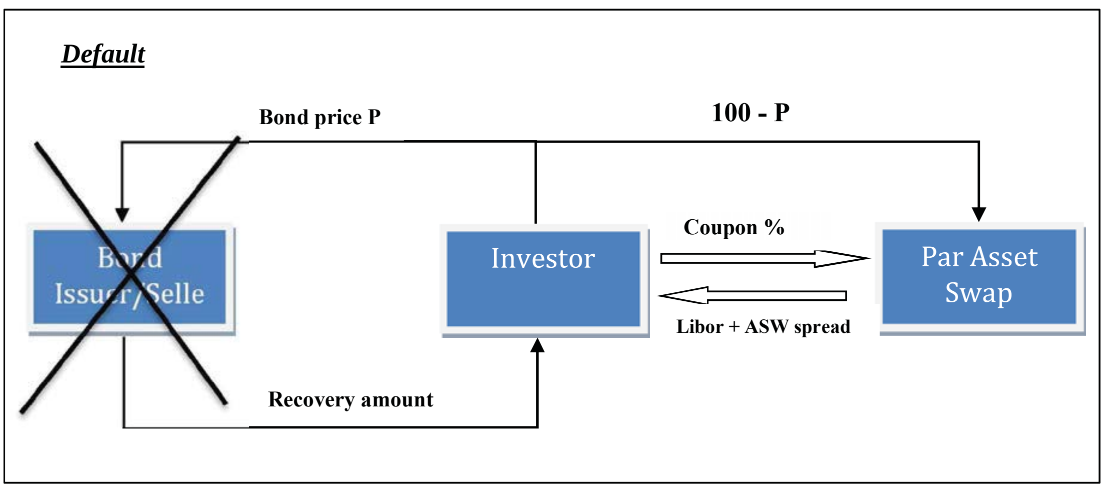
The spread over LIBOR, S_{ASW}, is known as the par asset swap spread, and is chosen in such a way so as to make the present value of the asset swap equal zero at trade inception. The spread is completely determined by the current value of the bond, its tenor and its coupon characteristics. The par asset swap spread gives an indication of the credit risk inherent in a bond, since it is the premium received on top of LIBOR (a proxy of risk-free rate) for bearing the default risk associated with the bond. For this reason, the par asset swap spread is often used as a proxy of credit spread for corporate bonds (Elisade, Doctor, & Saltuk, 2009).

Figure 4
Cash flow in par asset swap contract

An investor pays par to the asset swap counterparty and receives the cash value of the corporate bond (this amount is then used by the investor to buy the bond in the market). At bond coupon dates, the investor pays the asset swap counterparty the coupon payments received on the bond, in return for a payment of the floating rate $LIBOR$ and a fixed spread S_{ASW}. The asset swap typically expires with the original maturity of the underlying bond. Assuming, the underlying bond does not default, at expiry the investor receives back the par amount from the bond issuer.



In case of bond default, the investor will lose outstanding coupons and principal redemption on the bond but receive a recovery amount from the bond issuer. However, investor is obliged to continue to make payments on the asset swap contract until original bond maturity.



CHAPTER 2
LITERATURE REVIEW
CREDIT RISK MODELLING

2.1 INTRODUCTION

The main topic of the current thesis is an empirical investigation of aspects of credit risk markets. Before proceeding with this task, in the present chapter, we will provide a broad review of the main research in the field of credit risk modelling, touching upon both theoretical and empirical works. There are two main theoretical approaches to credit risk modelling, namely "structural" and "reduced form" models, and we will cover each in turn.

A natural point to start talking about the development of credit risk modelling is the paper by Merton (1974). In this paper Merton identified relationships between problem of pricing options (Black & Scholes, 1973) and corporate debt with default risk. This approach values a firm's debt as an explicit function of the firm's assets values and its capital structure. In the original paper (Merton, 1974), Merton proposed a very simple liability structure for the firm, with the firm issuing only zero-coupon bonds of fixed maturity and a default that could only occur on the maturity date. Merton's model was extended to include more complex liability structure and variable time of default by Black & Cox (1976), Geske (1977), Mason and Bhattacharya (1981), Leland (1994), Hull & White (1995), Longstaff and Schwartz (1995), Anderson and Sundaresan (1996) and Zhou (2001) among others. The development of the option-pricing technique and its applications to the investigation of the corporate liabilities is essence of the so-called "structural" approach to the credit risk modelling.

An alternative approach for modelling credit risk was first introduced and developed by Jarrow and Turnbull (1992) and Jarrow and Turnbull (1995). These types of models take the firm's default time and recovery rate processes as exogenous, and model the dynamics of the parameters, for example the hazard rate, that drive the default and recovery processes. These models came to be known as “reduced-form” models.

In what follows, we shall provide a review of the literature associated with these two approaches to modelling credit risk, their comparison and extensions in more detail.

2.2 STRUCTURAL FORM MODELS

MERTON MODEL (1974)

In this paper, Merton adopted the principles of option pricing (Black & Scholes, 1973) to the valuing corporate debt. This was done by adapting the firm’s capital structure and the default assumptions to the requirements of the Black-Scholes model. Merton assumed that a firm has the simplest capital structure consisting of just equity and debt. In addition to shareholders’ equity, the firm is assumed to have issued a single zero-coupon bond, which promises to pay an amount K at the maturity date T. Time t value of firm’s equity is denoted as E_t and time *t* value of the firm’s debt is D_t. The firm’s asset value V_t is sum of equity and debt values:

$$V_t = D_t + E_t \tag{1}$$

Additionally, Merton assumed absence of transactions cost and taxes, the ability to buy and sell the asset in any quantity, including short-sale, trading that is continuous in time, validity of Modigliani-Miller theorem (the value of the firm is invariant to its capital structure), and a flat term structure of interest rates that was known with certainty. According to the Merton the dynamics for the value of the firm’s assets through time can be described by a stochastic process:

$$dV/V = \left(\mu - \frac{1}{2}\delta^2\right)dt + \sigma dz \tag{2}$$

Where μ is instantaneous expected rate of return on the firm's assets and σ is constant standard deviation of return on firm assets, dz *i*s a standard Wiener process.

It is assumed that when the debt matures (i.e $t = T$), the firm must either pay promised payment K to the debt holders or bankruptcy. Thus, if at maturity T, V(T)-K>0, the firm will pay the bondholders because the value of equity is positive. On the other hand, if at maturity V(T)-K<0, then the firm will not make a payment and default. In other words, the ability of shareholders to pay off the debt at maturity and remain at positive equity depends on whether the value of firm's assets exceeds the debt's face value at maturity. Therefore, equity value at maturity can be expressed as:

$$E(T,T) = \ max\{0, V(T) - K\} \tag{3}$$

The value of equity at maturity has the same structure as a payoff from a European call option with strike K, written on the firm's assets. As a consequence, the payoff to debt holders at maturity T is equal to the minimum of the face value of the debt and asset value of firm:

$$\begin{aligned} D(T,T) &= \ min\{K, V(T)\} \\ &= K - max\{0, K - V(T)\} \\ &= V(T) - \ max\{0, V(T) - K\} \end{aligned} \tag{4}$$

From this expression it can be see that value of debt at maturity can be expressed in either of the two ways equivalent ways: the first one is equal to the promised payment, K, less the payoff on a European put option written on the firm's assets with exercise price equal to K; the second one is equal firm's value less the equity's value, which is equal a payoff from European call option written on the firm's assets and having strike price K.

Applying the Black-Scholes pricing formula, Merton derived the solution for value of equity and debt. The value of equity and debt at time t (t<T) is given by:

$$E_t(V_t, t) = V_t\Phi(d_1) - Ke^{-r(T-t)}\Phi(d_2)$$
$$D_t(V_t, t) = V_t - E_t(V_t, t) \quad (5)$$

Here Φ is the distribution function of a standard normal random variable

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} exp\left[-\frac{1}{2}z^2\right] dz$$

$$d_1 = [\log(V_t/K) + (r + 1/2\sigma^2)\tau]/\sigma\sqrt{\tau}$$

$$d_2 = d_1 - \sigma\sqrt{\tau}$$

Where $\tau = T - t$ denotes the time until the debt matures, σ^2 is instantaneous variance of the return on the firm per unit time.

Note that, in the Merton model default can only occur at maturity time T and probability of default is given by $\{V(T) \leq K\}$. Recovery rate is determined by the liability structure of firm: $\nu_T = V(T)/K$ if V(T)<K.

CRITICISM OF MERTON MODEL

Merton's model was a breakthrough in our understanding of credit risk. Its main achievement was to apply the principles of option pricing theory for the study of credit risk modelling. However, in order to do this Merton's initial model made some unrealistic assumptions. His theory, therefore, was in some sense a tradeoff between realistic assumptions and an elegant simplification of a very complex task. Thus, the main criticism of Merton's model is that it is too simple to provide a useful and realistic description of actual credit risk markets. Let us look at some of the main assumptions in more details (Jarrow, 2009):

The first assumption is the constancy of interest rate. In reality one has to deal with stochastic interest rates (Heath, Jarrow, & Morton, 1992), which generate a fundamental risk inherent in all fixed income securities including the credit risky ones. In order to make credit risk models more realistic this assumption should be relaxed (Longstaff & Schwartz, 1995), (Lando, 2004(2)).

The second assumption is that the firm has a very simple capital structure. It is assumed that the firm has a single issue of zero-coupon debt. In reality the balance sheets of modern firms are more complex, containing multiple coupon-paying debts with different maturities and different seniorities in the event of default. Furthermore, the capital structure of the firm is not static as in Merton's model but may dynamically change during the time. Various papers expand the original Merton's model to incorporate a realistic capital structure (Black & Cox, 1976), (Geske, 1977), (Mason & Bhattacharya, 1981), (Leland, 1994), (Anderson & Sundaresan, 1996)among the others.

The third assumption of the model is that recovery rates, in the event of a default, follow the absolute priority rule and are completely determined by the value of the firm's assets at maturity. In reality the absolute priority rule are typically disregarded. Several papers extend Merton's model to avoid this limitation (Longstaff & Schwartz, 1995), (Anderson & Sundaresan, 1996).

Another drawback of Merton's model is that the default can happen only at maturity T. This issue is related to the second assumption of a simplified capital structure, and is related to the fact that the firm has only issued a single bond that matures at time T. In this framework, there is no possibility for an earlier default, no matter what happens with the firm's value at times $t < T$. Merton's model was extended to incorporate possibilities of early default by Black and Cox (1976) and Mason and Bhattacharya (1981), who introduced certain types of barriers and safety covenants to account for early default.

The predictability of default is another disadvantage of Merton's model. Due to the fact that the default can occur only at the maturity of debt and the fact that the value of the firm's assets follows a geometric Brownian motion, the default event becomes highly predictable as one approaches the maturity date. As a result, the model generates very low short-term credit spreads. As a solution to this problem Zhou (2001), Huang and Huang (2003) and Lando (2004(2)) extended Merton's type model by allowing the firm's assets to follow a mixed jump-diffusion process, which are examples of the general class of semimartingale models (Jarrow, 2009). The other extensions are stochastic volatility (Fouque, Papanicolaou, & Sircar, 2000) and Levy process (Cont & Tankov, 2004). In addition, Jarrow (2004) argues that all structural form models have a problem of complete knowledge of insider information that can only be available to the firm's managers. He tries to emphasize that modeler should have continuous and detailed information about all the firm's assets and liabilities, which is not always fully and easily observable.

The main criticism of Merton's model concern's with the non-tradability and non-observability of the firm's asset value process. Merton's model assumes that the firm's asset value is continuously observable and tradable. This assumption is crucial for the arbitrage pricing argument, which values corporate debt as a long position in risk-free bond and short position in a put option that can be dynamically replicated by continuously trading in the firm's asset and risk-free bonds. For almost all firms (except perhaps some financial firms) this assumption does not hold, and a firm's assets cannot be traded either directly or indirectly.

The last criticism is valid for all Merton type models, and is inherent in the general approach of the structural models. The reduced-form models, which we shall describe in following subsection, were introduced to overcome this problem. Although reduced-form models overcome the problem of non-observability/non-tradability, the default event in these models is exogenously generated. For this reason, structural models remain the preferred tool when one is trying to study credit risk modelling from a fundamental perspective. With all their shortcomings, the structural models are crucial for generating an economic understanding of credit risk. For this reason, before proceeding to an overview of reduced-form models, let us look at some extensions of Merton's model in more details.

2.2.1 FIRST PASSAGE TIME MODELS: EXTENSION TO MERTON (1974)

First passage time models were introduced shortly after the Merton's model (1974) to avoid one or more of the unrealistic assumptions describe above. The main characteristic of these models was that the default could happen at any time during the life of the debt, not restricted to the time of maturity. Merton's model was initially extended by Black & Cox (1976) who allowed for the possibility of a more complex capital structure and introduced the possibility of default happening at intermediate times before the maturity of the last debt obligation. Following this, Geske (1977) extended the model for the case of interest-paying debt. Below, we discuss these and other main papers in more detail.

BLACK AND COX (1976)

The aim of the authors was to make some general statements on valuation of the corporate securities and look at the effect of safety covenants, subordination arrangements and restrictions of the financing of interest and dividend payments.

The main assumptions were as follows:- Interest rates are constant; individuals may take short positions; trading takes place continuously; there are no taxes, indivisibilities, bankruptcy costs or transaction costs; the firm's value follows a diffusion process with variance proportional to the square of the value. Overall, these assumptions are quite similar to Merton's model.

The first improvement that Black & Cox brought into the Merton's framework was by allowing default to happen any time during the life of the debt. This was made possible by introducing safety covenants, which give a right to the bondholders to bankrupt or reorganize the firm if it is doing poorly according to some standards. In other words, if firm's value drops to a pre-specified level (lower barrier, which may change over time), then the bondholders have the right to force the firm into bankruptcy and take the ownership of the assets. Safety covenant serves as a protection mechanism for the bondholders against bad corporate performance.

The second improvement to Merton's model by Black & Cox was the introduction of a more complex capital structure. In order to do this, authors introduced subordinated debt with a junior bond for one class of debt holders and senior bond for the second class into the model. In other words, they assumed that at the maturity date payment could be made to the junior debt holders only if full payment to the senior debt holders has been made.

The Black & Cox model generates credit spreads that are more consistent with those observed in the corporate debt market. This is an improvement in comparison with Merton's model, which leads to credit spreads that are much smaller than the ones observed in the market (Jones, Mason, & Rosenfeld, 1984). The model incorporated safety covenants, subordination arrangements and restriction on the financing of interest and dividend payments. Their results show that these provisions increase the value of bonds and have a significant effect on the behavior of the firm's securities.

Despite of the fact that Black & Cox model was one of the first and fundamental improvements of the Merton's model, it still uses some unrealistic assumptions and limitations of the traditional Black-Scholes-Merton framework for valuing risky debt. (Longstaff & Schwartz, 1995) criticized an assumption of constant interest rate and pointed out that this assumption is difficult to justify in valuation model for risky fixed-income security. The other weakness of the model is the assumption that assets are allocated among corporate claims according to the rule of absolute priority in case of default. However, later evidence showed that, in event of default, absolute priority rules are disregarded (Franks & Torous, 1989), (Franks & Torous, 1994), (Eberhart, Moore, & Roenfeldt, 1990), (LoPucki & Whitford, 1990), (Weiss, 1990), (Betker, 1991).

GESKE (1977)

In this paper Geske (1977) applied the technique for valuing compound options for valuing risky coupon bonds. He derived the valuation equation for the risky coupon bond with an arbitrary number of coupon payments and a final principle payment in discrete time. The main improvement to Merton's model was in allowing for an interest paying debt, whereby the default could occur on any coupon payment date in the event of non-payment, in which case the debt holder would take control of the firm.

Geske assumes a joint log-normal dynamics for the firm's value process and return on a market portfolio. At each coupon-payment date the firm either pays the coupon or defaults and transfer the ownership right (which in the framework of structural approach is a call option on firm's value) to the bond holder. This produces a model mathematically analogous to an option on an option, i.e. a compound option.

Geske proceeds by the incorporating of various indenture restrictions such as sinking funds, safety covenants, debt subordination and payout restrictions in his model. He modifies the valuation formulae to account for these indenture restrictions.

To sum up, the Geske's model extended the original Merton's model, by incorporation of the coupon payment into the risky debt valuation. In the same line with (Black & Cox, 1976), this model modified the conditions for the default and tried to make more complex liability structure.

MASON AND BHATTACHARYA (1981)

As we have discussed previously, Black and Cox (1976) extended Merton's model by introducing a safety barrier, a lower level for firm value such that if the firm value fall below it, the debt holders take over the firm. Black & Cox introduced this approach in a framework of diffusion process. Mason and Bhattacharya (1981) considered the problem of risky debt valuation with a safety barrier in the case where firm's value follows a discontinuous sample path.

Mason & Bhattacharya assumed that the change in the value of a firm is described by a jump process, and used a Poisson process to model these discontinuous movements. In their model, the dynamics of the firm's value$V$, follows a Poisson jump process of the form:

$$dV/V = (\mu - \lambda\kappa)dt + dY$$

Where μ is instantaneous expected rate of return, λ is mean number of jumps per unit time, ($d\lambda$ is the probability of the Poisson event in the time interval t), *k=E(S-1)* where *(S-1)* is the random percentage change in the firm value given the occurrence of Poisson event, dY is the Poisson process. In analogy with Merton's original paper, Mason & Bhattacharya assume that the firm's capital structure consists of only an equity and a single discount bond. The safety covenant (default barrier) has the same structure as in (Black & Cox, 1976). The authors proceeded to write down an integro-differential equation for the valuation of an arbitrary claim on the firm's asset value, which was an extension of the Black -Scholes equation to the case of jump processes. The solution was found along the lines of (Cox & Ross, 1976) by deriving the first passage time distribution and the effective distribution associated with the firm value dynamics and safety covenant.

The binomial jump dynamics considered by Mason and Bhattacharya converges to the Gaussian Wiener dynamics as the mean number of jumps per unit of time is made very large, $\lambda \rightarrow \infty$ and the amplitude of jump is made progressively smaller, $\delta \rightarrow 0$. The authors showed that in this limit, their results converge to the (Black & Cox, 1976), as might be expected. However, in the general case, authors showed that there might be a significant differential impact the value of the safety covenant between continuous and discontinuous models.

LELAND (1994)

Leland (1994) analyzed the value of corporate debt and optimal capital structure of the firm. He presented closed form results, relating the value of corporate debt and optimal capital structure with such parameters as firm risk, taxes, bankruptcy cost or bond covenants, in the framework when firm assets value follow a Merton type diffusion process with constant volatility assuming a constant interest rate.

The valuation equation for the bond has the general structure as in Black and Cox (1976), with the difference that Leland assumed that the bond price has no explicit time dependence. This simplified the problem by converting the Black-Scholes type differential equation into an ordinary differential equation, with boundary conditions determined by payment at maturity contingent on the event of bankruptcy. Leland extended the previous models by incorporating of bankruptcy cost and tax benefits into the boundary conditions. He ended up with a simple algebraic expression for the value of debt as a function bankruptcy costs, tax, as well as boundary conditions dependent on firm's capital structure and risk.

2.2.2 SECOND GENERATION STRUCTURAL-FORM MODELS

In the 1990s, the first passage time models were extended by considering stochastic interest rates, time dependent and stochastic default barrier and incorporation of jumps in the asset value process. This brought more realism to the models, however significantly raised their analytical complexity. The structural approach was significantly improved by the so-called second generation structural-form models (Elizalde, 2006), which were primarily developed in Longstaff and Schwartz (1995), Kim, Ramaswamy and Sundaresan (1993), Hull and White (1995), Nielsen, Saa` - Requejo and Santa-Clara (1993) and Anderson and Sundaresan (1996) among the others.

LONGSTAFF AND SCHWARTZ (1995)

In this article, Longstaff and Schwartz (1995) introduced an approach to valuing risky corporate debt, incorporating both default and interest rate risk. They specified the stochastic term structure of interest rates and correlation between default and interest rate. An important implication of their results is that correlation between default and interest rate had a significant effect on the properties of the credit spread. In contrast to the Black and Cox (1976), Longstaff & Schwartz assumed an exogenously determined constant default barrier K. In addition, they also relaxed an assumption of strict absolute priority in case of defaults that underlies the original approach to valuing risky debt.

The main assumptions of the Longstaff & Schwartz model are as follows. The firm's asset follows a geometric Brownian motion, analogous to Merton's model. The dynamics of the short-term riskless interest rate follows a Vasicek type process (Vasicek, 1977):

$$dr = (\alpha - \beta r)dt + \upsilon dZ$$

Where α, β, υ are constants and dZ is a Weiner process. The correlation between the asset Wiener process and interest rate Wiener process is a constantρ. The value of the firm is assumed to be independent of the capital structure of the firm. Furthermore, the model assumes a constant default barrier *K.* In addition, the authors incorporated an arbitrary fixed recovery rate. The authors, proceeded to derive a partial differential equation for the value of an arbitrary contingent claim as a function of the underlying value of the firm process and the interest rate process. The authors derived the solution to the equation closed, albeit a complex, form.

Authors criticized the traditional approach of modelling of risky debt values in which the interest rate is assumed constant and only factor determining credit spreads is firm value. They showed that credit spreads are negatively correlated to interest rates and that the duration of a risky bond depends on correlation with interest rate. Their results suggested that the impact on valuation of credit spreads due to the change in interest rate is more important than that caused by typical changes in firm's value.

An analysis of credit risk under a different dynamic for the interest rate process was considered in Kim, Ramaswamy and Sundaresan (1993), where a Cox-Ingersol-Ross process was considered, and by Briys and Varenne (1997) who considered a generalized Vasicek process. The incorporation of stochastic interest rates to the modelling of credit risk was an important step towards realism for structural models.

ANDERSON AND SUNDARESAN (1996)

Anderson and Sundaresan (1996) applied elements of game theory to the problem of valuing credit risk. In their paper, Anderson & Sundaresan incorporated an extensive form game determined by the terms of the debt contract and applicable bankruptcy laws to valuation of risky debt contracts. They modified the Merton approach, where bankruptcy was determined only by the state of the nature and the contract, by allowing both the owner and the creditor to take initiative. On the one side, it gives the firm's owner the right to choose to underperform on his debt contract, even when the firm's health allow him to fully meet his obligations. On the other side, the creditor is also given a score for choosing how to approach a potential bankruptcy. The main assumption is that once the debt contract has been established, the creditor and owner choose actions in a way consistent with their self-interest.

The main idea of the game is as follows. V_T is the value of the firm observed at the maturity date T and the owner choose a debt service S_T . If $S_T \geq GS_T$ (where GS is contracted amount) then the game ends, and debt holder receives his dues. Otherwise, if $S_T < GS_T$ the creditor should chose between accepting and rejecting. If the creditor accepts this proposal, he receives a payoffs S_T and the firm owner ends up with $V_T - S_T$. If the debt service is rejected the payoff to the debtholder is $\max(V_T - R, 0)$ and payoff for the owner is 0, where R is a constant liquidation cost. The equilibrium in this game is achieved by deriving the decision rules for the creditor and firm owner that give the best response in light of the payoffs.

Their results show that the amount by which the bankruptcy leads to a rise in the yield spreads depend on the degree of leverage and the volatility of the underlying assets. The results show that a proper accounting for costly bankruptcy can better explain observed credit risk premia, in the form of yield spreads on traded risky debt, than the standard Merton type framework.

2.2.3 STATE DEPENDENT MODELS

Another direction of the theoretical research within the framework of structural models involves extending the standard model with regime switching. Recent literature has considered states to represent macro-economic factors (eg. stages of the business cycle) as well as external rating of the firm. In this framework cash flow, value of firm's assets and debt, bankruptcy costs, and default policy could be state dependent. These models allow for the incorporation of fundamental macro and micro economic factors into the study of credit risk modelling. In addition, these types of models improve standard structural form models by mitigating the problem of the predictability of default.

Hackbarth, Miao and Morellec (2004) developed a model with regime switching in aggregate shock. In their paper, the authors analyzed the impact of macroeconomic conditions on credit risk and capital structure choice. They developed a structural form model in which the cash flow of the firm depends on both idiosyncratic and aggregate shocks that reflect the state of economy. Their analysis revealed that when aggregate shock shifts between expansion and contraction, the default policy of shareholders is determined by different default barriers for each state. Therefore, aggregate shocks generates some variation in the present value of future cash flows to current cash flows that might lead the firm to default after the change in macroeconomic conditions.

The main assumptions of their model was as follows. They assumed risk-neutral agents, in a setting with constant interest rate. The firm's operating profit is given as

$$p(x_t, y_t) = x_t y_t$$

where y_t is an aggregate shock reflects states of economy; x_t is idiosyncratic shock that shows the firm-level productivity uncertainty. Idiosyncratic shock follows the geometric Brownian motion.

$$dx_t = \mu x_t dt + \sigma x_t dW_t$$

Aggregate shock y_t takes two values y_l and y_h corresponding to an expansion and contraction phases. The transition between the two phases follows a Poisson process. The authors write down a differential equation for the value of the corporate debt in the two regimes. Following this, they derive an analytical solution for the value of the firm, equity and debt as well as default policy.

Based on their analysis, the authors made several empirical predictions. In their model, when the aggregate shock shifts between different states, the optimal default policy is characterized by different barriers for each state and they are countercyclical with higher default rate in recession. Credit spreads are higher in the recession than in expansions. The market leverage should be countercyclical. The debt capacity of firms also depends on economic conditions and is larger (up to 40%) during expansions. A firm can adjust its capital structure dynamically with changes in economic conditions and adjust it more often and by smaller amounts in booms than in recessions. In contrast with previous structural form models, the state dependent model is able to generate non-trivial credit spreads for short-term corporate debt. In Guo, Miao and Morellec (2005), the authors analyses the impact of discrete changes in the growth rate and volatility of cash flows on firm's investment decisions.

Drobetz and Wanzenried (2004) empirically tested these types of models on a sample of 91 Swiss firms. They concluded that macroeconomic conditions affect the speed of adjustment to target leverage. Haas and Peeters (2004) empirically show that higher GDP growth increases the adjustment speed based on dataset from Estonia, Lithuania, Bulgaria. Despite the few empirical papers mentioned above, State Dependent Models were mostly developed theoretically and their potential success in the future modelling depends on their empirical applications and predictive abilities and is still an open area of research.

2.3 REDUCED-FORM APPROACH

INTRODUCTION

An alternative approach for modelling credit risk, known as the reduced-form approach, was introduced by Jarrow and Turnbull (1992), Jarrow and Turnbull (1995), and developed by Duffie and Singleton (1996), Duffie and Singleton (1997), Duffie and Singleton (1999), Lando (1998), Jarrow, Lando and Turnbull (1997), Madan and Unal (1998), Artzner and Delbaen (1995), Jarrow and Protter (2004) and Jarrow, Lando and Yu (2005), amongst others.

In reduced-form models default is based on an exogenous Poisson process. Its main advantage is that default need not be linked to the dynamics of a firm's assets and liabilities. Therefore, one does not require a detailed information about the value of firm's assets and liabilities. On the other hand, generating default based on Poisson process can provide richer dynamics for the term structure of credit spreads and better capture effects of various additional factors on default intensity (Jarrow & Protter, 2004).

To introduce credit risk in the framework of a reduced-form approach it is necessary to make an assumption that a firm may default on one of its liabilities with positive probability prior to the zero-coupon bond maturity date. If this happens, the firm will not be able to pay back the face value of zero-coupon bond.

According to Jarrow (2009), a modeler observes a random default process, which from a mathematical perspective is characterized by a random process d_t which takes values 0 if default has not happened and 1 if the default has taken place. At each time instance, the occurrence of the default event is governed by a Poisson process with an intensity $\lambda_t = \lambda_t(X_t) \geq 0$. This intensity depends on the vector state variables X_t, where state variables relevant to the credit risk can be interest rate, GDP, inflation, house prices, etc. The interpretation of the default intensity $\lambda_t(X_t)\Delta t$ is probability of default over a small time interval $[t, t + \Delta t]$, assuming that the default did not happen before time t. The default event in this framework is not predictable and comes as a surprise to the market.

The last thing we need to define in order to complete formulation of reduced–form approach is the payoff of the firm's debt in event of default. When a firm defaults prior to the zero-coupon bond date of maturity, the bond receives a recovery payment that is less than face value promised. The recovery rate is usually modeled as a stochastic process and assumed to be part of information observed by the modeler. In practice, for simplicity, one often assumes a constant recovery rate.

In the literature three different constant percentage recovery rate processes are used:

The first one is recovery of face value (Merton (1974)):

$$R = \delta K, \quad \delta[0,1]$$

The second one is recovery of treasury:

$$R = \delta K p(\tau, T), \quad \delta[0,1]$$

Which implies that upon default the defaulted debt is worth a constant percentage of default-free zero-coupon bond, (Jarrow & Turnbull, 1995).

The last one is recovery of market value:

$$R = \delta L_{\tau-}$$

where $L_{\tau-}$ is value of debt issue an instant before default, (Madan & Unal, 1998), (Duffie & Singleton, 1999). It states that debt is worth a constant fraction of its value an instant before default.

The value of a credit-risky bond in the framework of reduced-form models is given by a risk-neutral expectation of the discounted bond payoff, and has the form (see Jarrow, (2009) for a review):

$$D_t = \mathbb{E}\left[R_\tau e^{-\int_t^\tau r_s ds}\mathbb{I}_{\tau\leq T} + Ke^{-\int_t^T r_s ds}\mathbb{I}_{\tau>T}|\mathfrak{F}_t\right] \tag{6}$$

Where $\mathbb{E}[\ldots|\mathfrak{F}_t]$ is the expectation under a risk neutral probability measure. The first and the second terms within the expectation are the discounted payouts in the event of default and no-default respectively.

STRUCTURAL MODEL VERSUS REDUCED FORM MODEL

It is interesting to compare structural models with the reduced form, and look at the advantages and problems of each of the two approaches. The primary difference in the two approaches comes from the difference in the assumptions about the information available to market participants (Jarrow & Protter, 2004), (Jarrow, 2009).

The structural model assumes a complete knowledge of the detailed information about the value of the firm's assets and any internal or external factors that might affect the company. This is the so called firm manager's information set. This informational assumption implies that the default time of the firm is predictable, which is not necessarily the case in practice. On the other hand, the reduced form model assumes knowledge of less detailed information and was constructed to be consistent with the information that is available to the market. This information assumption implies that the default time is unpredictable. Jarrow & Protter (2004) argue that structural models potentially transform into reduced form models when the information set changes and becomes less detailed.

The relation between structural and reduced form models was also discussed by Duffie and Lando (2001), who viewed the market as having management's information set together with accounting induced noise. They showed that in the absence of the accounting noise, the default event becomes completely predictable. However, in the presence of the accounting noise, it becomes impossible to observe the asset value process, thereby making a default event a surprise.

The work by Cetin, Jarrow, Protter & Yildirim (2004) used an alternative way to model the market information set. They constructed the market information set as a reduction of the manager's information set. Based on their approach, the authors came to similar conclusions as Duffie & Lando (2001). The other important papers that studied the relation between the two modelling approaches include Kusuoka (1999) and Blanchet-Scalliet & Jeanblanc (2004).

The question about the performance of the models, structural vs reduced-form, strongly depends on the context. The structural models prove to be particularly useful in modelling and analyzing the dependency of credit risk on fundamental factors. They provide a link between the credit quality of a firm and the firm's economic and financial conditions, as well as broader macro/micro-economic factors (Elizalde 2006). On the other hand, reduced-form models are particularly well suited for practical pricing and hedging purposes (Jarrow, 2009). This is because the parameters of the stochastic processes in the reduced-form models are based on the market observable information set. Furthermore, reduced-form models are explicitly formulated in terms of risk-neutral expectations, which makes for easier calibration. That said, it is worth pointing that structural form are actively used in the industry. One of the main applications of structural form models in practical applications is the KMV model, used to calculate the expected default frequency of firms. In addition, structural models are often used practice for valuing credit derivatives dependant on correlation of two or more underlying credits.

JARROW AND TURNBULL (1995)

In this work, the authors develop a new technique for pricing and hedging derivative securities involving credit risk. The main principle of the new method is to apply the foreign currency analogy used in Jarrow & Turnbull (1992), whereby the payoff from a risky security is decomposed into a certain payoff and "spot exchange rate". The stochastic term structure of default free interest rates and stochastic maturity specific credit-risk spread are assumed to be given. The risk neutral approach is employed in order to price derivative securities. The main difference of new methodology from already existing ones (structural models) is that the capital structure is irrelevant and bankruptcy can occur at any time.

The price of a risky zero-coupon bond issued by a company XYZ is decomposed as:

$$v(t,T) = p(t,T)e(t)$$

Where $p(t,T)$ is value of default free zero-coupon bond paying certain dollar at maturity, and $e(t)$ is time t dollar value of one promised XYZ dollar delivered immediately and analogous to a "spot exchange rate". This method is convenient for analyzing the term structure of a risky bond in terms of $p(t\ ,T)$ and payoff ratio $e(t)$. The exchange rate between the XYZ dollar and the ordinary dollar is known at maturity and is either 1 or R (recovery), depending on whether a default has occurred or not. The authors develop a two period model, and discuss the issues associated with calibration and pricing in this simple setup. They formulate the necessary and sufficient conditions for the model to be arbitrage free and complete. Following this, they give a pricing formula for arbitrary contingent claim within this model. Following this, the authors extended the two-period discrete trading economy to its multi-period continuous-time limit. The authors developed a general framework for valuing credit risky securities that can be applied to corporate bonds, options on debt, vulnerable options, swaps, etc.

JARROW, LANDO, TURNBULL (1997)

In this work, the authors present the model for valuing risky debt with an explicit incorporation of firm's credit rating, which serves as indicator of the probability of default. The work was based on the model developed in (Jarrow & Turnbull, 1995) and characterized the bankruptcy process as discrete state space Markov chain in credit ratings. The paper presents a no arbitrage model for the term structure of credit risk spreads and their evolution through time.

The authors started from a discrete trading economy. The distribution for the default time was modeled using a time-homogeneous state space Markov chain which is specified by the transition matrix:

$$Q = \begin{pmatrix} q_{11} & q_{12} & \cdots & q_{1K} \\ q_{21} & q_{22} & \cdots & q_{2K} \\ \vdots & & & \\ q_{K-1,1} & q_{K-1,2} & \cdots & q_{K-1,K} \\ 0 & 0 & \cdots & 1 \end{pmatrix}$$

The state space *S={1…K}* shows different credit classes that started from the highest (1) and ended with bankruptcy (K). The element q_{ij} reflects actual probability of going from state i to state j in one time step. In this framework, the probability that the default does not happen before or at time T is given by:

$$\hat{Q}_t^i(\tau^* > T) = \sum_{j \neq K} q_{ij}(t,T) = 1 - q_{iK}(t,T)$$

Where $q_{ij}(t,T)$ is the probability of transitioning from state i to state j in time steps between t and T, and it is assumed that the firm was in state i at time t. $\tau^* =$

$inf\{s \geq t: \eta_s = K\}$ is time of bankruptcy. The authors derived the value of risky zero-coupon bond issued by a firm in credit class i at time t:

$$v^i(t,T) = p(t,T)\left[R + (1-R)\tilde{Q}_t^i(\tau^* > T)\right]$$

Where R is the recovery rate and $\tilde{Q}$ is transition matrix for credit classes.

Credit risk spread in this model is given by:

$$s(t,T) = 1_{\{\tau^* > t\}} \log\left[\frac{\delta + (1-\delta)\tilde{Q}_t^i(\tau^* > T)}{\delta + (1-\delta)\tilde{Q}_t^i(\tau^* > T+1)}\right]$$

Since $\tilde{Q}_t^i(\tau^* > T) > \tilde{Q}_t^i(\tau^* > T+1)$, the credit spreads are always strictly positive in this model.

The authors applied the model to analyze hedging credit risky derivatives against rating jumps. In addition, the model was extended for to continuous time. In continuous time, the transition between ratings is assumed to follow a Poisson process with intensity given by the matrix of transition intensities λ_{ij}. This matrix reprents the transition rates of jumping from credit class i to credit class j.

The probability transition matrix for jumps between time t and T are found by solving a Kolmogorov type differential equation. The rest of the analysis is identical to the discrete time case.

MADAN AND UNAL (1998)

Madan & Unal divided default risk into the timing and recovery risks. The default components were explicitly priced as if they were traded in the futures market. The authors presented an estimation methodology evaluating recovery risk and then construct implicit prices of contingent claims which reflect purely the timing risk. The proposed method of pricing risky debt and parameters of the model was estimated based on data for Certificates of Deposits between 1987 and 1991.

The authors separated the risky debt into "survival security" and "default security". The survival security pays a dollar if there is no default and nothing otherwise and faces only the timing risk of bankruptcy. The default security pays rate of recovery in case of default and nothing otherwise and faces only risk of recovery in default. The timing risk of bankruptcy can be defined as the likelihood of the firm default over the next period and the risk of recovery in default is defined as variation in the creditor payout rate conditional on default.

Several assumptions were used in the article in order to develop expressions for the forward /futures prices for the survival and default securities and as a result for risky debt. The first one is that default payouts are independently identically distributed across time and states (iid). The second one is that default timing risks are a function of time specific information, which is independent on interest rate movement. The main achievement of this work was to show how to use the price of junior and senior debt to identify the parameters of the processes describing the bankruptcy timing and recovery risks embedded in default.

LANDO (1998)

This work presented a framework for valuing credit risky financial instruments for Cox processes (also known as doubly stochastic Poisson process). In his work, Lando extended and generalized the model presented by Jarrow, Lando & Turnbull (1997) by introducing dependency in transition rates between credit ratings on state variables. The model was also generalized by incorporating state dependence in the risk premia allowing for stochastic changes in credit spreads even between ratings transitions.

In this framework, the probability that the default happens at time τ, greater than T, given that at initial time t we are in the state i, is given by

$$P(\tau > T|i) = \mathbb{E}\left[\exp\left(-\int_t^T \lambda_{iK}(X_s)ds\right)\right] \qquad T \in [t, T_f]$$

The credit risky bonds are valued using formula (6). An important advantage of the new framework was the analogy of pricing approaches to credit risk and interest rates. In effect, the valuation approach of credit risky securities became analogous to the valuation approach for interest rate derivatives in stochastic interest rate models.

DUFFIE AND SINGLETON (1999)

In this article, the authors present another model of the term structure of bonds and contingent claims that are subject to default risk. It is different from previous models in the way of parameterization of losses at default in terms of the fractional reduction in the market value that occurs at default.

Assume that measure h_t is the hazard rate of default at time t measured in the risk neutral probability measure, L_t is the expected fractional loss in the market value in the case of default at time t conditional on information available up to that time. We assume that the riskless securities are valued in terms of a short rate process *r*, whose dynamic is provided in the risk neutral measure. For an arbitrary credit-risky contingent claim *X* can be valued as if it is default free, if one replaces the usual short rate process *r* with the default adjusted short-rate process $R = r + hL$.

$$V_t = \mathbb{E}\left[exp\left(-\int_t^T r_s ds\right)X_{\substack{credit\\risky}}\right] = \mathbb{E}\left[exp\left(-\int_t^T (r_s + h_s L_s)ds\right)X_{\substack{default\\free}}\right]$$

In their paper authors show how their framework can be applied to the valuation of the corporate bonds (callable and noncallable). In both cases the hazard rate h_t and the fractional default loss L_t cannot be separately found from data on the defaultable bond price, because h_t and L_t enter the pricing equation only through the mean-loss rate $h_t L_t$. They also developed a defaultable version of the (Heath, Jarrow, & Morton, 1992) interest rate model based on the forward-rate process associated with R.

JARROW AND YU (2001)

Another extension of the reduced form model was the incorporation of counterparty risk. The counterparty risk in the current context refers to the risk that default of firm's counterparty can affect its own default probability (note that this usage of counterparty risk is broader than the currently common usage, where counterparty risk specifically refers to the credit risk present in derivative transactions). This issue was previously analyzed in Jarrow and Turnbull (1995, 1997), Duffie and Huang (1996) and was developed in the paper by Jarrow and Yu (2001).

Each firm has a unique counterparty structure that arises from relation with other firms in the economy. For example, the group of firms can be highly interdependent that a single default can stimulates a cascade of defaults. In Jarrow and Yu (2001), reduced form model is generalized by including default intensities dependent on the default of counterparty, so as to incorporate firm-specific information provided by the market. Authors based their work on the reduced form model of Lando (1998) which allowed for dependency between credit risk and market risk through the use of Cox process. In the original model, the intensity of default is a stochastic process dependent on a set of economy-wide-state variables, which was modeled as continuously varying diffusion processes. The innovation of Jarrow and Yu (2001) model was the inclusion of jump processes in this set of state variables, thereby capturing the dependence among several default processes allowed for strong correlation between firm-specific risk factors.

The final pricing formula for defaultable bonds extended to including the possible interdependent default risk is given by (Jarrow & Yu, 2001):

$$v^i(t,T) = R^i p(t,T) + \mathbb{I}_{\tau>t}\left(1 - R^i\right)\mathbb{E}\left[exp\left(-\int_t^T (r_s + \lambda_s^i)ds\right)\right]$$

Where *p(t,T)* is time t price of a default free zero-coupon bond that pays one dollar at time T;$v^i(t,T)$ denote the time-t risky zero-coupon bond maturing at T; r_t is spot rate process; $R^i \in [0,1)$ is a recovery rate, which is exogenously specified constant fraction of a dollar paid from each unit of bond in case of default. Crucially, the default intensity λ_s^i is allowed to depend on the credit state of the counterparties. The expression above can be interpreted in a simple intuitive manner. The first term is the recovery rate that is received for sure and discounted to time t, and the second term is the residual $1 - R^i$ in the event of absence of default also discounted to time t. The second term depends on the counterparty risk through the default intensitiesλ_s^i.

The authors applied their method to price credit derivatives such as default swaps and showed how mispricing is produced by models that ignore counterparty relations.

JARROW, LANDO, YU (2005)

This work analyzes the general specification of default risk premium in the context of reduced-form models. Authors argue that because the reduced-form technique models default risk by using standard term-structure techniques, it is natural to use the same structure for the risk premia of default intensity processes as we used for the short rate process in usual term-structure models. In this case, the drift adjustment on the state variables when moving from a real probability to martingale probability measure might be interpreted as "default risk premium" or "price of default risk". Authors argue that "drift change in the intensity" constitutes a restriction on the set of possible default risk premia. They presented that this restriction can be justified through a suitably defined notion of conditional diversifiable default risk. Their results show that there is equivalence between the martingale and empirical default intensity functions for diversifiable default risk.

2.4 EMPIRICAL WORKS

In the previous subsections we looked in details at the two different approaches to theoretical modelling of credit risk, discussed their advantages and disadvantages, and reviewed the key publications where these approaches were developed. In this subsection we turn our attention to the empirical testing of these models. Since there is a huge body of empirical literature, covering a broad spectrum of issues in credit risk modelling, in this section we restrict our discussion to just the main direction of empirical research of structural and reduced form models. We leave the detailed discussion of empirical literature related to topics covered in this thesis to the corresponding subsequent Chapters.

2.4.1 EMPIRICAL WORKS IN STRUCTURAL MODELS

Although there is large number of papers dealing with the theoretical aspects of structural models, covering it's extensions and improvements, the literature covering the empirical testing of structural models is quite limited. Emo, Helwege and Huang (2004) argued that there is only a limited number of papers to consider structural models to evaluate their ability to predict price and spreads. One of the reasons for this is the difficulty in obtaining corporate bond price data for academic research. Below, we consider the main approaches to empirical analysis of structural models that have been considered in academic literature.

DIRECT APPROACH

Jones, Mason and Rosenfeld (1984) was one of the first papers to empirically investigate Merton's model. The authors implemented the model on a sample of firms with simple capital structures and secondary market bond prices. The aim of the paper was to test the predictive power of the structural form models. They used data from 27 firms on a monthly basis from January 1975 to January 1981. They showed that model's price predictions are typically higher than the observed prices on average. The authors also show that Merton's model works better for the low-grade bonds and pricing errors depend on such parameters as maturity, leverage, equity variance, time period. Ogden (1987) conducted a similar type of research but using prices from new offerings. He showed that the Merton type model under-predicts spreads by 104 basic points (i.e. overpredicts the price). Both authors works concluded that Merton's model suffers in performance due to non-inclusion of stochastic interest rates.

Lyden & Saraniti (2000) compared Merton (1974) with Longstaff and Schwartz (1995) model using individual bond prices (prices for non-callable bonds of 56 firms). They concluded that both models underestimate yield spreads and lead to errors related with maturity and coupon. In contrast to Jones, Mason and Rosenfeld (1984) and Ogden (1987), Lyden & Saraniti (2000) concluded that there is little impact from stochastic interest rate variation.

There is also a sizable literature studying the general parameters predicted by the structural models, such as correlation between interest rate and spreads, shape of credit term structure et al. Sarig and Warga (1989), Helwege and Turner (1999), He, Hu and Lang (2000) examined the shape of credit yield curve predicted by structural models. Delianedis & Geske (1998) investigated bond rating changes. Collin-Dufresne, Goldstein and Martin (2001), Elton, Gruber, Agrawal and Mann (2001), studied the changes of bond spreads. Duffie (1998), Neal, Rolph and Morris (2001) looked into the relationship between bond spreads and Treasury yield. Huang and Huang (2003) analyzed real default probabilities implied by structural models.

Emo, Helwege and Huang (2004) compared the Merton (1984) model with four newer extensions such as Geske (1977), Longstaff and Schwartz (1995), Leland and Toft (1996) and Colline-Dufresne and Goldstein (2001(2)). Their aim was to show that innovations in structural models might lead to improvement in prediction of risky bond prices. They applied all models based on sample of 182 non-callable bonds with simple capital structure taken in the period of time between 1986 and 1997. The authors revealed that the Merton (1984) and Geske (1977) models generate spreads that are too small compared with spreads observed in the market. On the other hand, Longstaff and Schwartz (1995), Leland and Toft (1996) and Colline-Dufresne and Goldstein (2001) generate spreads that are too high compare with observed spreads. They concluded that all tested models share the problem of inaccuracy, generating either too small or too large spreads, and the resulting average spread prediction error is not informative. In contrast with previous literature they also found no support for the fact that underestimation of yield spreads is related with maturity.

The main conclusion of majority of works on testing of Merton type models was that there was limited empirical evidence to support these models. In addition, these models typically predicted smaller spreads than observed (i.e. predicted higher prices).

CALIBRATION APPROACH

Another way of implementing structural models in practice is called the calibration approach. The main idea of this approach is to back out the values of firm's asset and asset volatility from the observed price of the firm's equity and it's historical behaviour. These backed out values of firm's asset and asset volatility are then used for estimating the price of the firm's bond based on Merton type formulae. The theoretical price can then be compared with the corporate bond prices observed in the market. This approach was used by Delianedis and Geske (1998), Delianedis and Geske (2001) and Huang and Huang (2003). The general conclusion of these works was analogous to conclusions in the direct approach, in that structural models typically under-predict bond yield spreads. In particular, Huang and Huang (2003) concluded that the structural models predict lower portion of the spread for investment grade bonds, and a higher fraction of the spread for high-yield bonds.

MAXIMUM LIKELIHOOD APPROACH AND OTHER METHODS

Duan (1994) suggested a Maximum Likelihood method for analyzing structural models. Their approach was further extended by Ericsson and Reneby (2005). Assuming a log-normal distribution for asset values, they used the maximum likelihood method to estimate from observable variables like the equity price. Authors argue that their method works better compared to the calibration method when leverage is not constant.

This method was extended by Duan and Fulop (2005) who accounted for the fact that observed equity prices potentially can be contaminated by trading noise. The authors argued that observed equity prices could deviate from their equilibrium value because of the microstructure of noise. In the paper they introduced some nonlinear filtering algorithm that help to evaluate the likelihood function for equity priced observed with trading noises and conducted maximum likelihood estimation of a Merton type model. By implementing this techniques to the 30 Dow Jones and 100 randomly selected firms they revealed that ignoring the fact of the trading noise in equity price observations results in significant over-estimation of the firm's assets volatility.

Bruche (2005) applied the Simulated Maximum Likelihood method originally developed by Durbin and Koopman (1997) for estimation of the structural bond pricing models. Simulated Maximum Likelihood Estimation permits for both classical and Bayesian inference techniques. In this paper Bruche analyzed and compared Simulated Maximum Likelihood method with the other two methods such as the calibration method and Maximum Likelihood method considered in Ericsson and Reneby (2005). By using Monte Carlo simulations as well as application to real data he showed that the price data on any traded claim together with information about the balance sheet used in estimation significantly improve efficiency. He argues that this method has a number of benefits. Firstly, it uses all data that contains information about asset value of the firm, for example price of equity, credit derivatives to improve efficiency of the estimation. Secondly, this approach can deal with irregular spaced data and missing observations, which is typical for the corporate bond markets due to the fact that some bonds are not frequently traded.

2.4.2 EMPIRICAL WORKS IN REDUCED FORM MODELS

Although the current thesis will not consider empirical aspects of reduced-form models, for the sake of completeness, in this subsection we provide a broad overview of the key works that study reduced form models from an empirical perspective.

Madan and Unal (1998) analyzed the certificates of deposit issued by 300 thrift institutions over January 1987 to December 1991. The model of instantaneous default risk was used to relate the time variation in average thrift certificate of deposits to variations in average thrift stock prices, returns to an index of low-grade bonds.

Duffie and Singleton (1999) analyzed and estimated the price of default risk based on reduced form model. The authors used the maximum likelihood to estimate a two-factor square-root diffusion model of the default-free interest rate. In addition, they assumed that the instantaneous probability that a given firm default on its obligated bond payments follows a square-root diffusion process. The data contained month-end observations on the non-callable corporate bonds from January 1985 to December 1994, with majority of the bonds rated investment grade. The aim of the paper was to determine the features of the data that were well described by the model and those that were inconsistent with the model. In order to estimate this model the author adopts the method suggested by Chen and Scott (1993). The analysis revealed that the single-factor models of instantaneous default probability (examined square-root model) face difficulties to match the dynamic behaviour of corporate bond term structures. It also shows that models of instantaneous default risk have a very limited ability to price instruments with payoffs that depend on the defaults of multiple firms.

Lando and Skodeberg (2002) estimate and analyse credit rating transitions and rating drift based on continuous time observations. By applying semi-parametric regression techniques authors test for two types of non-Markov effects in rating transitions, such as the previous rating dependence and the duration dependence. They revealed the significance of this effect, especially for the downgrade movements. Using a large set of data (the source of rating migration reports is Standard & Poor) authors studied the difference between two estimators, one based on the discrete-time cohort method and the other based on the continuous observations. Their data covered 17 years of rating history taken from S&P, and contained a total of 6659 rated firms from 1981 to 1997. Authors concluded that it is important to estimate transition data based on the full story of rating transitions using one of the suggested estimators (max-likelihood or Aalen-Johansen), in this case default probabilities are non zero even for the highest rating category.

Cheva and Jarrow (2004) examine the forecasting accuracy of bankruptcy hazard rate models using data of US companies in the period between 1962 and1999. The number of bankruptcies included in this database is 1461, which was significantly more than what has appeared in the academic literature before. As a first step, the authors re-estimate the Altman (1968), Zmijewski (1984) and Shumway (2001) models. Their results show that the dynamic hazard rate model of Shumway (2001) has more accuracy in the prediction of bankruptcy then the other considered models. Following this, the authors show the importance of including an industry effect in the hazard rate estimation. They argue that previously little attention has been paid to this effect due to the limited number of bankruptcies in the data. Their results show that industry effect impacts both the intercept and slope coefficients in the forecasting equations. After completing the analysis with yearly observations intervals, authors conducted a similar analysis with monthly observation intervals and obtained a significant improvement for forecasting ability of the procedure.

The recent work of Figlewski, Frydman and Liang (2012) examines how general economic conditions impact defaults and major credit rating changes by fitting reduced form Cox intensity model with firm specific rating related and macroeconomic variables. The rating related firm specific variables used in the model are: initial rating class, current rating class, recent upgrade or downgrade, years since first rated. These were used as dummy variables. There are 14 macroeconomic variables in total. These were divided in to three main groups: general macroeconomic conditions, which show the health of the economy; direction of economy, which show whether economy improving or worsening; financial market conditions. Data on the history of credit event was drawn from the Moody's Default Research Database for the period between 1981 and 2002. Authors concluded that incorporation of rating related variables into reduced form model of default intensity lead to significant increase in explanatory power. Their results also reveal that macroeconomic factors added to the specification have a weak effect on the changes of coefficients for the rating based factors. Overall the results were consistent with findings from earlier studies. For example, the credit ratings reflected intensity differences correctly in every case, that higher rated firms had lower intensity of default than lower rated firm and had higher upgrade intensity. In addition, authors found some evidence for the "rating drift effect" and for the "ageing effect". The authors show that the intensity of the occurrence of the credit events was different for firms beginning as an investment grade and were downgraded to speculative class and firms that started as speculative and have been upgraded than for the firms that are the same investment or speculative grade category as they started in. The authors also show that direction of economy and financial conditions variables are more important in modelling downgrade transitions than the general macroeconomic conditions variables.

2.5 CONCLUSION

In this chapter we have given a broad review of main direction of research in credit risk modelling. We provided a general introduction to the two main strands of modelling, namely structural and reduced-form models, as well as focused on presenting a systematic overview of the key literature covering both theoretical and empirical research. For a detailed exposition of theoretical models of credit risk we refer the reader to two fundamental monographs Duffie and Singleton (2003) and Lando

(2004(2)). In the following chapters we shall consider concrete empirical topics, covering corporate bond yield spreads and CDS-bond basis. In these chapters we shall review the more specialized literature that relates to the corresponding topics.

CHAPTER 3
DETERMINANTS OF CORPORATE BOND SPREADS: EMPIRICAL EVIDENCE FROM US MARKETS

3.1 INTRODUCTION

In this chapter we shall conduct an empirical investigation of the main determinants of corporate bond yield spreads in the US domestic market, covering a period between 2003 and 2011. In the current section, we shall begin with a general introduction to the bond market and provide the key motivations for our research.

The bond markets play a crucial role in the global financial system, providing a venue for the effective channelling of funds between borrowers and savers, be they sovereigns, corporates or even individuals. It is a massive market, with an outstanding global notional that totalled $95 trillion in 2010. The US bond market is by far the largest debt market in the world, with an outstanding notional value of $35 trillion at the end of 2010. The US bond market is divided between the four major sectors: government treasury bonds ($8.8 trillion), mortgage-backed bonds ($8.5 trillion), corporate bonds ($7.5 trillion), and municipal bonds covering the remainder (Maslakovic, 2011).

Corporate bond markets have long been an important source of capital for large corporate entities. This market also serves as an important venue for investments by large institutional investors and financial organizations. The attraction of bonds as an investment has especially grown during the economic recession as many investors were looking for less risky assets in the volatile market conditions. Risk aversion attitude and flight to quality has increased demand for government bonds. However, corporate bonds have offered the potential for higher returns. A crucial aspect of the corporate bond market that makes it particularly attractive to both investors and borrowers is the presence of a highly liquid secondary market. The daily trading volume in the (secondary) US corporate market was up to $16 billion by 2010. The market mostly operates without a central exchange, and trades over-the-counter (OTC) with hundreds of dealers playing the role of market makers. In addition, corporate bonds are also sometimes listed and traded on exchanges.

In many ways, the corporate bond markets serve as a barometer for the state of the economy. The price information in this market is an indicator of investor confidence and their expectations for the future (Hagenstein, Mertz, & Seifert, 2004). For example, the credit spread of a corporate bond (measured as the difference between its yield and the yield on a riskless bond of same maturity) is a concrete indicator of the market's view on the risk of default of the issuer on its bond obligations. The recent financial crisis (2007-2011) showed unprecedented high credit spread level for all rating groups, and become an interesting platform for the analysis of the drivers of credit spreads. Although, there has been a significant amount of theoretical research on various models of pricing credit risk, there has not been an equivalent amount of empirical research.

From a historical perspective, the modern theoretical approach to credit risk can be traced to Merton (1974), who showed that a holder of corporate bond can be seen as an owner of riskless bond who has issued a put option on the value of the firm's asset to the firm's shareholders. As a result, Merton pointed out a direct link between the credit and equity markets. His work generated a strong wave of empirical analysis of corporate debt market (see Chapter 1 and next section for an overview). The equivalence of a corporate bond and a short put option on firm's asset directly points at the importance of volatility in the pricing of the bond (Black & Scholes 1973). The volatility in question is the volatility of firm's assets, which in normal circumstances is well proxied by the corresponding equity volatility.

The impact of volatility on bond prices was studied in detail by Campbell and Taksler (2003). Their study was motivated by an observation that in 1990s the US corporate bond and equity markets behaved in a seemingly inconsistent manner, with a steady increase in equity prices and a simultaneous rise in corporate yield spreads. Campbell and Taksler (2003) pointed to equity volatility as the main driver of this effect. The authors pointed out that volatility has opposite effect on stock and bond prices, negatively affecting the bondholder by increasing the probability of default while at the same time increasing the value of the equity holder. They showed that equity volatility was one of the most important determinants of corporate bond yield spreads for the period between 1995 and 1999.

One of the main motivations for the current work was to extend the analysis of Campbell & Taksler using an extended dataset covering a period between 2003 and 2011. This period incorporates a relatively stable period prior to 2007, as well as an unprecedented financial crisis. The period in question is quite different from the period considered by Campbell & Taksler in the joint behaviour of equity prices and equity volatility (see Figure 5). In particular, the period of financial crisis saw a sharp decline in equity prices as well as a sharp rise market volatility. Both these events contributed to an increase of credit spreads to a historically high level (see Figure 6).

The main objective of this work is to empirically investigate the factors that determine corporate yield spread before and during the financial crisis in the US corporate bond market. In particular, following the line of Campbell & Taksler (2003), we analyze if equity volatility is an important determinant of corporate bond spreads. In this work we ask the question of how much of the corporate – treasury yield spread can be explained by equity volatility as well as other macro-economic/firm-specific/market factors. We work in the framework of Merton's structural model of credit risk, and conduct our empirical study based on large daily panel data set of US corporate yield spreads covering most recent period of time between 2003 and 2011.

Figure 5

S&P 500 and VIX Index over period between 2000- 2013 (normalized to their corresponding values in 2000). S&P500 is a US stock market index. VIX Index is an index of S&P500 implied volatility.

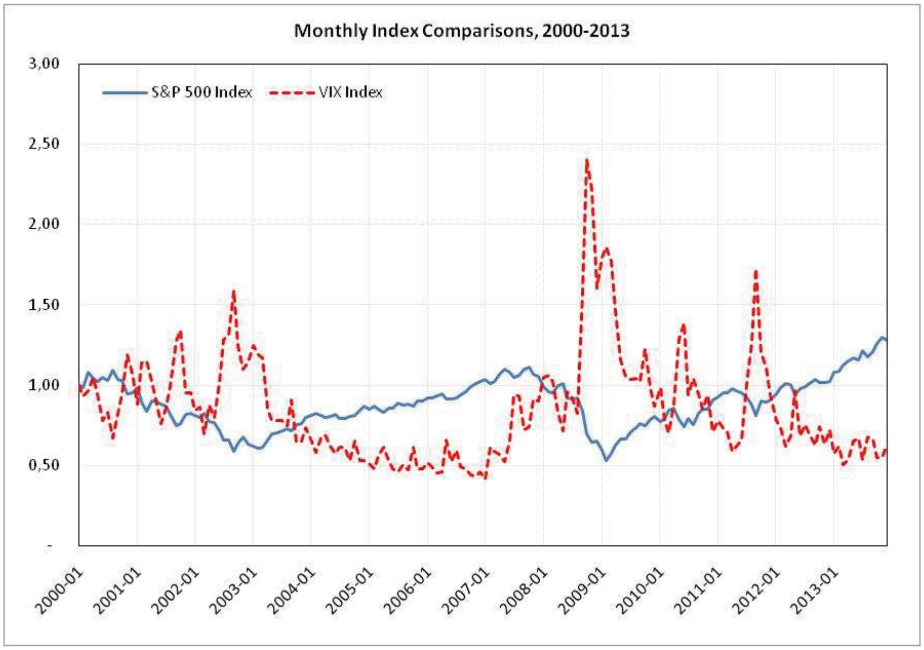
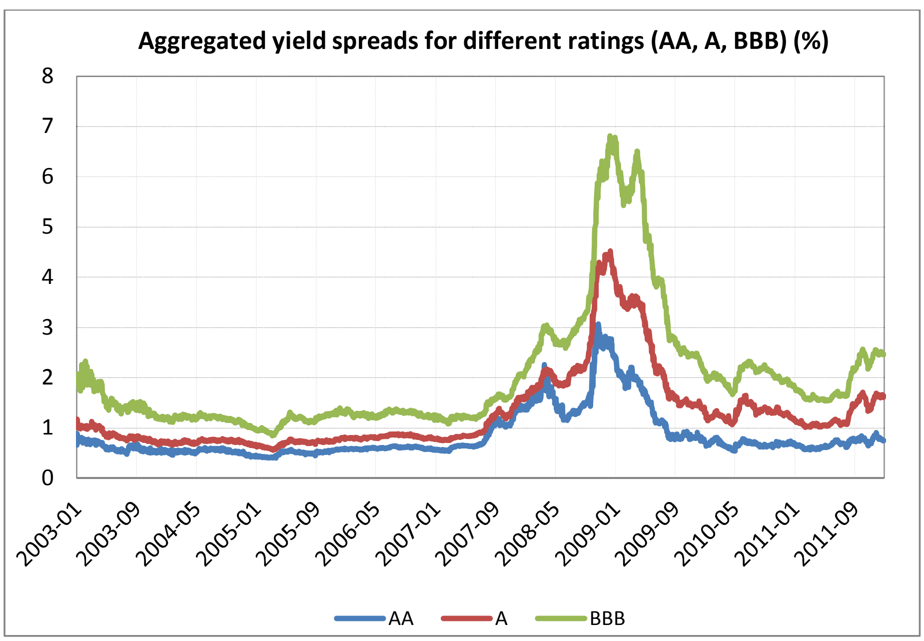


Figure 6

Average yield spreads for different ratings (AA, A, BBB), 2003 to 2011 (in percent).



This chapter is organized as follows. Section (3.2) reviews the empirical literature relating to the analysis of credit spreads determinants and in particulars its link with equity market. Section (3.3) presents the main determinants of credit spreads. The determinants are either taken from the prescriptions of Merton's models or are taken based on previous empirical studies. Section (3.4) describes our panel data consisting of pricing data for corporate bonds and the restrictions we imposed on it. It also describes how other data such as equity and accounting information was collected from various databases and inter-linked. Section (3.4.2) examines main trends in corporate bond spreads between 2003 and 2011. It also provides a statistical characterization of our final dataset and shows significant widening of credit spreads in period of the Great Recession. Section (3.5) describes methodology we use to analyze the data together with presenting the results of our estimation. We present evidence that the increase in equity volatility during the crisis significantly increased the cost of borrowing, however the sensitivity of this effect is significantly smaller than was reported in previous literature (Campbell & Taksler, 2003). We test the robustness of our findings to issuer fixed effect, random sampling and several other specifications of regression. We also present comparative results of main determinants of credit spread for different rating categories (IG and HY), as well as considering Lehman Brothers collapse as a break point. Finally, in Section (3.6) we conclude with a summary of our main findings.

3.2 EMPIRICAL LITERATURE

LITERATURE ON RELATION BETWEEN CORPORATE BONDS AND STOCKS

Structural models of credit risk show a close link between market prices of different claims such as stocks and bonds because their values ultimately derive from the value of the firm's assets (see Chapter 2). Ever since the first formulation of the structural model (Merton 1974) there has been an effort to empirically validate it and test its predictions. A general review of the early empirical works on testing structural models was presented in Chapter 2. In this section we shall focus on empirical works that looked at the link between credit risk and stock market. The literature covering this topic is quite limited. Early works started from studying the link between corporate bond market and stock market. Later works moved to include analysis of the CDS market.

Early empirical literature that analyze co-movements of the stock and corporate bond returns found small but a statistically significant relationship (Blume, Keim, & Patel, 1991), (Cornell & Green, 1991), (Fama & French, 1993). These studies were based on aggregate portfolio performance data with relatively low frequency. Kwan (1996) analyzed the same relationships but used data with higher frequency (weekly changes of corporate bond yields). The works of Keim and Stambaugh (1986) and Campbell and Ammer (1993) studied the relationships between stock and bond returns at aggregate level. More recent literature on this topic includes works of Alexander, Edwards and Ferri (2000), Collin-Dufresne, Goldstein and Martin (2001), Hotchkiss and Ronen (2002), Campbell and Taksler (2003), Longstaff, Mithal and Neis (2003), Norden and Weber (2009), Blanco, Brennan and Marsh (2005), Yu (2004), Bednarek (2006), Zhang (2009), Figlewski, Frydman and Liang (2012) amongst others. Below, we look at some of these works in bit more detail.

Fama and French (1993) tried to identify five common risk factors in the returns on stocks and bonds. The stock market factors they chose were: overall market factor; factors related to the firm size and book-to-market equity. The bond market factors were maturity and default risk. They showed that stock returns have shared variation due to the stock market factors and they are linked to bond returns through shared variation in the bond-market factors. The bond market factors capture the common variation in bond return (except for the low rated bonds). They concluded that all chosen factors explain average return on stock and bond.

The work of *Kwan (1996)* examined contemporaneous correlation and cross-serial correlation between individual stocks and individual bonds issued by the same firm. Analyses were based on the closing transaction data for 702 corporate bonds, issued by 327 firms in the period between 1986 and 1990. It was found that the stock returns and bond yield changes are negatively correlated. Author showed that individual stocks and bonds are driven by firm-specific information that is related mostly to the mean value of firm's underlying assets. The work found that current bond yield changes are significantly correlated with the issuing firm's lagged stock returns, but current stock returns do not seem to be related to lagged bond yield changes. Kwan (1996), in line with previous works, came to a conclusion that high-grade bonds behave like Treasury bonds, so that AAA rated bonds are driven mainly by the riskless interest rate and are uncorrelated with the issuing firms' stock. On the other, the low-grade bonds are much more sensitive to their issuing firms' stock, but insensitive to the riskless interest rate.

Alexander, Edwards & Ferri, (2000) analyze the relationship between the daily stock and high-yield bond returns at the individual firm level for the period between 1994 and 1997. The purpose of study was to examine if these two sets of returns provide new evidence on the impact of agency conflict between shareholders and bondholders. Their results showed that the excess return on a high-yield bond have a statistically significantly positive but economically weak correlation with excess return on the issuing firm's stock over the long period of time even though negative co-movement occured around announcements of wealth-transferring decisions or plans. Their analyses reveal that agency conflict between bondholders and stockholders may lead to divergence in their returns and is a likely factor in the low time-series correlation between the return of the stocks and bonds.

Hotchkiss & Ronen (2002) examined the informational efficiency of the high yield corporate bond market based on the daily and hourly price data from the January to October of 1995. Applying a VAR (vector autoregressive model), they found that the stocks do not lead bonds in reflecting firm-specific information. They showed a significantly positive but economically weak contemporaneous correlation between stock and bond returns, which was judged as not causal relationship. The results show that information is quickly incorporate into both bond and stock prices even considering a short-term horizon.

Longstaff, Mithal, & Neis (2003) analyzed the lead-lag relationships between CDS spread changes, the corporate bond spreads and the stock returns for US firms. Their result, in contrast to Hotchkiss & Ronen, show that both stock and CDS markets lead the corporate bond market. This fact provides support for the hypothesis that the information firstly flows in to stock and credit derivatives markets and that in to the corporate bond market. However, in their study there was no clear lead of the stock market with respect to CDS market.

Collin-Dufresne, Goldstein, & Martin (2001) analyzed the determinants of credit spread changes in a contingent-claims framework. Authors proposed the following determinants of credit spread changes: change in the probability of future default; the change in the recovery rate; liquidity change; in addition authors included several liquidity, macroeconomic and financial variables. They found that increase in the risk free rate lowers the credit spread for all bonds and that the volatility is a significant factor in the determining of credit spread changes. The results of estimation show that the factors suggested by the traditional model of default risk explain only 25% of the variations in credit spreads. Also, in contrast with predictions of structural model, the aggregate factors are more important than the firm-specific factors in determining credit spread changes. Authors concluded that the dominant component of monthly credit spreads changes in the corporate bond market is driven by local supply/demand shocks that are independent of changes in credit risk and typical measures of liquidity.

Campbell & Taksler (2003) analyzed the effect of equity volatility on corporate bond yields. The main task of the work was to determine the variables that determine corporate bond yields cross-sectionally and over time. They conducted a regression analysis of corporate bond yield spread over a range of variables (equity volatility, credit rating, accounting data, macroeconomic and other data). One of the main findings of this work was that volatility is an important determinant of corporate bond yield spreads, contributing at least as much as credit rating. The uncovered effect was much stronger than was predicted by Merton. A second finding was that credit rating capture some of the information that is not contained in the volatility, so that coupled with equity volatility the two factors explain a sizable amount of bond spreads. In particular, credit rating explains more of the yield spread than accounting data. In addition to the cross-sectional analysis, the authors analyzed the time-series data. They used S&P and Moody's corporate bond yield indexes in the period from 1963 to 1999. They show that the equity volatility helps to explain not only recent movements in corporate yield spreads, but also their long-term upward trend.

Blanco, Brennan, & Marsh (2004) analyzed the time series properties of credit default swap prices in conjunction with matching corporate bond spread data in the framework of structural models. The aim of the paper was to answer the questions: firstly, whether bond and credit default swap markets equivalently price default risk; secondly, whether credit risk price discovery takes place in cash bond or credit derivative market. They analyzed the factors that could influence changes in CDS prices and bond spreads. The determinant factors were chosen following Collin-Dufresne, Goldstein and Martin (2001), and included: the change in spot interest rate, change in the slope of the yield curve, change in the equity prices, and change in equity volatility. Authors showed that the theoretical arbitrage relationship linking bond credit spreads over the risk-free rate to CDS prices holds well on average for most of the companies. The bond spreads appear to react more to the market-wide variables such as changes of interest rate, slope of the yield curve. On the other hand, CDS prices react more to firm-specific factors such as the stock prices and volatility.

Yu (2004) examined the risk and return of the “capital structure arbitrage”, which exploits the mispricing between a company’s debt and equity. The analysis was based on structural models. The author looked at the deviation of CDS market quotes from their theoretical counterparts and proposed a convergence-type trading strategy, which was analyzed using 44,044 daily CDS spreads. The results showed that capital structure arbitrage was very risky and not practical.

Bednarek (2006) examined the idiosyncratic and market volatility of the stock returns in the cross-section of credit rating. In this work the stock volatility was modelled as an autoregressive process. The stock return volatility was estimated from the data in the cross-section of credit rating based on the period between 1970 and 2004. Author based his analysis on a procedure of estimation stock return volatility proposed by Schwert (1989). The results show that predicted market volatility differs strongly across credit ratings. The equity volatility was then translated into asset volatility. The author showed that a simple structural model of credit risk was able to generate credit yield spreads for the low-rated bonds close to the historical spreads when the recent trends in the stock volatility are taken in to account.

Bystrom (2005) analyzed the relationships between CDS spreads, equity prices and volatility in iTraxx market. The study used the data of the daily closing quotes for seven sectoral iTraxx CDS Europe indexes for the period between June 2004 and April 2005. The work estimated the degree of contemporaneous and cross-serial correlations between the iTaxx market and the stock market. Author showed a significant correlation between iTraxx CDS index spread and spread changes on the one hand and stock prices return on the other hand, which revealed close a link between the two markets. Study showed a tendency for iTraxx CDS spreads to narrow (widen) when stock prices rose (fell). Furthermore, the stock market seems to lead the CDS market in transmitting firm-specific information. The results also showed that the stock index return volatility is significantly correlated with iTraxx CDS index spreads.

Zhang(2009) analyzed and compared the reaction of CDS and stock prices to a variety of credit related events such as news of economic distress, financial distress, mergers and acquisitions, SEC probes (round-trip trading, fraud, insider trading), accounting irregularities and leverage buyouts (LBO). The analysis was based on the daily quotes on CDS spreads for over 1000 North American obligors in the period between January 2001 and December 2005. The empirical results reveal that CDS prices dramatically increase, by 37% to 96%, on a single day in response to credit event news. The strongest reactions of the CDS prices are associated with leverage buyouts, followed by SEC probes, M&A, and financial distress. On the other hand economic distress had the lowest effect. In addition, the work examined whether the equity market is efficient enough to capture the information reflected in the CDS market. The stock prices fall by 2% to 9% in the response to the economic distress, financial distress, SEC probe, M&A. However, they rise by 7% on the leverage buyouts news. The author argues that, with exception of leverage buyouts news, the stock market might reveal information about negative credit events before the CDS market. However, the information revealed in the stock market seems less accurate than the CDS market for some types of event. For example, stock prices overreact to the news of SEC probe, and under-react for financial distress news.

Norden & Weber (2009) examined the relationship between CDS, corporate bond and stock markets using an international data sample. Authors analyzed monthly, weekly and daily lead-lag relationships in a vector autoregressive model and the adjustment between markets caused by cointegration. The study used the data set that included 58 firms with observations between 2000 and 2002. The results showed that the stock returns are significantly negative associated with CDS and bond spread changes. The stock returns lead CDS and bond spread changes. The stock returns were least predictable and the bond spread changes the most predictable variables at all data frequencies. Another finding was that CDS market is more sensitive than bond market to the stock market and the strength of the co-movement increase for lower credit quality and larger bond issues. The final finding was that CDS market influences (contribute) more to the price discovery than the bond market and this effect is more significant for firms in US than in Europe.

The purpose of this section was to provide the reader with a broad overview of the range of empirical research over the past two decades dealing with the relationship between credit risk and stock behaviour. In what follows, we shall limit our analysis to the main topic of the current research, namely, an empirical investigation of relation between credit risk on the one hand and stock prices and volatilities on the other.

3.3 THEORETICAL DETERMINANTS OF CREDIT SPREADS

The modern approach to credit risk modelling begins with Merton's structural form model (Merton 1974). Over the years there have been several important improvements and extensions of this model (see Chapter 2). However, Merton's original model remains important due to its ability to capture the essential determinants of credit risk on the one hand, and its simplicity on the other. Another advantage of the model is the small number of assumptions and parameters, which make it particularly attractive for empirical testing. We shall use Merton's model in order to uncover the main determinants of credit spreads as well as to formulate expectations about the effect of these determinants.

Before proceeding, let us recap the main tenets of the model and present some of the results that will be useful for our analysis. In Merton's model, a zero-coupon corporate bond is shown to be equivalent to a long position on a zero-coupon risk-free bond together with a short position in a put option on the value of the firm's asset with the strike equal to the notional of the bond (See details of Merton's model in Chapter 2.2). The price of the bond is given by using the Black-Scholes formula for pricing a European put option (See formula (5) in Chapter 2). The expression for price of bond can be transformed into an expression for the bond credit spread ($CS(t,T)$), defined as the difference between the yield on risky bond and the yield on the corresponding risk-free bond:

$$CS(t,T) = -\frac{\ln[x_t N(-d_1) + N(d_2)]}{T-t}$$

$$d_{1,2}(x_t, t-T) = \frac{ln x_t \pm 1/2\sigma_V^2(T-t)}{\sigma_V\sqrt{T-t}} \tag{7}$$

$$x_t = V_t e^{r(T-t)}/\mathrm{K}$$

In the above expressions N is the cumulative probability distribution function of standard normal, σ_V is volatility of the firm's assets value, V_t firm's assets value, K is the notional value debt, and r is risk free rate. Thus, the model predicts that the credit spread is affected by asset value, volatility of the asset value, risk-free rate, maturity and leverage.

3.3.1 MAIN DETERMINANTS

In our empirical investigation, we define the credit spread *CS(t)* of a given corporate bond to be the difference between yield to maturity of this corporate bond and the risk free rate of the corresponding maturity taken from the US treasury zero rate curve.

We shall look at the dependency of the credit spread on a range of equity, accounting and macro-economic variables. In what follows we shall list and explain the various determinants of the spread that will be considered in our analysis.

EQUITY VOLATILITY

Structural form model predicts that credit spreads are dependent on the volatility of firm's asset value (see formula (5)). The higher the asset volatility the more probable that the assets value of firm falls lower than value of firm's debt, thereby increasing the chances of default. For this reason, higher asset volatility is expected to lead to a lower price of the firm's debt, i.e. a higher credit spreads. Since firm's asset is typically an unobservable quantity, we shall use the firm's equity volatility as a proxy for the volatility of its assets. For, firm's who's asset value is sufficiently far from default (in the framework of Merton's model) this is a good assumption, since most of the fluctuations in the asset value are attributable to variations in equity. Following, the approach of Campbell and Taksler (2003), we used a standard deviation of daily excess returns relative CRSP value-weighted index for each firm's equity over the preceding 180 days as a measure of equity volatility.

CREDIT RATING

The credit rating evaluates the credit worthiness of a company, and its ability to pay back its debt. Ratings are produced by credit rating agencies such as Standard and Poor's, Moody's, Fitch, DBRS or Dun & Bradstreet. The rating, in theory, incorporates qualitative and quantitative information about the company together with agency's judgments and experience in determining what public and private information should be considering in giving a rating to a particular company. The credit rating is used by market participants to gauge the likelihood a bond default, and therefore affects its price. A lower rating on a bond indicates a higher probability of default, and so will require additional premium in terms of a higher yield spread in order to remain attractive to investors. Thus, in general, one can expect a widening of credit spreads with lower ratings. In this work we take the average of Moody's and S&P ratings adjusted to the seniority of instrument and rounded to not include the "+" and "-" levels.

MACRO VARIABLES

In the line with Longstaff and Schwartz (1995), Collin-Dufresne, Goldstein and Martin (2001) and Campbell and Taksler (2003) we choose treasury level and TED spread as our main macro determinants. The motivation behind this choice is as follows.

Treasury rate level

In the framework of Merton's model, an increase in interest rate is associates with increase in expected growth rate of firm's assets, which reduces the probability of default, thereby leading to narrowing of credit spreads. On the other side, lower interest rates, are typically an indicator of recession in the economy and are associated with higher credit spreads. Based on previous empirical literature (Longstaff & Schwartz, 1995), (Campbell & Taksler, 2003), (Collin-Dufresne, Goldstein, & Martin, 2001) we expect a negative relation between the level of term structure and corporate bonds spreads.

Ted spread

The TED spread is defined as the difference between the interest rate on interbank loans (LIBOR) and short-term US government debt (T-bill). Since, since LIBOR reflects the credit risk of lending to large commercial banks, The TED spread is typically seen as an indicator of credit risk in the general economy. Bigger TED spreads are associated with an expectation of a rise in the risk of default on interbank loans. In the time of financial distress, the TED spread tends to increase. This process is always related with a downturn in US stock market, and indicates a reduction in funding liquidity. We include TED spread in our list of determinants, in order to have a proxy of demand for funding liquidity. The expected relations of TED spread and credit spread is positive, due to the fact that bigger TED spreads are associated with a flight to quality or liquidity, corresponding to situations were investor require additional compensation for holding corporate bonds (resulting in wider credit spreads see Campbell and Taksler (2003)).

ACCOUNTING VARIABLES

A key determinant of credit risk in the structural approach is the ratio between, K and V, i.e. the ratio between the total notional of debt to the value of the firm's asset. This ratio is known as the Leverage ratio. Leverage is the amount of debt used to finance a firm's assets, such that companies with more debt are considered to have a higher leverage. Structural form model predicts that default is triggered when the leverage ratio equals unity. Therefore, credit spreads are expected to have a positive relation to leverage. This relation was shown in works of Blume, Lim and MacKinlay (1998), Campbell and Taksler (2003) and Collin-Dufresne, Goldstein and Martin (2001). Following these works, we choose the firm's total debt to capitalization as a proxy of its leverage.

The other important determinant of credit spread are the accounting variables that characterize the financial health of a company. If a balance sheet shows a financially healthy and stable company, the perceived probability of this company defaulting is reduced, thereby leading to a reduction in the credit spread. As a proxy, characterizing the financial health of a company, we choose operating income to sale following Blume, Lim and MacKinlay (1998) and expect a negative relation to spread (if operating income to sale increases the credit spread should narrow, and vice versa).

BOND CHARACTERISTICS

In our empirical analysis, we also include two bond specific control variables, the coupon rate and time to maturity. Following arguments of Elton, Gruber, Agrawal & Mann (2000), the coupon rate affects the amount of tax to be paid with higher coupon are taxed more throughout the life of the bond and as a result affect attitudes of investors to payouts. Lower coupon bonds are more desirable than higher coupon bonds. We expect positive coefficient.

Time to maturity variable is expected to have positive relation with credit spread, since the long-term debt seems more risky than short-term debt. There is much more uncertainty in long-term than in short-term, and as a result investors require additional compensation for holding long-term debt. However, this argument does not necessarily work in case of a persistent crisis, where main uncertainty occurs in short run and investors expect recovery of economy and rapid growth in the long-run. As a result, in this situation, the long-term investments can look less risky. This shows that there is an ambiguity on the sign of the effect of time to maturity on credit spreads.

3.4 DATA DESCRIPTION

3.4.1 DATA CONSTRUCTION

3.4.1.1 BOND DATA

CORPORATE BOND DATA

The corporate bond data we have used in our analysis comes from the MarkIt Group. The MarkIt's Bond dataset contains independent historical pricing data on corporate and government bonds across all investment grades and countries for a period between January 2003 and December 2011. The dataset consists of the daily composite bond prices as well as issue/issuer-specific information such as bond identifier, issuer identifier, maturity, coupons, rating, sector, region, country, non-standard features (e.g. callability, floating coupon, etc.).

Several restrictions were imposed on the original MarkIt bond dataset in order to construct our sample dataset. Firstly, we excluded unrated bonds. Secondly, all samples were restricted to fixed rate US dollar bonds (i.e. excluded bonds with floating rate coupons). Thirdly, the corporate bonds with different features such as callable, puttable, sinking finds, convertible, structured were excluded from our dataset. Fourthly, we restricted our analysis to only include senior unsecured debt (SNRFOR). We excluded bonds with other seniority or credit enhancement from the sample (e.g. junior subordinated (JR SUBUT2), preferred, secured debt and asset-backed). This was done because, as argued in Campbell and Taksler (2003), the yield spread on these asset-backed bonds reflects mainly creditworthiness of the collateral rather than the creditworthiness of the issuer. In addition, we removed non-USD denominated bonds from our sample. Finally, to ensure the robustness of our data, we have restricted our analysis to composite price contributions (MarkIt requires at list three prices to produce a composite).

Following Duffie (1998) we grouped bonds by maturity, classifying them as short-term if they have from 2 to 7 remaining years, medium-term is they have from 7 to 15 years and long-term if they have 15 to 30 remaining years. We exclude bonds with less than 2 years to maturity.

Finally, we calculate the yield to maturity for each data point. The clean prices (i.e. price excluding any accrued interest) provided by MarkIt were converted into yield to maturity using Excel's standard YIELD function. The coupon rate and years to maturity required for this calculation were extracted from the dataset as general characteristics of corporate bond. We eliminate the top and bottom 1% of spreads from the analysis in order to reduce apparent errors in the MarkIt dataset.

Following the cleaning procedures outlined above, our dataset of bonds consists of ten business-sector categories (Industrial, Utilities, Financials, Technology, Consumer Goods, Healthcare, Consumer Services, Telecommunications, Services, Basic Materials, Energy), six rating categories (AAA, AA, A, BBB, BB, B) and three bands of maturities (short 2-7 years, medium 7-15, long 15-30 years). After matching with other databases (such as equity and accounting databases) we were left with approximately 1 532 000 different bond-daily transactions coming from 602 distinct bond issuer companies.

The final dataset was divided into two main credit grade groups based on rating categories. Investment grade IG group includes corporate bonds with credit rating from AA to BBB and high yield group includes bonds with rating start from BB and lower (BB and B). Follow the arguments in Campbell and Taksler (2003) and Elton, Gruber, Agrawal & Mann (2000) corporate bonds with credit rating AAA (Aaa) were eliminated from the analysis, due to the generic problems with this data category that has been persistently uncovered in empirical research.

RISK FREE BOND DATA

The treasury curve was obtained from US Department of Treasury. These curves are derived from treasury bond prices using a quasi-cubic hermite spline function, and are available on the Treasury web page (http://www.treasury.gov/Pages/default.aspx).

The treasury curve data consisted of daily curve data for the period between 2003 and 2012. The individual curves were given as a set of 10 discrete values of the yield corresponding to a set of standard maturities. A Matlab interpolation code was written in order to obtain the set of risk free yields corresponding to the set of date/maturity data points in our corporate bond data set. Finally, the corresponding credit yield spreads were calculated by taking the difference between the corporate yield to maturity and the corresponding risk free yield for every bond-date data point.

3.4.1.2 EQUITY DATA

For the purpose of our investigation we required equity stock price data. In addition, in order to 'match the correct bonds with the correct equity', we needed procedure to match the bond issuer identifiers in MarkIt data source with their corresponding company identifier in the equity dataset.

We collected data of daily stock prices from CRSP database (from the CRSP annually updated Stock Security Files). The stock file covered the period between 2001 and 2011. The CRSP database holds data for all companies traded on NYSE, AMEX and NASDAQ stock exchanges. For each transaction, the equity data was taken for at least 180 days prior to the bond trade in order to calculate mean and volatility. The details about the procedure for matching data between the two databases (MarkIt and CRSP) are provided in Appendix 1.

CALCULATION OF EQUITY VOLATILITY

Following Campbell and Taksler (2003), to characterise equity volatility, we use standard deviation of daily excess return relative to CRSP value-weighted index for each firm's equity over the 180 days before the bond transaction date:

$$\sigma = \sqrt{\frac{1}{180}\sum_{i=1}^{180}(R_i^{excess} - \mu)^2}$$
$$\mu = \frac{1}{180}\sum_{i=1}^{180} R_i^{excess} \tag{8}$$

Where R^{excess} is daily excess return relative CRSP value-weighted index, μ is mean over 180 days.

An important practical issue was to identify whether the stock was traded constantly during the period of volatility calculation. If a stock stopped trading for a while and started trading again after some time, its price will jump significantly, which will significantly affect volatility. In order to avoid such issues, we restricted consideration to calculation of the standard deviation for returns which do not exceed 120 days gap in trading.

The CRSP dataset was also used for calculating market share of the company, defined as the ratio of capitalization of the individual company divided by the total capitalization of the market (CRSP value-weighted index). This variable was included in our analysis in order to study the effect of relative company size on its credit spread.

3.4.1.3 ACCOUNTING DATA

Another major component of our analysis is the accounting data. The accounting data was obtained from the COMPUSTAT database [1] (COMPUSTAT, North America, Fundamentals Annual). The accounting data consisted of annual data that covered the period between 2001 and 2012. Once again, we refer the reader to Appendix 1 for a detailed description of the matching procedure between COMPUSTAT and our bond and equity datasets.

CALCULATION OF ACCOUNTING VARIABLES

Following Blume, Lim and MacKinlay (1998) and Campbell and Taksler (2003) we used *Total debt to capitalization* and *Long term debt to assets* in order to characterize leverage level of the company and *Operating income to sales* in order to characterize financial health of company.

Total debt to capitalization was calculated as [total long term debt (DLTT) + debt in current liabilities (DLC) + average short term borrowing (BAST)] to [total liabilities (LT) +market value of equity (calculated daily from CRSP)]. *Long term debt to asset* was calculated as [total long term debt (DLTT)] to total asset (AT).

The accounting data was obtained from the COMPUSTAT database. Total long term debt corresponds to debt obligations due more than one year from the company's balance sheet date. Debt in current liabilities is the total amount of short-term notes and the current portion of long-term debt (debt due in one year). Average short-term borrowing is the approximate aggregate short-term financing outstanding during the company's reporting year. Total liabilities variable corresponds to the current liabilities plus long-term debt plus other non-current liabilities, including deferred taxes and

[1] http://wrds-web.wharton.upenn.edu/wrds/

investment tax credit. Market value of equity was calculated based on CRSP daily pricing data as company's current stock price multiplied by its number of outstanding shares (1000* Price*(Shares outstanding)).

We note that the two proxies of leverage ratio were not used simultaneously in the estimations, in order to avoid problem of multicollinearity. However, we ran estimations using both the variables individually, and also have used them in analysis of the interaction effect to verify the consistency of the results.

Operating income to sales was calculated as [operating income before depreciation (OIBDP)] to Net Sales (SALE). Operating income before depreciation includes effects of adjustments for cost of goods sold as well as selling, general and administrative expenses. Net sales are the gross sales reduced by cash discounts, trade discounts, returned sales and allowances for which credit is given to customers, for each operating segment.

Note that all of the accounting variables were defined as ratios, so that the corresponding regression coefficients have an interpretation of change in yield spread per unit change in the corresponding ratio.

3.4.1.4 MACROECONOMIC DATA

Following earlier works of Collin-Dufresne, Goldstein and Martin (2001) and Campbell and Taksler (2003) we use the daily series of 10-year Benchmark Treasury rate to describe Treasury rate level. Data was collected from Federal Reserve Bank database available from WRDS (Wharton Research data services) with daily frequency between 2001 and 2011. The TED spread was calculated as the difference between the three-month LIBOR and the three-month T-bill interest rate. LIBOR and T-bill data were collected from Federal Reserve Bank database available from WRDS with daily frequency between 2001 and 2011. Ted spread was calculated in percentage points.

3.4.2 DESCRIPTIVE STATISTICS

The tables below provide a high-level summary of our final dataset, following the merger of all the constituent datasets (bond, equity, accounting & macro). In total were left with 1,532,698 composite price data points, including approximately 1,200,000 investment grade (IG) bonds (AA, A, BBB ratings) and 350,000 high yield (HY) bonds (BB, B ratings). In the following analysis, we shall primarily focus our analysis on IG bonds. For this reason, we provide a detailed descriptive statistics for this data category below.

In the IG group, the data was divided between 519,438 short-term, 377,424 medium-term and 351,026 long-term bonds. The financial sector had the most prices 202,734 and the Telecommunications Services sector had the least 49,303. Half of our IG group data corresponds to BBB rated bonds 642,705, over 40% correspond to A rating (540,838), and the least number of transactions are on AA credit rating. The largest number of data falls in 2011 (193,479) and the least in 2003. The least number of transactions in our dataset sample falls into AA long term bonds (12,504). There are no transactions for the AA long term and medium term bonds in Utility sector. Campbell and Taksler (2003) explained this anomaly by the fact that utility sector most often issue bonds with call provisions (we have restricted our data to no call/put provision). The dataset does not have any data for AA long term bonds in Energy and Basic Materials, most likely for the same reason. We can notice that short term bonds have the largest number of transactions for all years compare to the bonds of other maturities, which might reflect the fact that short term bonds are usually traded more than others.

Table 1

Number of data points per rating, maturity bucket and years for IG bonds dataset.

Maturity	AA	A	BBB	Total
Short	37,956	222,925	258,557	519,438
Medium	13,885	162,091	201,448	377,424
Long	12,504	155,822	182,700	351,026
Years	**AA**	**A**	**BBB**	**Total**
2003	6,052	36,001	44,565	86,618
2004	8,325	59,140	73,149	140,614
2005	8,185	60,360	79,341	147,886
2006	6,434	56,757	72,568	135,759
2007	6,726	65,151	77,853	149,730
2008	5,772	56,485	62,157	124,414
2009	6,074	58,622	63,850	128,546
2010	7,056	62,801	70,985	140,842
2011	9,721	85,521	98,237	193,479
2003-2011	64,345	540,838	642,705	1,247,888

Table 2

Number of data points in each sector.

Sector	Number of transactions
Industrials	147,390
Utilities	109,770
Financials	202,734
Technology	70,774
Consumer Goods	167,413
Healthcare	113,538
Consumer Services	184,437
Telecommunications Services	49,303
Basic Materials	83,465
Energy	120,080

The set of tables (see from Table 3 to Table 4) represents average corporate bond yield spreads by credit ratings, maturity and year. We see that, for all sectors, the average yield spread for A rated bonds is almost 40 basis points (bp) higher than for AA rated bonds, and for BBB rating it is almost 65 bp higher than for As. In line with expectations, the highest average yield spread (217 bp) is observed for BBB rated long term corporate bonds, and the smallest average yield spread (66 bp) is seen in AA short term bonds.

Financial sector has the highest average yield spreads among all other sectors, 10-50 bp higher than all sectors for medium term bonds, and 10-20 basis points higher for long term bonds. The industrial sector has the smallest yield spreads for all maturities across all sectors.

We also notice that the average yield spread is significantly higher for the 2008 and 2009 (at the peak of the financial crisis). Spread starts growing from 2006 (105 bp) reaching a peak in 2009 (304 bp) and then declines to the 159 bp by 2011. The spread rose by a factor of over 2 in 2008 compared with previous years. Note that the average spread was also quite high in 2003, for example reaching 144bp for BBB rated bonds, which is comparable to levels of 2007 (pre crises year). Things finally seemed to start calming down in 2011, with AA spreads falling to 69 basis points.

Table 3

Average corporate bond yield spreads (in basis points) by credit rating and years to maturity for all sectors for IG bond dataset.

Rating	Short	Medium	Long
AA	65.78	90.47	105.92
A	114.84	129.39	144.10
BBB	169.76	198.65	216.56
Total	138.59	164.92	180.46
Sectors	**Short**	**Medium**	**Long**
Industrials	113.73	131.00	143.52
Utilities	125.42	143.97	170.59
Financials	165.19	194.85	200.47
Technology	142.67	167.81	157.12
Consumer Goods	127.35	164.11	223.73
Healthcare	126.03	145.45	157.63
Consumer Services	142.09	177.32	183.23
Telecommunications Services	143.61	153.48	198.77
Basic Materials	163.12	195.97	180.96
Energy	123.45	174.27	188.07

Table 4

Average yield spread per rating and year (basis points).

Years	AA	A	BBB	Total
2003	59.8	81.54	143.78	112.04
2004	52.64	72.2	116.9	94.3
2005	49.89	69.8	113.97	92.4
2006	59.72	82.1	127.79	105.46
2007	84.95	104.28	142.8	123.44
2008	169.88	238.13	335.95	283.83
2009	128.1	232.53	386.92	304.28
2010	67.92	129.82	202.64	163.42
2011	69.46	127.69	194.56	158.72
2003-2011	78.91	127.63	192.12	

Figure 7

Average IG yield spreads for different maturity buckets, 2003 to 2011 (in percent).

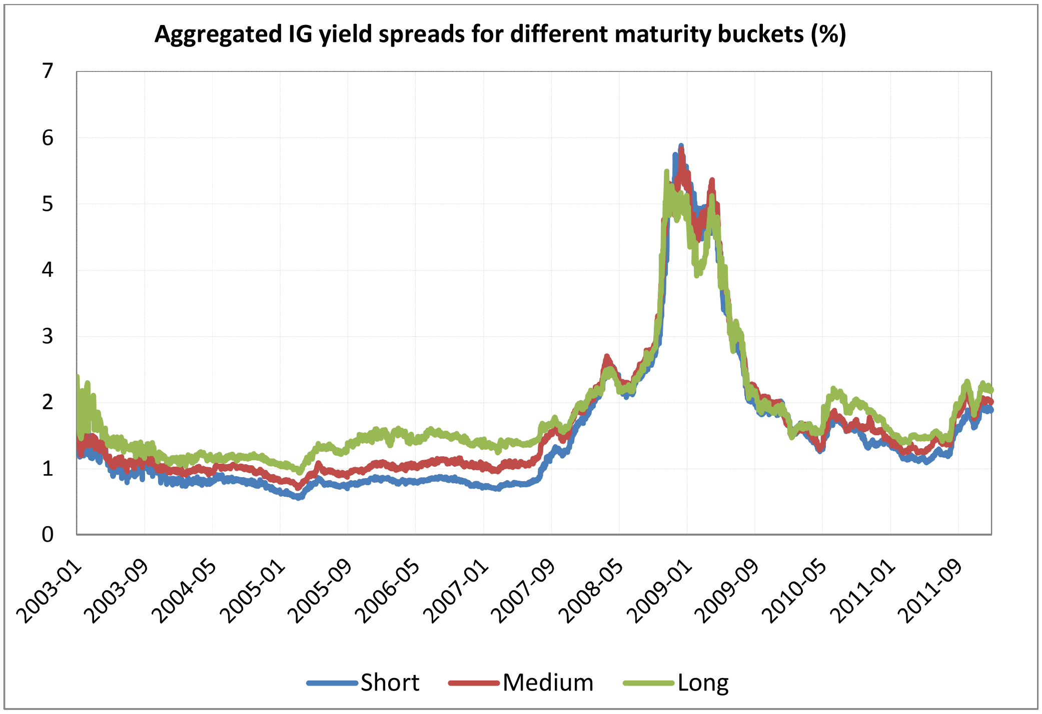


Figure 7 shows the behaviour the of credit spreads for various maturity bands. The figure shows that the spreads behave in a similar fashion across maturities, showing a significant increase for the period between 2008 to 2010. The short term bonds are typically considered to be less risky than the longer maturity bonds. For this reason one usually expects their spreads to be lower.

Figure 7 shows that, in the period before 2008, spreads for short maturity bonds are lower than those for medium and long maturities. However, during the peak of crisis 2009, we observe that short and medium maturity spreads typically exceeded those of long term debt, implying that short term debt was perceived more risky by the market than the longer term debt during the crisis.

Figure 8

Average yield spreads for different credit ratings (AA, A, BBB), 2003 to 2011 (in percent).

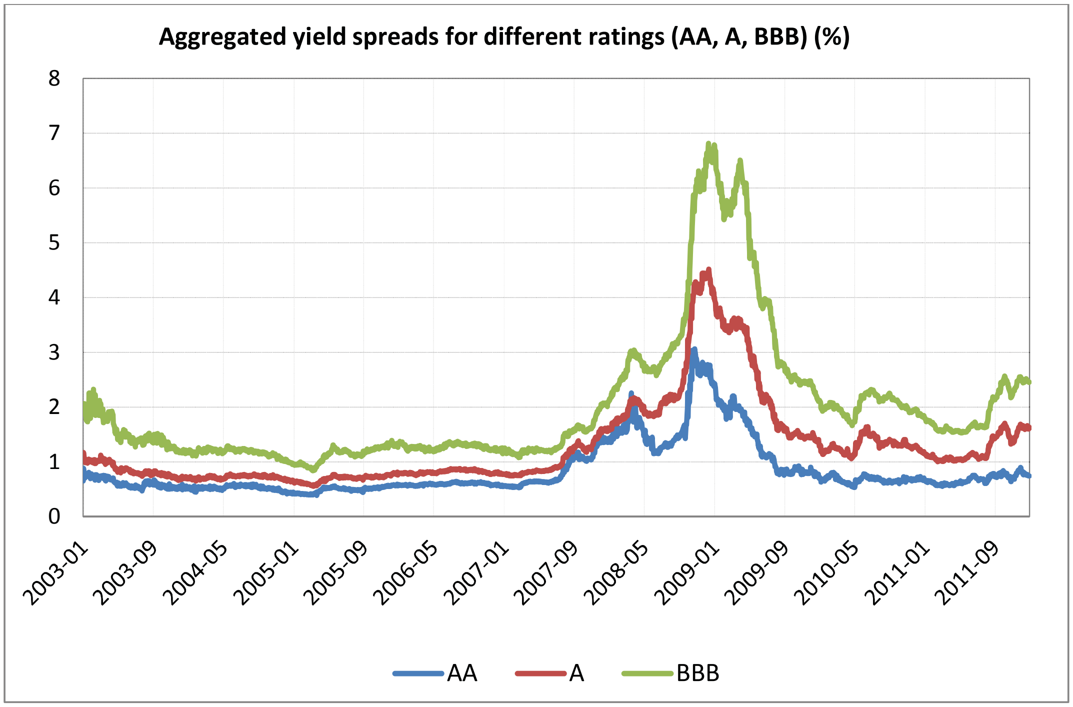


Figure 8 presents average yield spreads for different credit ratings (AA, A, BBB) for the period between 2003 and 2011. The AA bonds, which are the least risky bonds we consider, reached the peak at about 3%, while BBB bonds reached a high at 6-7%. The graph shows that AA spreads have two distinct peaks. The first peak happened at the beginning of 2008 and was followed by a significant decline to the 1% level. This peak is associated with by the sudden demise of Bear Stearns bank, which had an AA rating just days before it went down in March 2008. The corresponding peaks in A and BBB were less prominent and were a result of contagions. The second peak was much stronger for all rating groups and happening at the end of 2008. This peak was associated with Lehman Brothers' bankruptcy and the general financial crisis.

Figure 9 depicts an average yield spreads for the Aaa and Baa rated corporate bonds reported by Moody's. Yield spreads were taken from WRDS database (Federal Reserve Bank Reports, Interest Rates data) and were only available for the two presented ratings for a period between 1993 and 2012. Overall, Moody's spreads show the some tendency of increasing when the stock markets are weak and/or volatile (1998, 2000-2001 and 2008-2009). In Figure 10, we plot MarkIt data average yield spreads for BBB rated bonds along with Moody's spreads in order to compare spreads calculated from our dataset with those provided by a rating agency. We see that the two spread curves are very similar and closely trace each other.

Figure 9

Average yield spreads for the AAA and BBB rated corporate bonds from Moody's (in percent).

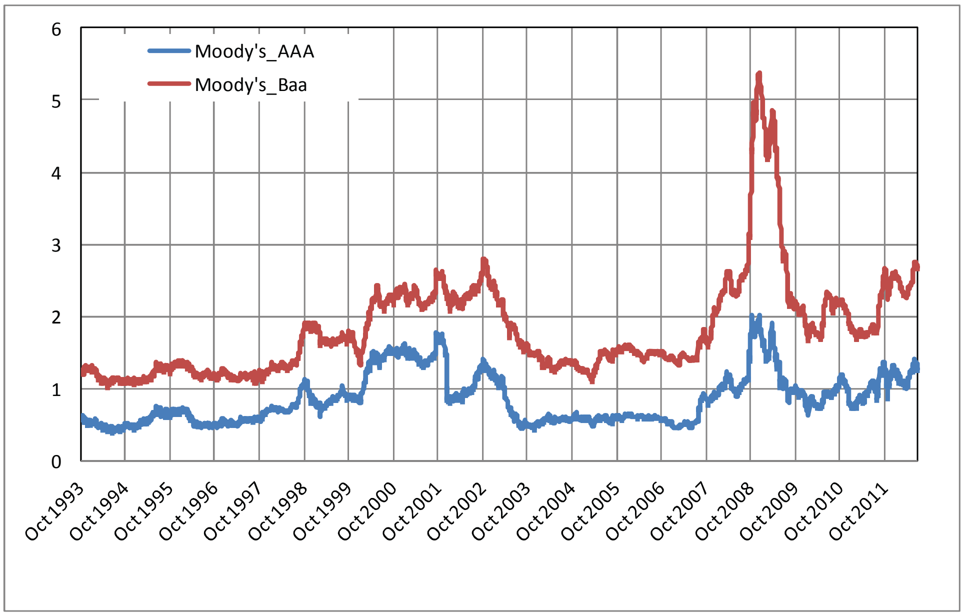
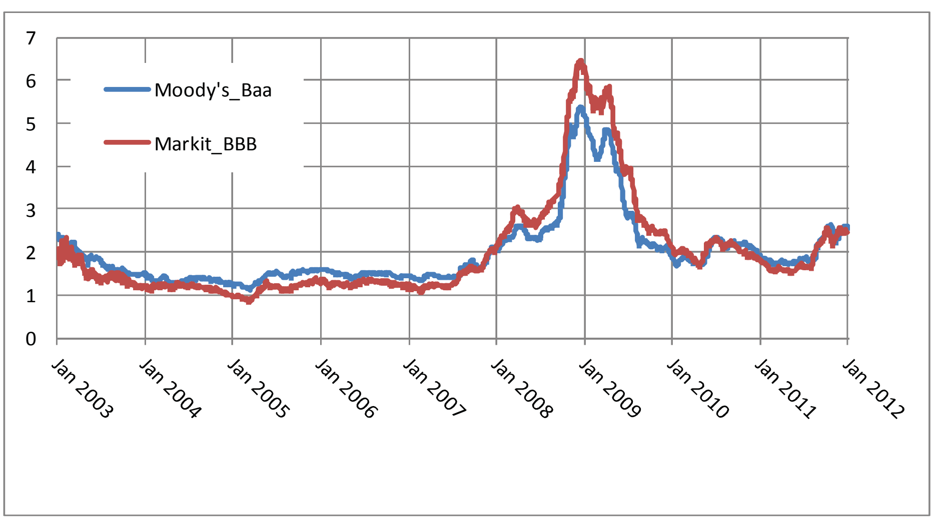


Figure 10

MarkIt data average yield spreads for BBB rated bonds and Moody's Baa spreads (in percent)



3.5 EMPIRICAL RESULTS

3.5.1 METHODOLOGY

In this section we present the methodology employed in our empirical analysis. We started by running an ordinary least squares (OLS) regression, treating each transaction as an independent observation. For each sample bond i and date t, we regress the credit spread CS_t^i as a function of our (equity, accounting, bond-specific and macro) variables over the period between January 2003 and December 2011:

$$\begin{aligned} CS_t^i = \alpha + \beta_1^i STDV(excessRET)_t^i + \beta_2^i Cap_t^i + \beta_3^i Rating + \beta_4^i OpIncToSale_t^i \\ + \beta_5^i Lev_t^i + \beta_6^i r_t^{10} + \beta_7^i TED_t + \beta_8^i Coup_t^i + \beta_9^i Mat_t^i + \epsilon_t^i \end{aligned} \tag{9}$$

Table below represents description of variables and our expectations on the sign of the regression coefficient.

Variables	Description	Predicted Sign
STDV(excessRET)	Standard deviation of daily excess return relative to CRSP value-weighted index	+
Cap	Capitalization of individual Company relative to the market	-
Rating	Dummy variable of credit rating	+
OpIncToSale	Operating income to sale	-
Lev	Leverage (Total debt to capitalization)	+
$\boldsymbol{r^{10}}$	Treasury Rate Level	-
TED	TED spread	+
Coup	Coupon rate	+
Mat	Years to maturity	+/- ?

In order to investigate how different credit spreads respond to determinants in different rating categories, we separate total dataset into Investment grade (IG) and High yield (HY) categories, and ran regressions for them individually. In order to investigate the effect of a crucial financial event (Lehman Brothers collapse) on credit spreads, we separate our time period in to two sub-periods, corresponding to before and after Lehman Collapse, and run regressions on these sets separately. We also analysed how different response of credit spread to its determinants for different corporate bond sectors, in particular financial and non-financial.

In order to demonstrate the robustness and consistency of our results, we analyzed the problems of possible cross-sectional and time-series variations in the data. We remove pure cross-sectional variation in issuer quality by estimating fixed effect for each bond issuer (IG bonds). We remove the time-series variation in average yields by estimating with 108 monthly time dummies (January 2003 to December 2011).

As our next step, in order to analyze how a firm's capital structure interacts with other determinants of the yield spread, we ran a regression with the inclusion of non linear interaction terms.

Finally, robustness of the results was further tested by conducting regressions on random subsamples of the data. In addition, the determinant variables were tested for multi-colinearity. Finally, as part of the robustness test, we repeated our main regressions, using alternative measures of credit spreads (CDS spreads and Par Asset Swap spreads).

3.5.2 ESTIMATION RESULTS

Table 5 reports the main results of our study. The table lists the estimated coefficients for a regression of corporate bond yield spread against explanatory variables listed in the first column. The coefficients are presented in basis points (bp). Columns from 1 to 8 represent different regressions, each of which included/excluded some of the determinants. For all of the regressions, we used daily panel data between 2003 and 2011.

Table 5
Structural Model Determinants of Corporate Bond Yield Spreads for Investment Grade Bonds

Using panel data between 2003 and 2011 for US corporate bond market, we regress corporate bond yield spreads against the list of variables (represented in the first column of the table). The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

Variables	1	2	3	4	5	6	7	8
STDV(excess RET)		**70.1** (79)		**70.34** (79)		**65.76** (77)		**66.04** (71)
Capital of Firm to Capital of Market		**-47.99** (-61)		**-15.49** (-27)		**-42.23** (-32)		**-7.18** (-23)
Downgrade from AA to A			**23.29** (42)	**1.92** (3)			**29.79** (43)	**11.97** (29)
Downgrade from AA to BBB			**78.6** (73)	**50.51** (65)			**80.71** (70)	**59.55** (63)
Operating income to sale					**-27.49** (-14)	**-16.8** (-11)	**-25.87** (-15)	**-16.25** (-11)
TD to Capitalization					**223.01** (49)	**154.37** (40)	**216.1** (33)	**153.36** (27)
Treasury Rate Level	**-56.67** (-45)	**-40.37** (-67)	**-56.12** (-42)	**-39.43** (-66)	**-55.05** (-45)	**-40.22** (-44)	**-54.55** (-47)	**-39.19** (-39)
TED Spread	**94.54** (24)	**69.38** (28)	**94.48** (23)	**69.17** (27)	**95.44** (23)	**71.55** (25)	**95.32** (22)	**71.27** (25)
Coupon	**29.02** (68)	**17.94** (73)	**21.69** (63)	**14.17** (72)	**24.69** (72)	**15.83** (69)	**17.79** (71)	**12** (60)
Years To Maturity	0.04 (1)	**0.6** (21)	**0.28** (7)	**0.76** (28)	**0.38** (10)	**0.79** (8)	**0.59** (11)	**0.94** (10)
Constant	**160** (17)	**120** (12)	**132** (26)	**46** (21)	**115** (26)	**134** (15)	**50** (10)	**122** (14)
R-squared	**0.37**	**0.57**	**0.41**	**0.6**	**0.43**	**0.60**	**0.46**	**0.62**
Number of transactions	1248893	1248893	1248893	1248893	1248893	1248893	1248893	1248893

The interpretation of the estimated coefficient is as follows. A unit rise in the independent variable leads to an expected rise in the credit spreads in bp equal to the corresponding regression coefficient. For example, looking at column 2, a rise in the standard deviation of daily excess return (STDV(excess RET)) by one percent leads to an approximately 70 bp rise in the associated credit spreads. In addition, a rise in the capitalization of the company relative to the market by 1% leads to a fall of 48 bp in credit spreads. We note that most of the variables presented in regression (9) have some ability to explain credit spreads.

In order to compare the overall performance of the various regressions in Table 5, we focus on the Adjusted R-squared. We note that adjusted R-squared is significantly improved once equity volatility is included. For example, Column 3 reports a regression with credit rating and macro variables. The adjusted R-squared increases from 0.41 to 0.6 once equity volatility is added to the regression (Column 4). A similar result is observed for other regression sets.

The coefficients for the standard deviation of excess returns show high significance with t-statistics in the range 71-79. Although one needs to take the conclusions of statistical significance based solely on these high numbers with a pinch of salt, because they reflect the size of the dataset these numbers are the highest across all variables included in regression. This clearly shows that volatility is the most statistically significant determinant of spreads. However, importantly, we note that the absolute magnitude of this coefficient is 3 times smaller than the value reported in Campbell and Taksler (2003).

Campbell and Taksler (2003) argue that all of the information content in credit rating should already be captured in the equity price. Our results seem to confirm this proposition, since the explanatory power of equity variables (column 2) is higher than the explanatory power of credit rating (column 3), judging by the adjusted R-squared for the two regressions. A possible explanation is that equity markets (daily frequency) reflect up-to date information regarding riskiness of a company, whereas credit rating are typically updated infrequently (quarterly and/or with a time lag). Another possible explanation is that during the current crisis investors lost some of the confidence/trust in the credit rating agencies, due to systematic inconsistencies and inaccuracies in ratings. For example, Lehman Brothers had credit rating AA just few days before bankruptcy.

The credit rating variables have a similar explanatory power as accounting variables. The regressions of corporate bond spreads on credit ratings (column 3) and accounting variables (column 5), individually, report an equivalent level of adjusted R-squared (0.41). In addition, we note the fact that regressing the two together, credit rating on top to the accounting variables (column 7), does not significantly increase the adjusted R-squared over accounting variables alone (increase of 3% over column 3). Although, it is sometimes claimed that credit ratings are designed to hold information not contained elsewhere, our results imply that they by and large reflect the level of information already contained in accounting variables. A possible explanation might be that credit ratings are build on the basis of accounting information of company. In addition, the credit ratings might not have been accurate enough during the crisis to contain valid information above that contained in accounting variables. In sharp contrast, adding equity volatility on top of the accounting variables improves adjusted R-squared by almost 17 percentage points (columns 5 and 6).

The estimated coefficients for two accounting variables, operating income to sale and total debt to capitalization, are statistically significant and show expected signs. Operating income to sale has a negative sign, meaning that an increase of operating income to sale leads to a fall in corporate bond yield spreads. The positive coefficient for total debt to capitalization implies a rise in spreads with increase in leverage, as can be expected. In addition, we note that Treasury Rate Level, TED Spread, Coupon, years to maturity variables shows expected sings and consistent with findings of Collin-Dufresne, Goldstein and Martin (2001), Longstaff (2002) and Elton, Gruber, Agrawal & Mann (2000).

We note that the TED spread, which is an indicator of macroeconomic health, shows a significantly higher estimated coefficient compared with findings of Campbell and Taksler (almost 4 times bigger). However, this is not surprising. The period between 1995 and 1999 is characterized by a steadily increasing S&P Index and a steadily increasing level of market volatility. In general, the increase in the S&P Index drive the credit spread down, whereas an increase in volatility drives spreads in to the opposite direction (up). The findings of Campbell and Taksler reflect the fact that volatility was more important than the rising S&P Index, driving corporate spreads up overall. However between 2007 and 2011 period, we observed a different scenario, with dramatically falling S&P and a simultaneously rising volatility level, with both factors pushing spreads up. We therefore attribute the change in the TED spread sensitivity of credit spreads to a difference in the macroeconomic climate.

To investigate further, we compare our findings for IG bonds with results for HY bonds. The qualitative difference between behaviour of IG and HY grade bonds has been reported in literature (Huang & Huang, 2003), (Bai & Collin-Dufresne, 2011), (Garleanu

& Pedersen, 2011). This should not come as a surprise since the markets for these categories are different. For example, pension funds are typically not allowed to hold HY bonds, whereas some hedge funds specialize on them. We report the results of our regression for HY bonds in Table 6.

We note a significant difference in the value of most of the regression coefficients (two times larger for HY). Comparing columns 2 and 3, one sees that the sensitivity to firm specific volatility (standard deviation of daily excess return) is almost two times bigger for HY bonds than for IG bonds. For HY bonds, volatility alone can explain more of cross-sectional variation in yield spreads than the credit ratings (adjusted R-squared for equity volatility is higher by 21 percentage points that adjusted R-squared for credit rating). As a result we conclude that the equity volatility is a key driving forces for the credit spreads in the HY segment. Size of other coefficients, such accounting variables (leverage ratio) and macro variables (Treasury level and Ted spread), is also about two times higher for HY bonds compared with IG. The coefficient for total debt to capitalization is 3 times bigger for HY bonds than for IG bonds, which supports the intuitive argument that a small change in the leverage of the lower rated bond lead to the much stronger effect on yields than for higher rated bonds. Another interesting thing to notice is that the estimate of sensitivity to years to maturity changes sign to negative for HY bonds consistently across all regressions. This leads to an interpretation that for HY bonds credit spreads reduce with longer time to maturity. This seems to be a consequence of the financial crisis, which has made short-term investments riskier than long-term ones. Finally, it is worth pointing out that the adjusted R-squared for high yield bonds exceeds investment grade bonds by almost 10%, reaching a level of almost 70% (regression 4). Overall, we conclude that HY credit spreads are more sensitive to the chosen determinants, especially to the equity volatility and TED spread, which is in line with predictions of Merton model.

In addition to previous discussion, which primarily focused on the sensitivities of the credit spreads to various factors, one is typically interested in having a sense of the economic significance of these factors in explaining the observed yield spreads. Table 7 reports the decomposition effect of each determinant factor on yield spread, thereby giving the reader an estimate of how much of yield spread variation is explained by each variable. The average effect is obtained by multiplying the standard deviation of each of our explanatory variables (columns 2 and 4) with their corresponding regression coefficient from Table 5 (IG) and Table 6 (HY column 8). We note that firm specific volatility, treasury rate level, TED spread and leverage variable explain the biggest chunk of yield spread variations. For IG bonds, the standard deviation of yield spread variations is 140bp, with 60bp attributable to equity volatility and 45 bp attributable the TED spread (the contributions are in general not additive), with smaller contributions coming from other factors. The magnitude of contributions significantly increases for high yield group of bonds in comparison with investment grade group.

Overall, one of our main conclusions is that for the period from 2003 to 2011, although firm specific volatility was an important factor driving spread up, it was significantly less prominent than reported by Campbell and Taksler (2003) for the period 1995 to 1999. The reason for this seems to lie in the fact that other factors, such us falling investors confidence level (TED spread), were equally if not more important in driving spreads up (sensitivity of spread to investors confidence level is much higher). However, our analysis also shows that equity volatility is the most statistically and economically significant factor determinant of corporate credit yield spreads. The second most important determinant, both statistically and economically, is the TED spread. In addition, Credit ratings and accounting variables also explain a significant variation in spread variations.

Table 6
Comparative table of Corporate Bond Yield Spreads Determinants for IG and HY credit rating category

Using panel data between 2003 and 2011 for US corporate bond market and different credit grade groups (IG and HY), we regress corporate bond yield spreads against the list of variables (represented in the first column of the table). The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	Regression 1		Regression 2		Regression 3		Regression 4	
	IG	**HY**	**IG**	**HY**	**IG**	**HY**	**IG**	**HY**
STDV(excess RET)	**70.1** (79)	**128.6** (61)			**70.34** (79)	**121.53** (59)	**66.04** (71)	**106.66** (55)
Capital of Firm to Capital of Market	**-47.99** (-61)	**-1155.1** (-45)			**-15.49** (-27)	**-951.5** (-42)	**-7.18** (-23)	**-620.5** (-28)
Downgrade from AA to A			**23.29** (42)		**1.92** (3)		**11.97** (29)	
Downgrade from AA to BBB			**78.6** (73)		**50.51** (65)		**59.55** (63)	
Downgrade from BB to B				**205.19** (56)		**74.38** (35)		**74.38** (35)
Operating income to sale							**-16.25** (-11)	**-19.21** (-6)
TD to Capitalization							**153.36** (27)	**467.64** (56)
Treasury Rate Level	**-40.37** (-67)	**-113.17** (-52)	**-56.12** (-42)	**-172.93** (-31)	**-39.43** (-66)	**-118.51** (-53)	**-39.19** (-39)	**-112.04** (-52)
TED Spread	**69.38** (28)	**101.19** (13)	**94.48** (23)	**170.87** (13)	**69.17** (27)	**104.64** (13)	**71.27** (25)	**104.68** (13)
Coupon	**17.94** (73)	**32.73** (63)	**21.69** (63)	**32.79** (39)	**14.17** (72)	**29.62** (59)	**12** (60)	**23.04** (56)
Years To Maturity	**0.6** (21)	**-1.16** (-11)	**0.28** (7)	**-3.86** (-25)	**0.76** (28)	**-1.05** (-10)	**0.94** (10)	0.18 (1.8)
Constant	160 (17)	308 (27)	132 (26)	711 (26)	46 (21)	336 (30)	122 (14)	212 (20)
R-squared	**0.57**	**0.67**	**0.41**	**0.46**	**0.6**	**0.68**	**0.62**	**0.71**
Number of transactions	1248893	267557	1248893	267557	1248893	267557	1248893	267557

Table 7
Effect decomposition for each variable on yield spread

Table below reports the characteristic contribution of the individual factors to variation of yield spread. Column 2 and 4 represent standard deviations of each variable for IG and HY. Column 3 and 5 reports actual effect of each variable on yield spread for IG and HY category in basis points. In order to calculate how much yield spread change die to each variable we multiply standard deviation of each variable to its estimate coefficient from Tables 5 (column 9) and Table 6 (column 9).

	IG	IG	HY	HY
Variable	**SD of Variable**	**SD*Estimate Coefficient (bp)**	**SD of Variable**	**SD*Estimate Coefficient (bp)**
Yield Spread	140 bp		326 bp	
STDV(excess RET)	0.91	**60**	1.38	**147**
Capital of Firm to Capital of Market	0.003	**-0.02**	0.0003	**-0.20**
Downgrade from AA to A		**12**		
Downgrade from AA to BBB		**60**		
Downgrade from BB to B				**74**
Operating income to sale	0.54	**-9**	0.23	**-4**
TD to Capitalization	0.14	**22**	0.14	**65**
Treasury Rate Level	0.81	**-32**	0.78	**-87**
TED Spread	0.63	**45**	0.68	**71**

REGRESSION BEFORE AND AFTER LEHMAN BROTHERS COLLAPSE

The Lehman Brothers bankruptcy was one of the largest bankruptcies in US history and involved a company with 600 billion dollars in assets. This event was a strong shock for the various spread determinants and the credit spreads itself. In order to quantify this effect, Table 8 presents the summary of regression results for financial and non-financial sectors in the periods before and after Lehman Brothers collapse on 15 September 2008.

Table 8
Comparative table of yield spreads determinants before and after Lehman Collapse for Financial and Non-financial sectors

Using panel data between 2003 and 2011 for US corporate bond market, we regress corporate bond yield spreads against the list of variables (represented in the first column of the table). Regression was performed for periods before Lehman collapse (January 2003 to August 2008) and after Lehman collapse (form October 2008 to December 2011). The standard errors of estimated parameters were adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	Before Lehman				After Lehman			
Variables	**Financial**		**Non-Financial**		**Financial**		**Non-Financial**	
STDV(excess RET)	**40.64**	**45.22**	**60.34**	**56.51**	**41.55**	**46.53**	**98.84**	**104.64**
	(13)	(12)	(80)	(70)	(54)	(56)	(47)	(47)
Capital of Firm to Capital of Market	**-12.43**	**-12.13**	**-14.71**	**-14.41**	**-105.38**	**-47.01**	-3.38	**-12.53**
	(-17)	(-15)	(-33)	(-30)	(-19)	(-10)	(-1.9)	(-7)
Downgrade from AA to A	**17.84**	**16.71**	**13.72**	**6.78**	**35.86**	**102.8**	**17.66**	0.85
	(17)	(18)	(32)	(12)	(11)	(19)	(14)	(0.63)
Downgrade from AA to BBB	**42.91**	**39.54**	**41.6**	**32.21**	**158.67**	**220.09**	**67.09**	**64.82**
	(24)	(28)	(75)	(57)	(30)	(41)	(48)	(47)
Operating income to sale	**-11.77**		**-23.27**		**-31.17**		**-55.17**	
	(-10)		(-18)		(-7)		(-28)	
TD to Capitalization	**18.98**		**218.27**		**224.99**		**255.44**	
	(11)		(77)		(41)		(35)	
Treasury Rate Level	**-29.81**	**-28.48**	**-8.85**	**-16.73**	**-79.31**	**-80.05**	**-51.05**	**-51.86**
	(-13)	(-12)	(-8)	(-18)	(-50)	(-42)	(-35)	(-35)
TED Spread	**61.93**	**60.27**	**68.29**	**61.19**	**82.54**	**82.25**	**75.32**	**75.94**
	(22)	(22)	(42)	(47)	(24)	(20)	(18)	(18)
Coupon	**4.09**	**4.61**	**5.61**	**7.86**	**19.66**	**23.17**	**16.95**	**19.77**
	(30)	(29)	(63)	(50)	(36)	(40)	(72)	(70)
Years To Maturity	**1.28**	**1.2**	**1.43**	**1.62**	**-0.39**	**-1.65**	**0.33**	**0.31**
	(40)	(31)	(61)	(43)	(-5)	(-21)	(11)	(10)
Constant	102	93	-79	6.8	154	118	-43	-13
	(9)	(7)	(-16)	(1.7)	(23)	(17)	(-11)	(-4)
R-squared	**0.68**	**0.64**	**0.55**	**0.48**	**0.63**	**0.59**	**0.66**	**0.64**
Number of transactions	132093	132093	619232	619232	68812	68812	417252	417252

Table 8 demonstrates that explanatory power (adjusted R squared) of financial sector spread determinants has tendency to fall after Lehman Brothers Bankruptcy by 5 percent. Almost all coefficients double in size, except equity volatility, which stays at the same level. The sensitivity to total debt to capitalization increased almost 10 times (225bp) after event. This result supports the claim that leverage became an important determinant of spreads in the wake of Lehman's collapse. Lehman borrowed significant amount of funds for investing in housing related assets, and its high leverage was one of the main reasons of its failure. Its leverage ratio increased dramatically during the last 5 years before going bust. Another interesting finding for the financial sector is that years to maturity coefficient changes sign to negative after Lehman failure. This indicates that in the aftermath of the Lehman collapse, corresponding to the height of financial crisis, holding short-maturity debt was typically much riskier than long-term debt.

Turning to non-financial sector, we observe slightly different tendencies for spreads. Firstly, after Lehman event the explanatory power of all determinants significantly increased (by 10 percent), making credit spreads more sensitive. Equity volatility coefficient increases in size to almost 100bp, which is twice as large as for financials. On the other hand, we note that the size of the total debt to capitalization coefficient did not change significantly before and after Lehman collapse. The magnitudes of the debt to capitalization coefficients suggest that this indicator was always an important determinant of spreads for non-financials, whereas for financials it became important only after Lehman's collapse.

CREDIT SPREAD SENSITIVITY OF MAJOR FINANCIAL INSTITUTIONS

In order to investigate the falling explanatory power of determinants for financial sector firms, we focus on attention on the giant systemically important financial institutions. The bonds belonging to these giant firms form a significant portion of our financials data, and a focus on this subcategory will shed light on the dynamics of spread sensitivities for the financial sector in general.

The general market expectation following Lehman's collapse was that the US government will not allow any further bankruptcies of systemically important financial companies to avoid any further deepening of the recession. Therefore, one would expect that these companies would become less sensitive to equity, ratings and accounting factors. In order to test our hypotheses, we perform regression on bond data belonging to large financial companies. We defined large financial companies using the Security and Exchange Commission order (15 Jul 2008) that put a restriction on short selling of shares of 19 major firms deemed systemically important. The restricted dataset contained 5 financial companies (since many of the 19 firms are not US based), and almost 80,000 data points (out approximately 200,000 data points for the whole US financial sector).

Table 9 presents the results of panel data estimation for restricted dataset of major US financial companies. We observe a significant fall in explanatory power after Lehman collapse. For example, in regression 1 explanatory power drops by 10%, and a similar tendency is observable for other regressions. The sensitivity to standard deviation of daily excess return falls three times after Lehman bankruptcy. On the other hand, the sensitivity to macro factors (TED spread, treasury level) becomes more prominent after Lehman's. Finally, in line with our previous results, we see that the coefficient for time to maturity changes sign after Lehman's collapse.

Our results support the prevalence of the "too big to fail" paradigm for financial firms amongst investors, particularly in the aftermath of the Lehman's bankruptcy. Firstly, the results show that overall the predictive power of our determinants reduced after Lehman's. Secondly, the results show that the sensitivity of credit spreads to company specific determinants, including equity and accounting factors, significantly reduced after Lehman's, whereas the sensitivity to macro factors increased.

Table 9
Determinants of Corporate Bond Yield Spreads for Major Financial Institutions before and after Lehman Collapse

Using panel data between 2003 and 2011 for US systemically important financial institutions, we regress corporate bond yield spreads against the list of variables (represented in the first column of the table).The regressions do not include credit rating since all of the considered firms were rated A, or higher. We report results for 4 different specifications of regression (Reg1 –Reg4) before and after Lehman Collapse. The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	Reg1		Reg2		Reg3		Reg4	
	Before	After	Before	After	Before	After	Before	After
STDV(excess RET)	**66.33** (29)	**22.52** (25)			**69.78** (24)	**25.95** (38)		
Capital of Firm to Capital of Market	**-41.33** (-19)	**-112.63** (-7)			**-5.62** (-5)	**-85.35** (-14)		
Operating income to sale	**-26.45** (-6)	**-65.18** (-5)	**-32.07** (-4)	**-268.77** (-21)				
TD to Capitalization	-124.53 (-1.9)	-7.08 (-0.2)	9.83 (1.7)	**335.51** (16)				
Treasury Rate Level	**-7.16** (-5)	**-89.1** (-26)	**-51.63** (-19)	**-90.65** (-16)	**-7.91** (-4)	**-91.55** (-33)	**-50.5** (-21)	**-88.73** (-16)
TED Spread	**46.01** (23)	**88.21** (17)	**81.5** (20)	**137.52** (12)	**51** (20)	**81.49** (22)	**82.4** (23)	**125.97** (11)
Coupon	-0.03 (-0.19)	**9.46** (14)	**2.5** (14)	**12.71** (13)	-0.07 (-0.46)	**10.74** (16)	**3.53** (24)	**15.2** (18)
Years To Maturity	**1.57** (46)	**-2.15** (-14)	**1.62** (44)	**-2.4** (-11)	**1.74** (48)	**-2.01** (-15)	**1.53** (48)	**-2.11** (-10)
Constant	121 (13)	460 (25)	229 (18)	347 (19)	14 (1.6)	425 (37)	241 (22)	408 (20)
R-squared	**0.86**	**0.77**	**0.68**	**0.63**	**0.85**	**0.76**	**0.67**	**0.55**
Number of transactions	49886	28766	49888	28766	49888	28766	49888	28766

INTERACTION EFFECT

In order to further investigate the predictions of Merton's model, following Campbell and Taksler (2003), we analyze how firm's capital structure interacts with main determinants of the yield spread. As interaction variables we choose long-term debt to assets and total debt to capitalization. We test the interaction of these variables with equity volatility and treasury rate. The motivation behind this choice is as follows. In the framework of Merton's model, the capital structure of the company has a direct effect on the sensitivity of the spread to equity volatility. We expect the volatility effect to be stronger for companies with higher debt. The increase in treasury rate level should reduce probability of default for companies with high long-term debt, because the nominal return on future investment will be higher than nominal interest cost of borrowing (company has already issued the bond at a fixed rate).

Table 10 presents results of non-linear regressions with added interaction variables. Results show highly significant positive effect for both interactions. We see a statistically significant positive interaction between a company's leverage and the equity volatility in explaining bond credit spreads. We also see a statistically significant negative interaction between the treasury rate and leverage variables. Finally we note that, with the inclusion of the interaction effect the explanatory power of regressions has increased by almost 20% while the value of the linear coefficients remains consistent with our previous results. Overall, the results show that the inclusion of interaction effect leads to expected results and is consistent with findings in literature (Campbell & Taksler, 2003).

Table 10
Interaction effects regression

Using panel data between 2003 and 2011 for US corporate market, we perform regression of corporate bond yield spreads against the listed in the first column variables. The variables include terms due to interaction effects. The interaction variables are leverage ratio multiplied by firm specific volatility and leverage ratio multiplied by treasury rate level. Columns 2 and 3 correspond to long term debt to assets as proxy of leverage. Columns 4 and 5 correspond to total debt to capitalization as proxy of leverage. The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	Regressions with Interaction variables			
	Long-term debt to assets	Long-term debt to assets	Total debt to capitalization	Total debt to capitalization
Interaction effects				
Interaction Variable * STDV of excess return		**142.38** (62)		**79.73** (64)
Interaction Variable * Treasury Rate Level	**-20.62** (-26)	**-54.58** (-20)		
Equity variables				
STDV of excess return (over180 days)		**36.19** (48)		**40.27** (59)
Market capitalization (relative to CRSP-value weighted index)		**-11.77** (-18)		**-10.44** (-13)
Credit rating				
Downgrade from AA to A	**31.41** (57)	**11.05** (28)	**22.94** (43)	**10.11** (25)
Downgrade from AA to BBB	**85.89** (75)	**57.83** (73)	**74.4** (70)	**59.82** (65)
Accounting variables				
Operating income to sales	**-26.35** (-14)	**-17.84** (-13)	**-19.68** (-15)	**-16.82** (-11)
Long-term debt to assets			**59.52** (21)	-4.64 (-2.22)
Total debt to capitalization	**246.2** (46)	**137.54** (22)		
Macroeconomic and other variables				
Treasury Rate Level	**-50.11** (-41)	**-26.21** (-39)	**-55.69** (-47)	**-39.91** (-40)
TED Spread	**94.43** (23)	**70.74** (57)	**95.19** (22)	**71.86** (56)
Coupon (%)	**18.13** (65)	**11.06** (40)	**20.84** (71)	**12.87** (63)
Years to Maturity	**0.63** (18)	**0.98** (11)	**0.29** (11)	**0.89** (10)
Number of transactions	1248891	1248891	1248895	1248895
Adjusted R-squared	**0.47**	**0.64**	**0.42**	**0.62**

3.5.3 ROBUSTNESS CHECKS

In order to test the robustness of our results and conclusions we have performed a range of tests. In this section we give a description of our approach methods and list the results.

FIXED EFFECT

Our results were obtained within the framework of regular OLS. This approach assumes no time or company specific structure within the dataset, and does not focus on explicitly determining heterogeneity across time or groups. In practice our dataset is a panel dataset and contains both, time dimension and issuer specific cross sections. It is therefore natural to study time-specific and cross-sectional variations in our dataset. The fixed effect estimation is a method to remove cross-sectional variations ((Wooldridge, 2002) pp. 446). This procedure is equivalent to an inclusion of section specific dummy variables and performing ordinary OLS. In our approach, we include issuer specific dummies in order to account for issuer specific variations, and include monthly time dummies to account for the time-series variations. Following prescription in Wooldridge (2002), we perform the Hausman test to determine if fixed effect is the appropriate panel estimation approach. The test produced p-value < 0.05, justifying the use of the fixed effect.

Table 11 presents results of the fixed effect regression, with and without monthly time dummies, for the 602 issuer specific cross-sectional dummies. The regression coefficients for the fixed effect are interpreted as the sensitivities of yield spreads of bonds, issued by a single issuer during a chosen time-period (when the time dummies are included), to the corresponding determinants. We note that, the size of coefficient for the standard deviation of daily excess return is almost unchanged compare with ordinary OLS, while the corresponding t-statistics remains significantly high. Average rating dummies and coupon variable were omitted from the regression due to the fact that they are subsumed by the issuer dummy. The coefficients of other determinants have expected signs and are consistent with our previous findings. We also note that the explanatory power (adjusted R-squared) for fixed effect increased almost 10% compared with OLS (see Table 5). This is not surprising, since one expects a increase in explanatory power if a significant number of additional variables are added. What is more important is that, as in the case of OLS regression, the adjusted R-squared increases significantly (by 10%), when equity volatility variable is included (columns 2 and 3).

Table 11
Regressions with Issuer Fixed Effects

Using panel data between 2003 and 2011 for IG rating category of US corporate market, we perform regression with fixed effect for each bond issuer of corporate bond yield spreads against the list of variables (represented in the first column of the table). We include 107 monthly dummy variables (January 2003 to December 2011) to represent unexplained time-series variation in average corporate yield spreads. Column 2 to 5 correspond to different specifications of regression with included and excluded monthly dummy variables and equity characteristics. The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	Reg1	Reg2	Reg3	Reg4
Issuer Fixed effect	Yes	Yes	Yes	Yes
107 monthly time dummies	No	No	Yes	Yes
STDV(excessRET)	**57.8** (63)		**41.74** (38)	
Capital of Firm to Capital of Market	-1.05 (-1.8)		**-36.18** (-23)	
Downgrade from AA to A				
Downgrade from AA to BBB				
Operating income to sale	**-13.53** (-10)	**-20.77** (-13)	**-14.78** (-12)	**-19.88** (-15)
TD to Capitalization	**364.65** (22)	**617.14** (34)	**309.5** (19)	**389.92** (24)
Treasury Rate Level	**-36.82** (-40)	**-46.2** (-43)	**-18.97** (-35)	**-19.24** (-33)
TED Spread	**72.09** (65)	**92.3** (75)	**5.13** (15)	**5.49** (15)
Coupon				
Years To Maturity	**0.91** (11)	**0.74** (7.7)	**0.9** (12)	**0.84** (10)
Number of transactions	1248476	1248476	1248476	1248476
R-squared within	**0.73**	**0.63**	**0.78**	**0.74**
Number of panels	602	602	602	602

RANDOM SAMPLING

Our investigation was conducted with an extremely large dataset of approximately 1.5 million data points, resulting in very large values for the t-statistics. These large values make the direct interpretation in terms of p-values and significance levels quite questionable. For this reason, in order to gauge the significance of our results, we conducted a test based conducting multiple regressions on randomly chosen smaller subsamples of the data.

Our approach was as follows:

- We take a random sample of 10,000 data points from our total dataset.
- Using this dataset, we perform our OLS regression.
- We repeat the procedure 1,000 times using different random subsamples.
- For each of the 1,000 regressions we store the results of the regression.
- Finally, we provide a histogram of the coefficient estimates and t-statistics.

The approach gives an indication on the significance and persistence of the effect for various determinants of credit spreads. In addition, the random sampling technique also helps to avoid the problem of time-series autocorrelation within the data, since randomly picked data subsets would be free of any autocorrelations. The graphs below present distribution of estimate coefficients and t-statistics for different variables. We restrict our presentation to just the histograms for R-squared and equity characteristics (Figure 11, Figure 12), with the remaining histograms taken out into Appendix 1, part B. The analysis confirms that the variables such as equity volatility, credit rating, treasury level, total debt to capitalization, Ted-spread, coupon rate, years to maturity are significant determinants of credit spread. In particular, equity volatility coefficient is consistently estimated with a positive value in the region of 65bp, and shows a significant t-statistics with an average of 63 (see Figure 12). On the other hand, market capitalization and operating income to sale showed much less stability across subsample regressions (see Appendix 1, part B). Finally, the histogram for adjusted R-squared (Figure 11) shows that the chosen determinants consistently explain around 62% of variation in credit spreads.

Figure 11

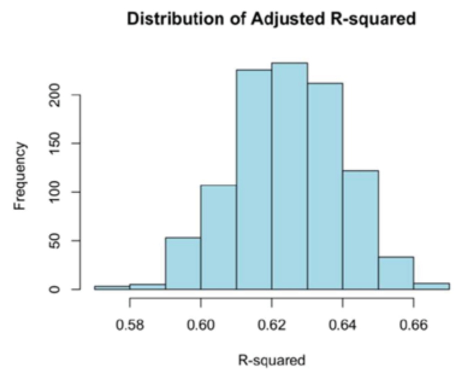
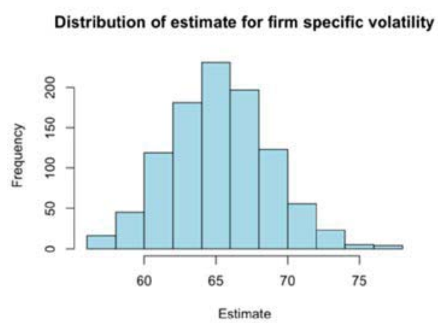
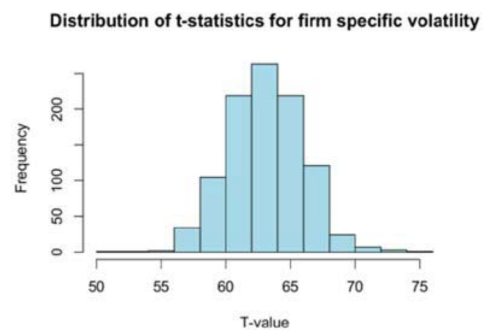
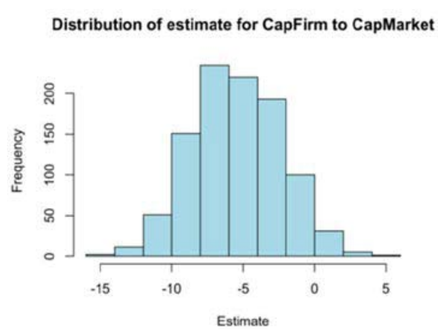


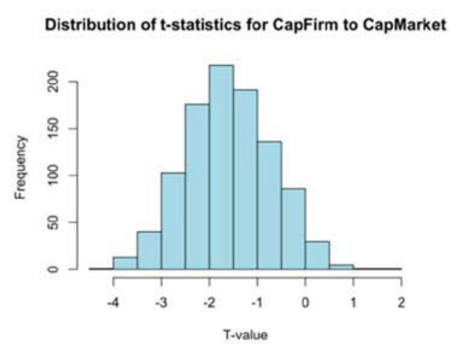
Figure 12

Distribution of estimate coefficients and t-statistics for equity volatility and market capitalization. We refer the reader to Appendix 1, part B, for analogous graphs for other coefficients.









CHECK FOR MULTICOLLINEARITY

As a part of the robustness check, we I investigated the multicollinearity between various explanatory variables. If two explanatory variables exhibit a high correlation with each other, their effect on the dependent variable cannot be decoupled, thereby leading to high uncertainties in estimation coefficients. Therefore, it is important to examine correlation between explanatory variables and exclude one of a pair of highly correlated variables before conducting a multivariable regression. For quantitative variables, correlation is measured by the Pearson correlation coefficients given in Table 12. . We did not detect any evidence of high (greater than 80%) correlation, and therefore are justified in conducting the regression analysis with the chosen variables.

Table 12
Correlation matrix for explanatory variables

	1	2	3	4	5	6	7	8
1. Treasury Level	1	-0.34	-0.07	0.09	-0.22	-0.06	0	-0.02
2. Yield Spread	-0.34	1	0.45	0.24	0.63	-0.18	-0.09	0.25
3. TED-Spread	-0.07	0.45	1	0.01	0.27	0.01	0	-0.02
4. Coupon	0.09	0.24	0.01	1	0.13	-0.24	-0.03	0.13
5. STDV(excess RET)	-0.22	0.63	0.27	0.13	1	-0.12	-0.07	0.16
6. Capital Firm to Capital Market	-0.06	-0.18	0.01	-0.24	-0.12	1	0.05	-0.11
7. Operating income to sale	0	-0.09	0	-0.03	-0.07	0.05	1	0.11
8. TD to capitalization	-0.02	0.25	-0.02	0.13	0.16	-0.11	0.11	1

DETERMINANTS OF YIELD SPREADS IN THE PERIOD PRECEDING THE CRISIS

The period considered in our investigation (2003-2011) covered the greatest financial crisis of modern times (2007-2009). This period saw an unprecedented spike in credit spreads as well as unusual behaviour in most of the considered determinant variables. It is natural therefore to suspect that our results are mostly determined by the events during the financial crisis. For this reason, as part of our robustness testing, we were interested in testing the validity of our conclusions about the sensitivity of credit spreads to the various determinants in the period prior to the financial crisis, when the US economy was relatively stable. We take the period between 2003 and mid 2007 for this investigation. This period falls between the financial turmoil of 1997 (Asian crisis), 2001 (dotcom bubble) on the one hand and the financial crisis (post 2007) on the other. The relative calm of the chosen period (2003 to mid 2007) is reflected in the average credit spreads (Figure 8) in this period.

Table 13 presents the results for period between 2003 and mid 2007. Although the adjusted R-square decreases, results are mainly consistent with previous findings. All estimate coefficients have expected sign. Equity volatility variable remains an important determinant of corporate yield spreads, and its explanatory power is comparable to that of and credit ratings. All variables together explain approximately 47% of variation in yield spreads. The results are consistent with findings of Campbell and Taksler (2003), although as mentioned previously the sensitivity to equity volatility is almost 4 times smaller.

Table 13
Determinants of corporate yield spread in the period preceding Recession

Using panel data between 2003 and 2007 for US corporate market, we perform regression of corporate bond yield spreads against the list of variables (represented in the first column of the table). Column 2 to 9 represents different specifications of regression. The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	Pooled OLS (different specifications)							
STDV(excessRET)		**48.66** (90)		**45.04** (85)		**49.66** (95)		**46.55** (94)
Capital of Firm to Capital of Market		**-25.19** (-79)		**-7.94** (-30)		**-14.50** (-55)		3.79 (1.45)
Average Rating A			**5.3** (23)	-2.79 (-1.4)			**11.2** (15)	**9.55** (32)
Average Rating BBB			**45.85** (50)	**30.32** (55)			**46.95** (57)	**40.29** (49)
Operating income to sale					**-97.36** (-56)	**-74.63** (-48)	**-64.09** (-45)	**-57** (-37)
TD to Capitalization					**135.51** (67)	**129.56** (68)	**119.27** (67)	**124.1** (55)
Treasury Rate Level	-0.66 (-1.7)	**-7.14** (-12)	**-1.2** (-2.5)	6.38 (11)	1.41 (1.1)	**-9.47** (-18)	-0.44 (-0.06)	**-8.66** (-4.2)
TED Spread	**15.96** (10)	**31.69** (25)	**13.87** (9)	**30.06** (25)	**29.53** (22)	**45.39** (38)	**25.45** (19)	**42.86** (13)
Coupon	**14.73** (40)	**9.4** (45)	**10.35** (56)	**7.34** (47)	**11.96** (59)	**7.5** (45)	**8.46** (45)	**5.53** (44)
Years To Maturity	**1.62** (35)	**1.7** (34)	**1.71** (40)	**1.77** (46)	**1.66** (42)	**1.75** (39)	**1.75** (34)	**1.81** (60)
Constant	-8.2 (-3)	-70 (-29)	-5.2 (-1.8)	-68 (-31)	-13 (-5.4)	-89 (-41)	-21 (-8)	-19 (-12)
R-squared	**0.19**	**0.35**	**0.31**	**0.40**	**0.28**	**0.42**	**0.36**	**0.47**
Number of transactions	597351	597351	597351	597351	597351	597351	597351	597351

ALTERNATIVE MEASURES OF CREDIT RISK

In this subsection we conduct an analysis of credit spread determinants using alternative measures of credit spread, namely Par Asset Swap spread (ASW) and Credit Default Swap spread (CDS).

Par asset swap spreads:

The bond yield spread that we have used so far was defined as a spread above the treasury yield. Several authors (Hull, Predescu, & White, 2004), (Duffee, 1996), (Reinhart & Sack, 2002) argue that appropriate measure of credit risk strongly depend on the choice of risk free rate proxy. Authors argue that the choice of the Treasury curves as the measure of riskless rate has some advantages and disadvantages. The bond issued by government in the domestic currency has no credit risk so its yield should equal the risk free rate of interest. However, authors point out many additional factors, such as liquidity, taxation and regulation that can affect the yield of these bonds. The various non-credit-risk reasons typically push the yields on US Treasuries to be lower than the yield on other low risk bonds. For this reason, we look at the par asset swap spread as an alternative measure of credit spread used by practitioners (De Wit, 2006), (Elisade, Doctor, & Saltuk, 2009). We have introduced the concept of an asset swap and ASW in Chapter 1. In the current context, the crucial aspect of ASW is that it is a spread over LIBOR. The data on ASW was included in our original MarkIt dataset.

In Table 14 we present the various regressions including OLS, fixed and random effects, for IG and HY groups. The results in this table consistently support our previous findings. The only noteworthy difference in results is a slightly smaller TED spread coefficient and higher Treasury level coefficient. These facts are a direct reflection of choosing a spread over LIBOR in contrast to spread over treasury as a measure of spread. A noteworthy, result of choosing ASW as a spread measure, is a noticeable increase in the explanatory power of the regression (5-7%).

Table 14
Structural Model Determinants of ASW as proxy of corporate credit risk for corporate bonds

Using panel data between 2003 and 2011 for US corporate bond market, we regress asset swap spread, as alternative proxy of credit risk, against list of variables (represented in first column of the table). Column 2 to 5 presents pooled OLS, fixed and random effects for investment grade group. Column 6 to 9 presents analogous regressions for high yield group. The standard errors of estimated parameters are adjusted using Newey-West method and Driscoll and Kraay method for panel. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	IG				HY			
	Pooled OLS	Pooled OLS	Fixed Effect	Random Effect	Pooled OLS	Pooled OLS	Fixed Effect	Random Effect
STDV(excessRET)	**51.42** (21)	**47.99** (22)	**40.87** (20)	**41.07** (20)	**92.87** (15)	**78.7** (14)	**66.28** (11)	**67.1** (11)
Capital of Firm to Capital of Market	**-40.85** (-12)	0.39 (0.11)	11.17 (1.2)	8.06 (0.9)	**-1267** (-12)	**-674.5** (-6)	-657.56 (-2)	-713.68 (-2)
Downgrade form AA to A		12.88 (3)		**58.66** (4)				
Downgrade form AA to BBB		**63.78** (13)		30.76 (2)				
Downgrade form BB to B						**52.97** (5)		**48.73** (3)
Operating income to sale		**-11.72** (-4)	**-7.39** (-8)	**-7.5** (-8)		-37.06 (-3)	**-15.63** (-0.8)	-19.43 (-1.04)
TD to Capitalization		**137.32** (13)	**479.07** (11)	**447.94** (12)		**333.11** (9)	**755.03** (6)	**722.81** (6)
Treasury Rate Level	**-62.53** (-43)	**-62.07** (-48)	**-51.68** (-30)	**-52.28** (-31)	**-125.79** (-37)	**-127.22** (-36)	**-122.1** (-22)	**-122.38** (-23)
TED Spread	**40.23** (22)	**41.23** (26)	**45.95** (31)	**45.96** (31)	**69.66** (12)	**64.66** (11)	**56.6** (11)	**56.91** (11)
Coupon	**33.4** (28)	**28.14** (27)		**26.33** (12)	**40.49** (16)	**33.64** (13)		**24.06** (5)
Constant	**79.47** (8)	**35.75** (4)		-52.85 (-3)	**354.88** (13)	**297.22** (11)		**233.94** (5)
R-squared	**0.64**	**0.69**	**0.63**	**0.63**	**0.73**	**0.76**	**0.75**	**0.75**
Number of transactions	429826	429826	429826	429826	67691	67691	67691	67691

CDS spreads:

Finally, for the sake of completeness, we consider another measure of credit spread that has gained considerable interest in recent times, namely the CDS spread. The concept of a CDS instrument and CDS spread was introduced in Chapter 1. For the purpose of the current study, it is important to point out that CDSs are typically traded in a separate market from corporate bonds, with different set of typical buyers and sellers, market conventions and other idiosyncrasies. Even though, from arbitrage arguments it follows that the CDS spreads should be equal to bond yield spreads, this relationship is only approximate (Hull, Predescu, & White, 2004). For these reasons, an investigation of determinants of CDS spreads is of interest both in the context of the current work as well as in its own rite.

The daily CDS spread data was obtained from MarkIt for the period from 2003 to 2011. Following previous empirical works on CDS spreads (Blanco, Brennan, & Marsh, 2005), (Norden & Weber, 2009), we restricted our analysis to five-year CDS spreads with modified restructuring clauses (MR) (these are the most liquidly traded instruments). In Figure 13 we show the average CDS spreads for different credit rating groups. In the Table 15 presents results of our regressions. First 8 columns of table correspond to pooled OLS regressions with different specifications, while the last column shows results for a fixed effect panel regression.

Overall, we note that the results are consistent with our previous findings. The regression coefficients are consistent in terms of sign and magnitude with previous analysis. Once again, the only noticeable difference is the TED spread coefficient, which is almost three times smaller. An important difference for CDS spreads, is that the explanatory power of the regressions has fallen significantly. All together explanatory variables can explain only 47% of CDS spread variations and only 40% can be explained by equity characteristics and macro variables. The lower ability of our variables in explaining variations in CDS spreads compared with corporate yield spreads, points to existence of additional factors which may affect CDS market and do not affect the bond market. This results becomes particularly relevant during the recent financial crisis where one saw a persistently negative CDS-Bond basis (Bai & Collin-Dufresne, 2011), (Augustin, 2012), (Fontana, 2010). These results are closely connected to our analysis in Chapter 5 where we investigate the differences between the corporate CDS and bond markets and serve as motivations for that research.

Figure 13

Aggregated 5 years CDS spreads for different ratings (AA, A, BBB), 2003 to 2011 (in percent).

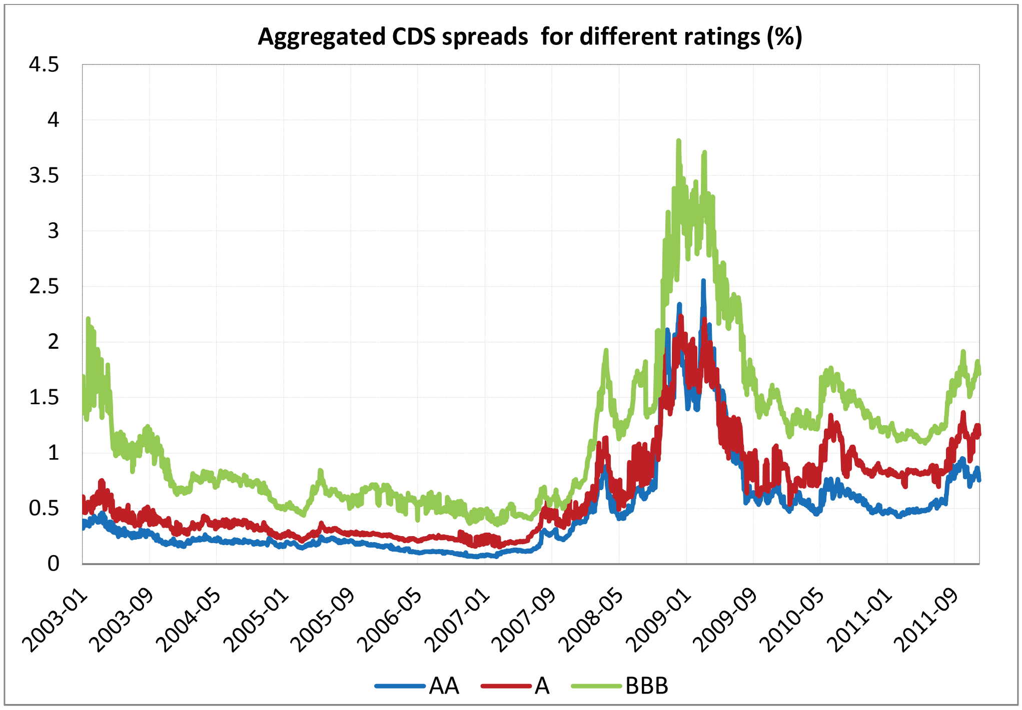


Table 15
Structural Model Determinants of CDS spreads for Investment Grade entities (AA, A, BBB)

Using panel data between 2003 and 2011 for US CDS market, I regress five-year CDS spreads with (MR) clauses against the list of the variables which are determinants of US corporate yield spreads (given in column 1). Column 2 to 9 present results of pooled OLS regression. Last column represents results of panel estimation. The standard errors of estimated parameters are adjusted using Newey-West method and Driscoll and Kraay method for panel. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

Variables	Pooled OLS (different specifications)								Fixed Effect
STDV (excessRET) (%)		**77.81** (8.7)		**76.72** (8.1)		**72.87** (9.4)		**72.18** (8.3)	**57.71** (7.9)
Capital of Firm to Capital of Market (%)		**-36.2** (-5.6)		-19.8 (-2.8)		**-23.9** (-5.6)		-4.9 (-0.79)	**-49.85** (-3.2)
Downgrade form AA to A			16.47 (2)	-17.7 (-2.4)			**30.85** (4.9)	6.1 (0.8)	**8.61** (4)
Downgrade form AA to BBB			**64.44** (8)	15.74 (1.7)			**64.08** (11)	**30.29** (3.2)	**8.69** (5)
Operating income to sale (ratio)					**-19.69** (-3)	**-11.76** (-3.5)	**-19.35** (-3.2)	**-11.82** (-3.5)	**-10.75** (-3.9)
TD to Capitalization (ratio)					**280.74** (12)	**226.93** (8)	**259.43** (8.8)	**215.38** (7)	**301.5** (10)
Treasury Rate Level (%)	**-51.1** (-19)	**-30.72** (-13)	**-51.34** (-19)	**-30.9** (-13)	**-48.05** (-25)	**-29.41** (-13)	**-48.5** (-24)	**-29.58** (-13)	**-27.9** (-15)
TED Spread (%)	**32.04** (7.7)	7.97 (2.2)	**31.52** (7.5)	8.2 (2.3)	**33.16** (10)	**10.49** (3.3)	**32.56** (10)	**10.45** (3)	**16.1** (8.4)
Constant	**267.9** (24)	**92.43** (5)	**226.27** (18)	**89.76** (5)	**202.36** (23)	47.36 (2.4)	**160.33** (16)	28.46 (1.2)	**151.6** (3.7)
Number of transactions	367825	367825	367825	367825	367825	367825	367825	367825	367473
R-squared	**0.13**	**0.4**	**0.17**	**0.42**	**0.24**	**0.46**	**0.26**	**0.47**	**0.66**

3.6 CONCLUSION

In this chapter, we analyzed the main determinants of the credit spread for US corporate bond market in period between 2003 and 2011, covering the period of financial crisis that began in 2007. The period between 2007 and 2011 was characterized by a sharp fall in investors' confidence level alongside an increased volatility in the markets. Both of these factors were responsible in driving credit spreads up to historically high level.

Firstly, we found that factors suggested by structural models of credit risk explain almost half of the variations in corporate yield spreads for relatively stable period of US economy (2003 to 2007) and more than half (62%) for total period including recession.

Secondly, in line with previous findings (Campbell & Taksler, 2003), (Landschoot, 2004), we have shown that volatility is an important determinant of the corporate bond spreads. However, our results show that the sensitivity of credit spreads to volatility is 3 times smaller than reported by Campbell & Taksler. We point out that during the recent crisis, both volatility and TED spread contributed to the increase in spreads. This is in contrast to the 1995-1999 period studied by Campbell & Taksler, where the TED spread was systematically narrowing. Our analysis shows that equity volatility has a stronger effect on yield spreads than the effect of credit ratings. An analysis of interaction effect showed that a higher leverage ratio leads strengthening of volatility effect, in line with predictions of Merton's model. Our results show evidence that credit ratings lost their power in determining credit spreads during financial crisis and explained no more than accounting variables. Other explanatory variables Treasury Rate Level, TED Spread, Coupon variables show expected sings and are consistent with findings elsewhere in literature (Longstaff F. A., 2002), (Collin-Dufresne, Goldstein, & Martin, 2001), (Elton E. , Gruber, Agrawal, & Mann, 2000). The credit spread of different rating categories, IG and HY, show significant difference in sensitivity to explanatory variables. HY spreads were typically more sensitive to the chosen determinants, in particular to equity volatility, leverage and TED spread. We show that our findings are robust to inclusion of fixed effects, random sampling estimation, non-linear effects and over different time periods (economically stable period and crisis period).

Thirdly, we investigate effect of Lehman's collapse on the behaviour of credit spreads for different sectors. We find evidence that financial sector companies behave differently to non-financial sector companies. We show that the explanatory power of financial sector spread determinants fell after Lehman's bankruptcy. An opposite tendency was observed for spreads of non-financial sector, where both the size of estimates and R-squared significantly increase. We interpret these findings as an indication that financial sector firms, particularly the large systemically important ones, were judged to be "too big to fail", and that there was a general feeling by the market participants that these banks will not be allowed to fail by the US after the catastrophic consequences of Lehman's collapse.

Fourthly, in addition to an analysis of corporate bond credit yield spreads, we conduct an analogous analysis for par asset swap spread and CDS spread, as alternative measures of credit risk. Overall, these measures showed results consistent with bond yield spreads. The signs and values of the regression coefficients were consistent across the various proxies of credit risk. For CDS spreads, we noticed a slight deterioration in the explanatory power. This reduction in R-squared for CDS spreads in comparison to bond yield spreads points to an existence of additional factors affecting the CDS market. We interpret this finding as an indication of the difference in pricing of credit risks in the bond and CDS markets. This fact serves as a motivation for our analysis in Chapter 5.

Existing literature on corporate bonds has primarily concentrated on the US corporate market. This is the case due to the fact that US market is the largest corporate bond market in the world and also due to a somewhat related fact of absence of data for other markets. An interesting extension of the current work, which we consider in Chapter 4, is the extension of analysis to different corporate bond markets. This analysis is important in order to compare different markets, picking out similarities and differences across countries and showing the overall consistency of the structural approach. In the next chapter we examine the UK corporate bond markets for the period between 2003 and 2012. To the best of our knowledge, it is the first empirical research work on determinants of credit spreads in the UK corporate bond market.

CHAPTER 4 DETERMINANTS OF CORPORATE BOND SPREADS: EVIDENCE FROM UK CORPORATE BOND MARKET

4.1 INTRODUCTION

The credit markets in most major economies, between 2003 and early 2007, were characterised by low volatilities and small credit spreads. This stability came to an end in the mid-2007 with the US subprime mortgage crisis serving as a trigger. As a result, credit spreads increase rapidly in most economies. The crisis attracted a lot of academic research on size of credit spreads and stimulated a new wave of research in other aspects of credit risk. However, the majority of empirical literature on the determinants of credit spreads focused on US data (see Longstaff and Schwartz (1995), Duffie (1998), Collin-Dufresne, Goldstein and Martin (2001), Elton, Gruber, Agrawal & Mann (2001), Campbell and Taksler (2003), Chen, Lesmond & Wei (2007), Bao, Pan & Wang (2011)) (Bao, Pan, & Wang, 2011)), partly due to it being the largest and the most liquid market and partly because of the availability of robust data for this market. The empirical literature on testing the empirical validation of credit risk models for non-US corporate bond markets is very limited. This literature includes investigations of credit risk in European corporate market Landschoot (2004), Fruhwirth, Schneider & Sogner (2010), as well as works focused on Japan's corporate bond markets such as Hattori, Koyama and Yonetani (2001), Packer (1999). The empirical literature of UK corporate bond spreads is very limited (Webber & Churm, 2007).

In our previous Chapter we analysed the determinants of credit spreads in US corporate bond market for the period between 2003 and 2011. In this chapter we extend our analysis to the UK corporate bond market. Although the UK corporate bond market is significantly smaller than the US market, there is still a lot of data available to make the analysis worthwhile. To the best of our knowledge, our research is the first work to study UK credit spreads and their determinants for the two markets covering the period of the financial crisis. The main motivation for our work was to test the predictions of Merton's structural model using an alternative dataset, as well as to look at the similarities and differences between the US and UK corporate bond markets. We study the various determinants of credit spreads in UK bond markets, including equity, bond specific, accounting as well as macroeconomic factors. In particular, we focus on the role of equity volatility. Examining yield spreads for a dataset consisting of daily panel of UK corporate bond spreads between 2003 and 2012, we present evidence that equity volatility explains a large portion of credit spreads, greater than credit ratings, accounting variables as well as macro factors.

As was mentioned above, the current Chapter is an extension of the investigation conducted in Chapter 3. For this reason, we shall skip the repetition of the theoretical background and motivations, referring the reader to Section 2 of Chapter 3 instead. In addition, for a general introduction to corporate bonds and bond markets we refer the reader to Chapter 1. The sections in the current chapter are organized as follows. Section (4.2) describes our panel data and the restrictions we imposed on it. It also describes how other data such as equity and accounting information were collected from various sources. The section examines main trends in the corporate bond spreads between 2003 and 2012 and provides a statistical characterization of our final dataset. Section (4.3) provides a description of the methodology used to analyze the data, as well as the results of estimations. We present evidence that an increase in equity volatility significantly increases the credit spreads and hence the cost of borrowing, however the effect is smaller than comparable results for the US market reported in previous literature. We show that our findings are robust to issuer fixed effect, random sampling and several other specifications of regression. We also present comparative results for different rating categories (IG and HY), as well as study the effect of two important financial events (Lehman Brothers collapse, quantitative easing). In addition, we analyse our data taking par asset swap spreads and CDS spreads as alternative proxies of credit spreads. Lastly, in this section we present the results of several robustness checks. In Section (4.4) is devoted to a comparative analysis of results for US and UK corporate bond markets. Finally, we conclude in Section (4.5).

4.2 DATA DESCRIPTION

Daily UK corporate bond data was obtained from MarkIt[2]. We restrict our analysis to composite price data. MarkIt collects daily bond prices from a large number of dealers, and calculates averages of all contributed prices and spread data, requiring at list three prices in order to produce a composite.

In addition to prices, the dataset also contains all issue and issuer-specific variables such as rating, sector, region, country and other non-standard features of corporate bond (callability, floating coupons, etc). Our UK dataset covers the period from January 2003 to August 2012. Overall, the empirical methodology closely follows the US market analysis.

4.2.1 BOND DATA

CORPORATE BOND DATA

We restrict our UK bond dataset to bonds denominated in British pounds (GBP). We removed bonds with non-standard features, restricting our analysis to non-callable, non-puttable, non-sinking fund, non-convertible and fixed-rated bonds. We also exclude issues with asset-backed and credit-enhancement features, and left only bonds corresponding to senior unsecured debt (SNRFOR). Bonds with less than 2 years to maturity were excluded from the analysis, and remaining bonds were grouped by maturity (short-term 2-7 yrs, medium-term 7-15 yrs, long-term 15-30 yrs). We also

[2] http://www.markit.com/Product/Pricing-Data-Bonds

separated the bond dataset into investment grade (IG) and non-investment grade high-yield (HY) categories, according to the ratings. Following the reasoning in Chapter 3, we excluded AAA rating bonds from our analysis. In addition to price data, MarkIt data set also contained other bond specific characteristics such as coupon rate and years to maturity. Finally, we calculated the yield to maturity on each bond in sample and its spread in comparison with the UK risk free rate (UK Gilts) of the same maturity. In order to reduce apparent errors in the data, we eliminated the top and bottom 1% of spreads.

Our final UK corporate bond dataset consisted of ten business-sector categories (Industrial, Utilities, Financials, Technology, Consumer Goods, Healthcare, Consumer Services, Telecommunications, Services, Basic Materials, Energy), five rating categories (Aaa, Aa, A, Baa, Ba, B) and three bands of maturities (short, medium, long). After matching with other datasets (equity and accounting data) we were left with approximately 250,000 different bond-daily transactions for 102 different issuers.

RISK FREE BOND DATA

The daily data for the nominal spot rates for different maturities between 0.5 yrs and 30 yrs, covering a period between 2003 and 2012, came from the Bank of England. In order to find a risk free rate for a given combination of date and maturity we used and interpolated our data using a routine written in Matlab.

4.2.2 EQUITY DATA

Equity and accounting data for UK based companies was collected from the DataStream database. Unlike the case of US companies, for UK companies we were not able to use the CUSIP identifier for matching bond an equity data. In order to link corporate bond data from MarkIt with equity and accounting data from DataStream we matched each firm by its name and ticker, and identified the corresponding unique company

DataStream number. The unmatched companies were eliminated from the analysis, leaving a total of 102 uniquely matched companies.

For the list of matched UK companies we collect daily closing price equity data from DataStream and calculated the corresponding daily returns. The equity data was taken for at least 180 days prior to the bond's trade in order to calculate mean and volatility. For this reason, our equity data covered the period between 2001 and 2012. Equity dataset was cleaned and all "bad data" (empty sells or unchanging price) was omitted from the analysis. We also delete from dataset few companies with infrequent equity data, in order to avoid jumps in returns and volatilities. As a proxy of UK equity market (market capitalization) we collect market value FTSE-ALL-Shares Index, which is a capitalization-weighted index aggregation of FTSE 100, 250 and SmallCap Index. The index contains a total 627 companies, and aims to represent at least 98% of the full capital value of all UK companies that qualify as eligible for inclusion (all companies listed in LSE). The daily index value was collected from DataStream database for period between 2001 and 2012. In order to calculate the firm-specific volatility we firstly calculated the difference between Stock return and FTSE-ALL-Shares index return to obtain daily excess return. Secondly, we used formula (8) from Chapter 3 to calculate volatility of excess return over 180 days. The capitalization of company relative to capitalization of market was calculate by taking ratio of the market value of individual company to market value of FTSE-All-Shares.

4.2.3 ACCOUNTING VARIABLES

In order to investigate how the corporate bond yield spreads are affected by accounting information of the company, following analysis in Chapter 3, we take two main accounting ratios, namely the leverage ratio and the operating income to sale ratio. The various components were collected from DataStream-Worldscope database (annual data), with *Market value of equity* collected daily. The accounting variables were calculated as percentages.

Leverage ratio was proxied by *Total debt to capitalization* and *Long-term debt to Assets* (the last one will be used for conducting interaction effect). *Total debt to capitalization* was calculated as *[Total Debt]* to *[Total Liabilities (LT) +Market value of equity]*. *Long-term debt to assets* was calculated as *[Total Long term debt]* to [*Total Assets]*. *Total Assets* represents the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets. *Long term debt* gives all interest bearing financial obligations, excluding amounts due within one year. *Total debt* represents all interest bearing and capitalized lease obligations, and is a sum of short and long term debts. The two proxies of the leverage ratio were included separately in regressions in order to avoid issues with multicolinearity. The two were used to check consistency of the results.

Operating income to sales was calculated as *[operating income before depreciation]* to *[Net Sales]*. *Operating income before depreciation* represents the operating income of a company before depreciation and amortization expenses have been deducted. *Net sales* gives gross sales and other operating revenue less discounts, returns and allowances.

4.2.4 MACROECONOMIC DATA

We have used two macroeconomic variables for our analysis, *level of term structure* and *TED spread*. The *level of term structure* was proxied by the yield on 10-year Benchmark Gilts. The *TED spread* was calculated as a difference between the three-month GBP LIBOR and the yield on three-month Gilts. The *TED spread* is an indicator of general risk perception and funding liquidity in the market. The daily series for Gilt rates and GBP LIBOR were collected from Bank of England for the period between 2001 and 2012.

In the analysis below, we will consider the effect of quantitative easing (QE) on the credit spreads. To proxy this effect, we took the quantity of assets purchased by the creation of central bank reserves (in millions GBP). This numbers are published with a weekly frequency by the Bank of England (Asset Purchase Facility). The time series start from March 2009 and end in September 2012.

4.2.5 DESCRIPTIVE STATISTICS

The Table 16 and Table 17, provide a summary of the number of bond-daily prices in various categories. We have 87,197 short-term, 90,880 medium-term, 68,079 long - term prices. From Table 17, it can be seen that the Consumer Services (73,860) and Financial (68,191) sectors have the largest number of data points, while Technology sector has the least (770). The greatest portion of all transactions (70%) fall within the A and BBB rating categories. Our dataset does not contain long term data for Basic Materials and Technology sectors and the medium term bonds for Healthcare.

The Table 18 and Table 19 present the average corporate bond yield spreads across credit ratings, sectors, maturity and year of observation. Table shows that A-rated bonds have a yield 60bp higher than AAs, and BBB-rated bonds yield around 50bp higher than As. A similar observation holds for HY bonds. A surprising result is that medium-term bonds have higher spreads than long term bonds for all rating categories. This seems to be an effect due financial crisis, when shorter term debt was sometimes seen to be more risky than longer term debt.

Table 16

Number of transactions per rating, maturity bucket and years.

Maturity	AA	A	BBB	BB	B	Total
Short	3,136	34,159	43,711	2,870	3,135	87,197
Medium	891	42,879	43,240	2,371	1,499	90,880
Long	1,256	49,310	16,969	167	377	68,079
Years	**AA**	**A**	**BBB**	**BB**	**B**	**Total**
2003	283	9,518	8,903	205	226	19,135
2004	635	13,202	12,585	366	658	27,446
2005	753	14,188	12,108	290	739	28,078
2006	430	13,144	9,649	682	486	24,391
2007	352	11,429	9,868	972	625	23,358
2008	302	10,958	9,579	845	556	22,314
2009	525	14,181	11,051	751	464	26,972
2010	789	16,205	12,208	495	579	30,276
2011	908	15,628	11,973	502	476	29,487
2012	306	7,895	5,996	300	202	14,699

Table 17

Number of transactions in each sector.

Sector	Short	Medium	Long	Total
Basic Materials	987	62	N/A	1,049
Consumer Goods	9,015	9,062	555	18,632
Consumer Services	31,261	28,281	14,318	73,860
Energy	5,259	1,504	44	6,807
Financials	16,051	28,536	23,604	68,191
Healthcare	1,158	N/A	1,189	2,347
Industrials	7,234	5,691	2,624	15,549
Technology	174	211	N/A	385
Telecommunications Services	4,235	6,248	8,408	18,891
Utilities	11,823	11,285	17,337	40,445

Yield spreads of all credit ratings have a tendency of significant increase in 2008 and 2009 compare with the relatively stable period in earlier years (2003-2005). The size of the yield spreads rose almost 4 times at the peak of financial crisis. After 2009, spreads stay relatively high, and have shown a tendency to increase from 2012 onwards.

Table 18

Average corporate bond yield spreads in basis points by credit rating and years to maturity for all sectors.

Rating	Short	Medium	Long
AA	65.14	146.63	96.74
A	124.76	156.87	128.71
BBB	177.46	200.04	197.3
BB	374.08	291.9	227.48
B	599.72	313.58	158.35
Total	174.57	183.42	145.63
Sectors	**Short**	**Medium**	**Long**
Basic Materials	77.32	431.34	N/A
Consumer Goods	200.41	225.15	223.78
Consumer Services	228.32	187.3	126.65
Energy	75.89	85.11	136.65
Financials	173.13	205.84	174.96
Healthcare	34.12	N/A	97.68
Industrials	133.22	135.46	94.87
Technology	176.43	144.47	N/A
Telecommunications Services	127.16	174.81	175.01
Utilities	122.69	124.87	115.61

Table 19

Average yield spread per rating and year (basis points).

Years	AA	A	BBB	BB	B	Total
2003	31.77	90.22	118.7	195.45	124.68	104.14
2004	40.63	96.55	114.93	210.43	141.99	106.29
2005	33.35	88.76	116.2	131.02	129.33	100.61
2006	35.94	98.41	115.96	153.84	116.21	106.15
2007	78.63	112.93	129.99	162.5	147.11	122.72
2008	140.09	237.6	310.23	418.28	694.59	286.22
2009	124.38	235.08	360.99	748.06	1300.95	317.13
2010	106.05	114.02	194.78	359.71	575.09	159.21
2011	128.93	145.14	212.74	361.65	967.97	189.05
2012	147.2	165.28	259.66	369.68	1290.67	223.04

Figure 14 presents the aggregated investment grade yield spread for different maturity buckets. The graphs show that the aggregated yield spreads for different maturities behave in a similar fashion, and increase significantly during the period from 2007 to 2010. In analogy with US discussion, we see that spreads for long term debt drop below the spreads for short and medium debt in the period after 2008. This is an indication that short and medium term debts were perceived more risky than long term debt during the crisis.

Figure 15 presents aggregated average yield spreads for different rating (for IG bonds). We see that the yield spreads were relatively stable and small for the period between 2003 and mid 2007, when even BBB spreads were not higher than 100bp. Following this period of calm, bond spreads shot up. AA-rated bonds reached a peak of 210bp, A-ratings reached a peak of 400bp during the height of the crisis, and BBB reached a high of 530bp. In analogy with US market, overall across the rating categories and maturities, we observe a smaller peak at the beginning of 2008, followed by significantly larger peak at the beginning 2009. The first peak is attributed to the failure of Bear Stearns bank in March 2008, while the second peak can be seen as a consequence of the market nervousness associated with Lehman Brothers' bankruptcy and its aftermath.

Figure 14

Aggregated UK corporate yield spreads for different maturity buckets, 2003 to 2012. (%)

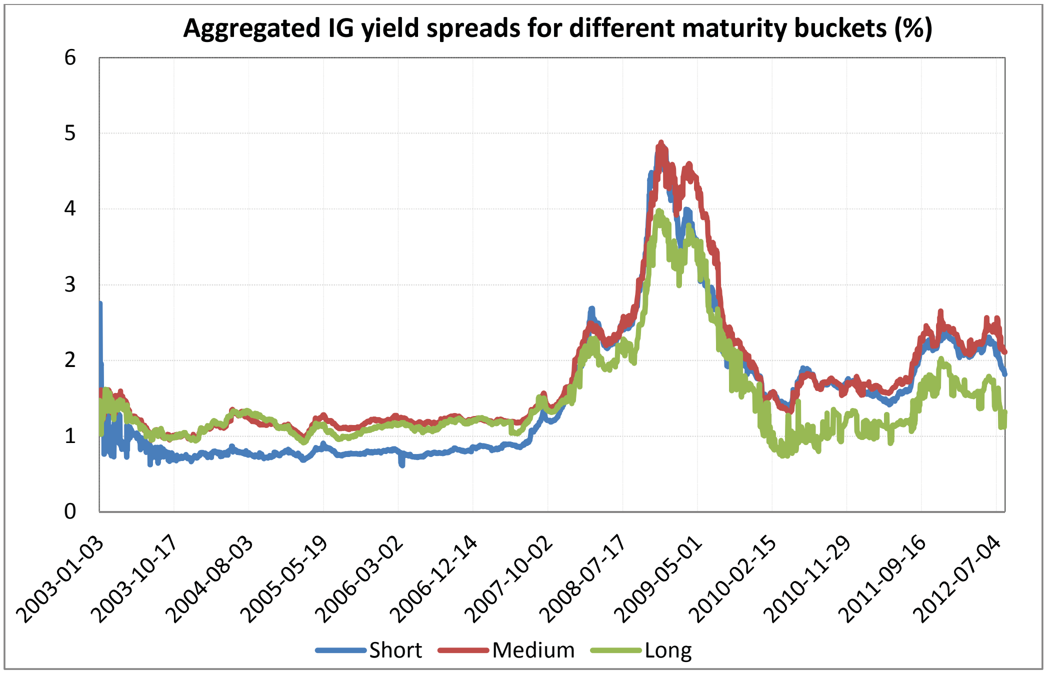
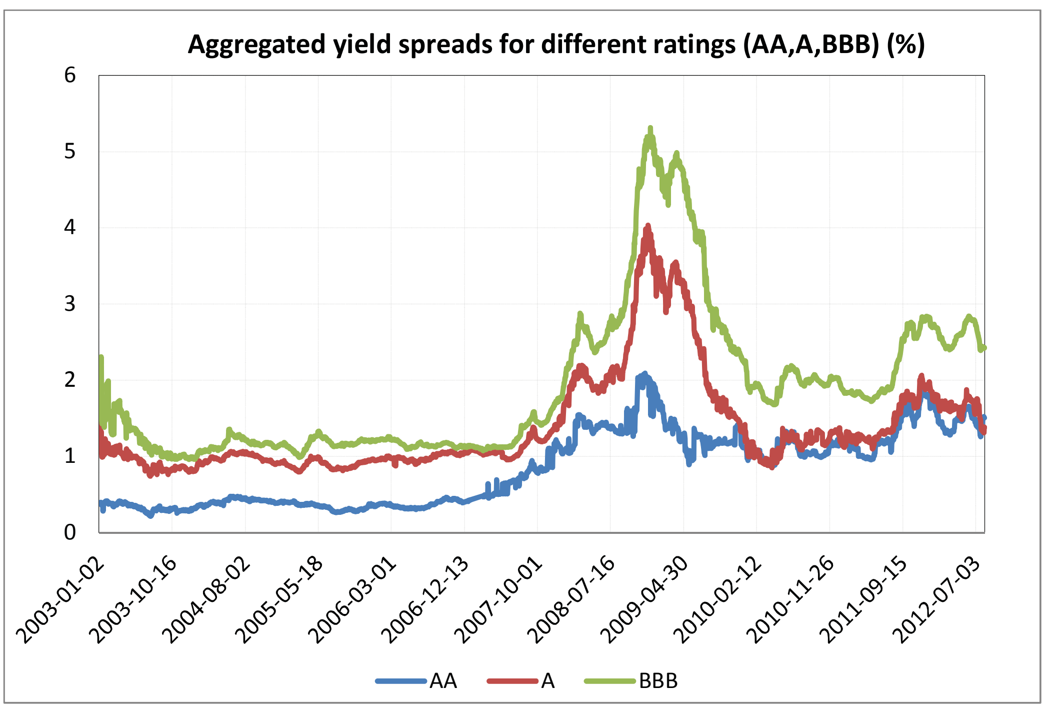


Figure 15

Average UK corporate yield spreads for different rating groups (AA, A, BBB), 2003 to 2012. (%)



In our analysis of UK corporate bond market we follow the methodology developed in Chapter 3. The reader is referred to subsection 3.5.1 for a detailed description. In order to have a self contained exposition but avoid repetition, below we summarize the main steps of our analysis:

I. We run ordinary least squares (OLS) regression for each sample bond *i* at date *t* with credit spread CS_t^i , the estimation equation is given by Formula (9) in Chapter 3. We estimate regression separately for different rating categories (IG and HY). Our expectations on the sign of the effect is provided in table below:

Independent Variables	Expected sign
STDV of excess return	+ (positive)
Firm Capital to Market Capital	- (negative)
Operating income to sale	- (negative)
Total Debt to Capitalization	+ (positive)
Level of Term Structure	- (negative)
TED Spread (proxy of market liquidity)	+ (positive)
Coupon	+ (positive)
Years to Maturity	- /+

II. We analyze the difference between spread determinants for financial and industrial (non-financial) sectors. In order to investigate the effect of Lehman's bankruptcy on credit spreads, separate our dataset into two subsets corresponding to time periods before and after Lehman's collapse, and separately run a regression for each subset.

III. We incorporated the quantitative easing (QE) variable in our regressions, in order to analyze how this policy affected the yield spreads. We estimated our regressions for a period 2009 and 2012, when the QE policy was active.

IV. In order to analyze how firm capital structure interacts with other determinants of the yield spread we ran a regression incorporating non-linear effects.

V. Finally, we conducted a range of robustness checks. Firstly, we removed pure cross-sectional variation in issuer quality by estimating fixed effect for each bond issuer (IG bonds). We also estimate panel random effect and ran Hausman test in order to compare the two panel data approaches. Secondly, we looked at the robustness and stability of our results by running regressions on randomly chosen subsamples of the data. Thirdly, in order to verify the stability of our results, we looked at the determinants of spreads during the period prior to the crisis. Fourthly, we looked at the determinants of credit spreads, taking par asset swap spreads and CDS spreads as alternative proxies.

4.3.1 ESTIMATION RESULTS

Table 20 presents results of the regression of corporate bond yield spreads against the various determinants for UK corporate bonds. The data consisted of daily spreads for 102 issuers, covering a period between 2003 and 2012. The regression coefficients are given in basis points (bp), with the associated t-statistics given in the parentheses. The standard errors of estimated parameters were adjusted using Newey-West method (Newey & West, 1987).

The sensitivity to *standard deviation of excess returns* is 60bp (column 2). This result is stable and highly statistically significant for all the variations of the regression (columns 2,4,6 and 8). As expected the sign of the coefficient is positive. Similarly, the *firm to market capitalization* estimate coefficient has an expected negative sign and stays highly statistical significant across all variations of the regression. The rating dummy variables for average rating (BBB) have positive and highly significant coefficient. On the other hand, average rating (A) dummy coefficient turns negative in regressions 4 and 8. Accounting variables such as *operating income to sales* and *total debt to capitalization* show expected signs for the regression coefficients. The coefficients for the macro variables, *level of term structure* and *TED spread*, also show expected signs and are highly statistical significance.

We note that macroeconomic variables and bond characteristics together explain just 33% of variation in bond spreads (see adjusted R-squared in column 1). The addition of equity variables to the regression increases the adjusted R-squared by 14% (column

2). The regression of spreads with either credit ratings (column 3) or accounting variables (column 5) produces an equivalent adjusted R-squared of roughly 35%, and implies that the explanatory power of the two sets is almost equivalent. Equity variables combined with credit ratings (column 4) improve explanatory power by 3% compared to a regression with equity variables alone. Therefore, credit ratings appear to contain at least some information, above that contained in equity data.

In addition to analysis of the IG group, we also performed our regression analyzes for HY bonds. The Table 21 presents results for the HY group, consisting of bonds with ratings lower than BBB (i.e. BB and B). As in the case for US HY group and in line with predictions of Merton's model, we see that sensitivity of spreads to the various factors is significantly larger than for investment grade bonds. For example, the sensitivity to *STDV of excess return* was roughly 150bp for HY bonds as compared to 60bp for IG category. Estimate coefficients for accounting, rating, macro variables are also typically 3 to 5 times larger for the HY group. The sensitivity to Gilt rates changes from 27bp for IG grade to 226bp for HY grade. This finding is in line with Duffie (1998) who showed that spreads have a negative sensitivity to Gilt rates, with sensitivity proportional to initial credit quality of the bond.

In terms of explanatory power for HY category, we see that equity volatility, relative market capitalization and macro variables (column 2) explain almost as much of variation in yield spreads as all variables taken together (column 8). For the HY corporate bonds, equity volatility is much more informative than credit ratings or accounting variables. This is further evident by comparing adjusted R-squared regression in column 2 (81%) on the one hand with that for regressions in column 3 (47%) and column 5 (58%) on the other. This finding most likely points to the fact that equity price data reflects latest and continuous updated information whereas ratings and accounting data are lagged in time. Surprisingly, comparing adjusted R-squared in columns 3 and 5 for HY bonds, we see that credit ratings explain less of the spread than accounting variables. This is in contrast to IG bonds, where the explanatory power of both variables was almost equivalent (column 3 and 5 in Table 20).

In order to have an estimate for the economic significance of various spread determinants for IG and HY groups, in Table 22 we present a decomposition of the variation of credit spread for the various determinants. The table shows that, for both IG and HY categories, the largest contributions to credit spread variations come from firm specific volatility, the Gilt rate level and the TED spread. The analysis of the table leads to the following conclusion. Firstly, equity volatility is important determinant of the corporate yield spreads for IG and HY categories. Secondly, size of the effect increase significantly for HY grade. Equity volatility and macro characteristics explain 80% of total variation in spreads for HY bonds. Thirdly, considered together, our explanatory variables explain 51% of spread variation for IG bonds (column 8 in Table 20) and 81% for HY bonds (column 8 in Table 21).

Table 20
Structural Model Determinants of Corporate Bond Yield Spreads for Investment Grade Bonds

Using panel data between 2003 and 2012 for UK corporate bond market, we regress investment grade corporate bond yield spreads against the list of variables (represented in the first column of the table). The Columns presents different specification of regression (with various combination of independent variables). The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	1	2	3	4	5	6	7	8
STDV of excess return		**60.24** (33)		**60.32** (33)		**57.21** (34)		**57.03** (34)
Capital of Firm to Capital of Market		**-14.1** (-38)		**-12.43** (-33)		**-12.08** (-44)		**-8.78** (-35)
Downgrade from AA to A			**40.57** (40)	**-20.98** (-19)			**8.89** (14)	**-25.72** (-22)
Downgrade from AA to BBB			**85.63** (53)	**18.29** (18)			**60.55** (72)	**19.72** (21)
Operating-income to sale					**-0.45** (-36)	**-0.19** (-24)	**-0.39** (-31)	**-0.16** (-19)
TD to capitalization					**1.4** (31)	**0.6** (18)	**1.67** (33)	**1.01** (27)
Treasury Rate Level	**-27.52** (-19)	**-27.1** (-34)	**-28.23** (-19)	**-27.42** (-33)	**-26.05** (-20)	**-26.34** (-36)	**-26.9** (-21)	**-26.59** (-35)
TED Spread	**163.18** (25)	**118.08** (30)	**160.9** (24)	**116.64** (29)	**157.39** (27)	**117.93** (33)	**154.47** (27)	**115.34** (32)
Coupon	**17.87** (31)	**13.99** (28)	**13.39** (26)	**10.88** (25)	**17.26** (31)	**14.22** (30)	**12.33** (26)	**10.82** (26)
Years to Maturity	**-0.16** (-2.5)	**-0.1** (-1.9)	**0.44** (7.3)	**0.49** (9.1)	**-0.55** (-8.5)	**-0.26** (-4.9)	0.07 (1.2)	**0.29** (5.7)
Constant	104 (13)	66 (14)	70 (8.8)	82 (18)	81 (11)	55 (11)	70 (10)	62 (14)
R-squared	**0.33**	**0.47**	**0.36**	**0.5**	**0.36**	**0.48**	**0.4**	**0.51**
Number of transactions	235540	235540	235540	235540	235540	235540	235540	235540

Table 21
Structural Model Determinants of Corporate Bond Yield Spreads for High Yield Bonds

Using panel data between 2003 and 2012 for UK corporate bond market, we regress speculative corporate bond yield spreads against the list of variables (represented in the first column of the table). The Columns presents different specification of regression (with various combination of independent variables). The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	1	2	3	4	5	6	7	8
STDV of excess return		**150.91** (17)		**151.2** (18)		**145.37** (17)		**146.2** (17)
Capital of Firm to Capital of Market		**-1188.3** (-7.2)		**-931.65** (-6.5)		**-914.78** (-5)		**-692.79** (-5)
Downgrade from BB to B			**197.99** (8)	**48.08** (3.5)			**80.45** (5)	**42.88** (3.2)
Operating income to sale					**-18.36** (-10)	**-3.48** (-5)	**-16.63** (-10)	**-3.14** (-4.2)
TD to capitalization					**11.84** (8.9)	**1.72** (2)	**10.69** (8.3)	**1.74** (2.1)
Treasury Rate Level	**-226.9** (-9.1)	**-147.91** (-11)	**-225.1** (-9)	**-151.25** (-11)	**-258.5** (-14)	**-160.8** (-13)	**-254.8** (-13)	**-162.6** (-12)
TED Spread	**382.02** (6.9)	**111.61** (4.2)	**405.25** (6.8)	**124.53** (4.4)	**246.02** (6)	**105.37** (4)	**268.45** (6.4)	**117.09** (4.2)
Coupon	**50.42** (4)	14.73 (1.6)	**46.73** (4.5)	**19.24** (2.1)	**32.17** (4.4)	16.51 (1.6)	**32.35** (5)	**21.13** (2.1)
Years to Maturity	**-5.36** (-2.7)	1.1 (1.3)	**-7.31** (-3.7)	-0.27 (-0.3)	**14.23** (4.4)	**4.59** (2.9)	**11.63** (4)	2.65 (1.7)
Constant	910 (5.7)	678 (7.2)	841 (5.7)	609 (7)	1083 (10)	688 (6.4)	1042 (10)	616 (6.5)
R-squared	**0.41**	**0.81**	**0.47**	**0.81**	**0.58**	**0.81**	**0.59**	**0.81**
Number of transactions	10409	10409	10409	10409	10409	10409	10409	10409

Table 22
Effect decomposition for each variable on yield spread

Table below reports the contribution of various to variation in yield spreads. Columns 2 and 4 represent standard deviations of each variable for IG and HY. Columns 3 and 5 report the effect of each variable on yield spread for IG and HY category in basis points. In order to calculate the contribution of each variable to yield spread variation, we multiply standard deviation of each variable by its estimate coefficient from Tables 20 (column 9) and Table 21 (column 9).

	IG		HY	
Variable	**SD of Variable**	**SD*Estimate Coefficient (bp)**	**SD of Variable**	**SD*Estimate Coefficient (bp)**
Yield Spread	125 bp		404 bp	
STDV(excess RET)	0.76	**43**	1.65	**241**
Capital of Firm to Capital of Market	1.39	**-12**	0.06	**-42**
Downgrade from AA to A		**9**		
Downgrade from AA to BBB		**60**		
Downgrade from BB to B				**43**
Operating income to sale	38.4	**-6**	13.2	**-41**
TD to Capitalization	14.1	**14**	13	**23**
Treasury Rate Level	0.82	**-22**	0.78	**-127**
TED Spread	0.38	**44**	0.4	**47**

SPREAD DETERMINANTS BEFORE AND AFTER LEHMAN'S BANKRUPTCY

In this subsection we look at the behaviour of credit spreads and their determinants, for financial and non-financial sectors, before and after the collapse of Lehman Brothers'. For this purpose, we divide our dataset into pre (January 2003 to August 2008) and post (October 2008 to August 2012) Lehman periods, and run our regressions for each subset individually. The results of the regression are given in Table 23. We firstly focus on the results for financial sector. Results show that after Lehman collapse the explanatory power of all variables decreases by 2-3% (see adjusted R-squared in columns 1, 2, 5 and 6). Overall, this results is consistent with our findings for the behaviour of the financial sector in US corporate bond market, where the effect was more prominent (decrease by 10%). Following the arguments for US market, the reduction in explanatory power can be understood as result of growing market consensus that big financial institutions will not be allowed to fail by the government.

The sensitivity of spreads to *firm capital to market capital* has an unexpected positive sign before Lehman's collapse, but changes sign to negative after Lehman's demise. This can be understood as follows. The UK financial sector data primarily comes from contributions of large financial companies that were similar to Lehman's. Prior to Lehman's collapse, there was a growing concern that these big companies could go bust. However, following Lehman's bankruptcy, on 13 October 2008, the UK Treasury infused 37 billion GBP into Royal Bank of Scotland Group, Lloyds TSB and HBOS Plc in order to protect UK financial sector from collapse. The fact that government guaranteed the big financial companies made them look relatively less risky than their smaller counterparts. We note that the equity volatility of the large financial companies, both in US and UK, was artificially reduced by a ban on short selling during the final quarter of 2008. This could explain the fact that the sensitivity of spreads to equity volatility increased by a factor of 1.5 for the period after Lehman's.

Turning to ratings as a determinant spreads, we notice that the coefficient for A-rating dummy changes sign to negative for the financial sector in the post-Lehman period. After Lehman's collapse, many of the previously AA-rated banks were downgraded to A-rating. For example, according to the Credit Report provided by S&P in January 2009 rating agency affirmed its A+/A-1 long and short-term counterparty credit rating on the Royal Bank of Scotland PLC (RBS) with related entities and A/A-1 on Lloyds Banking Group PLC. However, although these firms were downgraded, there was a growing market confidence that these institutions were too-big-to-fail, and would therefore not be allowed to default. For this reason, A-rating became associated with less risky companies, and as a result narrower spreads.

The results for UK non-financial sector show a qualitatively different behaviour. Table 23 shows that the explanatory power of all variables significantly increases after Lehman Collapse, by almost 25% (see adjusted R-squared in columns 3, 4, 7 and 8). Regression of spreads on equity volatility alone (columns 4 and 8) shows an increase in adjusted R-squared of 24% after Lehman's. The coefficient for *STDV excess return* increases by 80bp and its t-statistics rises almost 3 times. Thus, equity volatility becomes an even more important determinant of corporate yield spread for non-financial sector after Lehman's default. Also, note that the sensitivity of spreads to equity volatility becomes over 2 times higher for the non-financial sector in comparison with the financial sector after Lehman's. Finally we note that, credit rating does not significantly contribute to explanatory power of regression for financial sector for both periods. However, this is different for non-financial sectors, where adjusted R-squared increases by 6-7% when credit rating is included into the regression. We conclude that credit rating explains more of the yield spread for non-financial companies than for financial companies.

Table 23
Comparative table of yield spread determinants Before and After Lehman Collapse for Financial and Non-financial sectors

Using panel data between 2003 and 2012 for UK corporate bond market, we regress corporate bond yield spreads (IG) against the list of variables (represented in the first column of the table). Regression was taken for periods before Lehman collapse (2003 to August 2008) and after Lehman collapses (form October 2008 to August 2012) separately for financial and non-financial companies. The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

Variable	Before Lehman Collapse				After Lehman Collapse			
	Financial		Non-financial		Financial		Non-financial	
	1	2	3	4	1	2	3	4
STDV of excess return	**42.54** (12)	**41.81** (12)	**56.34** (13)	**64.11** (15)	**72.1** (15)	**67.97** (15)	**136.45** (48)	**182.71** (58)
Capital of Firm to Capital of Market	**26.79** (19)	**24.54** (23)	**-1.08** (-7.2)	**-6.18** (-38)	**-21.01** (-18)	**-12.19** (-13)	**-5.67** (-20)	**-18.59** (-42)
Downgrade from AA to A	**22.23** (4)		**10.83** (15)		**-59.67** (-9.3)		-2.23 (-1.7)	
Downgrade from AA to BBB	**17.91** (3.1)		**45.65** (38)		**-5.47** (-1.2)		**70.26** (35)	
Operating income to sale	**-0.05** (-3.7)	**-0.07** (-5)	**-0.32** (-12)	**-0.54** (-20)	**-0.07** (-3.9)	**-0.13** (-8)	**0.22** (8)	0.06 (1.65)
TD to capitalization	**1.84** (7)	**1.82** (7)	**0.36** (8)	**0.21** (4.4)	**2.05** (10)	**1.68** (9)	**0.43** (10)	**-0.43** (-9)
Treasury Rate Level	1.83 (0.75)	**1.45** (0.57)	-3.8 (-1.4)	-1.65 (-0.57)	**-30.18** (-10)	**-29.18** (-10)	**-34.19** (-33)	**-43.09** (-31)
TED Spread	**102.06** (14)	**102.88** (14)	**112.32** (16)	**115.01** (16)	**116.78** (14)	**121.62** (14)	**58.39** (21)	**31.17** (9)
Coupon	**2.36** (7.6)	**2.22** (8)	0.41 (-1.5)	**1.89** (8)	**31.11** (22)	**34.66** (26)	**27.57** (43)	**37** (45)
Years To Maturity	**2.43** (27)	**2.45** (27)	**1.67** (28)	**1.34** (20)	**-0.89** (-5.7)	**-1.13** (-8.7)	**-2.71** (-43)	**-4.44** (-47)
Constant	-96 (-6.7)	-70 (-6)	-10 (-0.7)	2.8 (0.19)	-32 (-2.1)	-84 (-5.3)	-115 (-28)	-102 (-18)
R-squared	**0.61**	**0.6**	**0.51**	**0.45**	**0.59**	**0.57**	**0.76**	**0.69**
Number of transactions	33603	33603	103459	103459	30261	30261	73118	73118

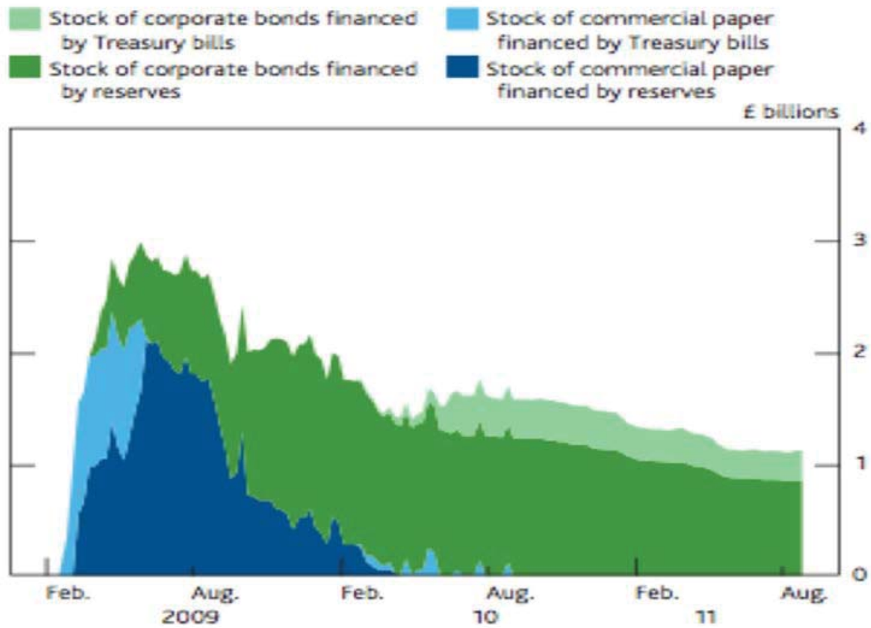
Why quantitative easing period might be important for credit spreads?

After the bankruptcy of Lehman Brothers (15 September 2008) the confidence in the world economy has failed, credit conditions were tightened and international financial markets were in panic. In order to response to intensification of the financial crisis, Bank of England, following some of the other central banks, took measures to loosen monetary policy and support demand. Firstly, The Bank gradually lowered interest rate to 0.5%. Secondly, they announced a program of large-scale purchase of public and private assets. The main purpose of this program was to inject money in to UK economy in order to stimulate nominal spending and achieve the 2% inflation target. This policy of injecting money into the economy, by effectively increasing the size of the Bank's balance sheet through purchasing assets financed by bank's money, is known as quantitative easing (QE). The main focus of the bank falls on purchasing large amount government gilts (UK government bond). However, in order to improve functioning of financial markets it also included purchase of high-quality commercial papers and corporate bonds (Joyce, Tong, & Woods, 2011). According to Bank of England Quarterly Bulletin 2011 (Joyce, Tong, & Woods, 2011), 200 billion GBP worth of assets were purchased in total (see Figure 16).

One of the effects of QE on economy is that it pushes up prices of assets bought as well as the prices of other assets. This mechanism works in following way, bank purchases assets and seller's money holding are increased. It changes the composition of the portfolios held by private sector in the direction of increased holding of broad money and decreased holding of long and medium –term gilts. Due to the fact that money and gilts are not perfect substitutes sellers may want to rebalance their portfolios by buying other assets- such as corporate bonds and equities or foreign assets - that are better substitutes. This is known as portfolio balance effect. This process will put upward pressure on the price of those assets. According to Joyce, Lasaosa, Stevens and Tong (2011) corporate yield spreads (both IG and HY) were flat around QE announcement, but went down significantly over the period of QE.

Figure 16

Amounts of purchases of corporate bonds and commercial paper during Quantitative Easing.



Source: Bank of England Quarterly Bulletin 2011 Q3

As discussed above, QE mainly involved the purchase of government securities and, to a smaller degree, commercial paper and corporate bonds. Thus, the direct effect of this purchasing process should be an increase in the prices of government bonds (reduction in their yields). As a result, we might expect of widening of spread due to the reduction of risk free yield in comparison with risky yield. On the other hand, there is an indirect effect of QE, due to rebalancing of investors' portfolios who purchase new assets to replace government bonds they sold to BoE. This would also involve purchasing corporate bonds. As a result QE changes yields on corporate debt by increasing liquidity in corporate bond market. Indirect effect leads to the increase in price of corporate bonds (fall in corporate yield spread) and we might expect reduction in the spreads. This analysis shows that there are two competing effects due to QE which drive yield spreads in opposite directions. However, the direct effect should dominate the indirect effect. This is because, re-balancing and other purchases may involve many other different asset classes, with only a small proportion belonging to corporate debt. Thus, if direct effect actually dominates indirect effect, then spreads should widen. If not, we would expect to see a very small spread reduction effect.

In order to study the effect of QE on UK corporate credit spreads, we regress our dataset of IG yield spreads for the period between March 2009 (corresponding to the start of QE) and August 2012, using all of the explanatory variables considered above and an additional variable characterizing QE. The corresponding QE proxy, *QE (weekly)*, is the quantity of assets purchased by the BoE over the week in millions GBP. Table 25 presents results of the regression.

Our results show a statistically significant negative relation between the corporate credit spreads and the amount of QE. The magnitude of the coefficient in column 8 suggests that a QE of 1billion GBP would lead to a 0.2bp fall in spreads. Given that the total QE for this time period summed to an amount 340 billion GBP approximately, the aggregate effect on spreads amounted to approximately 70bp. Our results show quite significant reduction of spreads due to the QE. This brings us to a puzzle, whereby the indirect effect of QE seems to dominate over the direct effect. Our investigation has not provided a clear explanation of this effect, and a study of this puzzle is an interesting avenue for further research.

The Table 24 present correlation coefficients for macro variables in period of quantitative easing. We note that the correlation between QE and treasury rate level variables is quite high. This is an indication of another indirect channel, through macro variables, for the effect of QE on bond spreads.

Table 24
Correlations of macro variables between 2009 and 2012

Variables	Treasury Rate Level	TED Spread	QE (weekly)
Treasury Rate Level	1	-0.57	-0.62
TED Spread	-0.57	1	-0.17
QE (weekly)	-0.62	-0.17	1

Table 25
Determinants of corporate bond yield spread in period of QE

Using panel data between 2009 and 2012 for UK corporate bond market, we regress corporate bond yield spreads (IG group) against the list of variables (represented in the first column of the table). We include in to regression additional variable QE (weekly). Column 2 to 9 presents different configurations of regression. The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	1	2	3	4	5	6	7	8
STDV of excess return		**46.6** (24)		**49** (28)		**43** (22)		**46.4** (25)
Capital of Firm to Capital of Market		**-20.7** (-38)		**-17.9** (-45)		**-18.7** (-53)		**-14.6** (-44)
Downgrade from AA to A			**47.3** (17)	**-11.3** (-7.6)			**16** (11)	**-22** (-15)
Downgrade from AA to BBB			**98** (36)	**39** (24)			**73** (27)	**34.7** (20)
Operating income to sale					**-0.39** (-44)	**-0.22** (-22)	**-0.34** (-39)	**-0.18** (-19)
TD to capitalization					**1.2** (27)	**0.5** (13)	**1.57** (40)	**1.01** (31)
Treasury Rate Level	**-13.1** (-5)	**-20** (-12)	**-13.7** (-5)	**-21** (-11)	**-13.9** (-7)	**-20** (-11)	**-14.41** (-6.7)	**-21** (-12)
QE (weekly)	**-0.0005** (-20)	**-0.0002** (-13)	**-0.0005** (-20)	**-0.0002** (-12)	**-0.0004** (-23)	**-0.0002** (-12)	**-0.0005** (-21)	**-0.0002** (-12)
TED Spread	**198** (22)	**145** (25)	**193** (21)	**140** (23)	**187** (28)	**143** (24)	**183** (24)	**136** (23)
Coupon	**42.1** (30)	**37.5** (32)	**35.6** (34)	**31.2** (37)	**42** (32)	**38** (30)	**35** (40)	**31.6** (24)
Years To Maturity	**-2.2** (-27)	**-2.1** (-26)	**-1.6** (-21)	**-1.58** (-26)	**-2.6** (-27)	**-2.3** (-31)	**-2** (-25)	**-1.79** (-20)
Constant	30 (2)	-10 (-1.3)	1.3 (0.08)	8 (0.7)	3.3 (0.2)	-18 (-1.7)	-2.2 (-0.18)	-34 (-3.1)
R-squared	**0.33**	**0.45**	**0.37**	**0.48**	**0.37**	**0.46**	**0.4**	**0.49**
Number of transactions	93814	93814	93814	93814	93814	93814	93814	93814

INTERACTION EFFECT

Following the analysis of interaction effect for US corporate credit spreads (see section 5.2 in Chapter 3), we have performed an analogous analysis for the UK market. The interaction variables chosen were *long term debt to assets* and *total debt to capitalization*. Two separate interaction variables, both proxying leverage, were considered in order to test consistency of the results. The variables were tested for interaction with *standard deviation of excess return* and the *benchmark gilt rate*. Table 26 presents results for different configurations of the regression. The columns show estimation results for different configuration of regression. Results show highly significant positive estimate coefficient for both leverage variables with standard deviation of daily excess return, in line with predictions of Merton's structural model. We note that, even allowing for interaction effect, equity volatility continues to play an important role in determining corporate credit spreads, as reflected in the higher adjusted R-squared in columns 2 and 3. Overall, we find that the signs and the magnitudes of the interaction effect as well as other determinants are consistent with results for US markets presented Chapter 3 and earlier analysis of Campbell and Taksler (2003).

Table 26
Interaction effects regression

Using panel data between 2003 and 2012 for UK corporate market, we perform regression of corporate bond yield spreads against the list of variables (represented in the first column of the table). The chosen interaction variables are long-term debt to assets and Total debt to capitalization. The regressions included interaction Variable * STDV of excess return and Interaction Variable * Treasury Rate Level as the non-linear variables. The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	Long-term debt to assets		Total debt to capitalization	
Interaction effects				
Interaction Variable * STDV of excess return		**1.62** (26)		**0.77** (20)
Interaction Variable * Treasury Rate Level	**-0.38** (-22)	**-0.67** (-29)		
Equity volatility				
STDV of excess return (over180 days) (%)		**22** (13)		**33.02** (25)
Market capitalization (%) (relative to CRSP-value weighted index)		**-10.53** (-32)		**-10.72** (-35)
Credit rating				
Downgrade from AA to A	**10.4** (16)	**-18.82** (-18)	**28.85** (20)	**-22.26** (-21)
Downgrade from AA to BBB	**72.2** (58)	**23.97** (28)	**70.09** (49)	**24.29** (30)
Accounting variables				
Operating income to sales (%)	**-0.36** (-28)	**-0.03** (-3.2)	**-0.36** (-30)	**-0.09** (-10)
Long-term debt to assets (%)			**0.61** (22)	**0.5** (10)
Total debt to capitalization (%)	**3.01** (30)	**1.04** (19)		
Macroeconomic and other variables				
Level Term Structure (%)	**-15.74** (-11)	**-7.75** (-9)	**-27.13** (-21)	**-27.21** (-37)
TED Spread (%)	**151.31** (26)	**107.06** (31)	**159.49** (28)	**116.08** (32)
Coupon (%)	**11.21** (23)	**10.52** (24)	**13.61** (29)	**10.71** (26)
Years to Maturity	**0.14** (2.6)	**0.36** (7)	**0.32** (5.6)	**0.41** (9)
Constant	36 (5)	45 (10)	69 (10)	106 (25)
Adjusted R-squared	**0.41**	**0.53**	**0.37**	**0.51**
Number of transactions	235538	235538	235538	235538

4.3.2 ROBUSTNESS CHECK

In order to test the robustness of our results and conclusions we have performed a range of tests. In this section we give a description of our approach methods and list the results. Our approach will closely follow the approach followed in Chapter 3. For this reason, we will skim quickly over motivations and implementation details and mainly focus on presenting results. We refer the reader to Chapter 3 for the further details.

FIXED EFFECT

In order to take into account time-specific and issuer-specific variation in our dataset we have performed a fixed effect panel estimation for our dataset. We included issuer specific dummies to account for issuer specific variations and monthly time dummies to account for time-series variations. Firstly, we performed the Hausman test to justify the use of fixed effect regression. The test produced p-value < 0.05, consistent with fixed effect estimation. Table 27 gives results for regressions for the fixed effect regression. The fixed effect estimate coefficients have an interpretation of spread changes over time, per issuer, as the corresponding determinant increases by one unit (typically percent). Overall, all other determinant's estimate coefficients have expected signs and consistent with previous findings. Furthermore, equity volatility continues to play an important role in explaining spreads.

Table 27

Regression with Issuer Fixed Effect

Using panel data between 2003 and 2012 for IG rating category of UK corporate market, we perform regression with fixed effect for each bond issuer of corporate bond yield spreads against the list of variables (represented in the first column of the table). The standard errors of estimated parameters are adjusted using Driscoll and Kraay method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	Fixed effect (within)
STDV (excess RET)	**58.27** (7.2)
Capital of Firm to Capital of Market	**-20.73** (-2.7)
Operating income to sale	-0.09 (-1.6)
TD to capitalization	**3.23** (4.8)
Level Term Structure	**-12** (-5.3)
TED Spread	**95.58** (18)
Years To Maturity	**-5.61** (-4.4)
Total Sum of Squares	206,850
Residual Sum of Squares	81,375
R-Squared	**0.61**
Number of panels	235
Number of observations	235,551

RANDOM SUBSAMPLING

In order to test the robustness and significance of our results, following the approach in Chapter 3, we ran multiple regressions on randomly chosen subsamples of our data. We refer the reader to page 90 for a detailed description of the methodology. The histograms below present distribution of the estimate coefficients and t-statistics for different spread determinants for IG bonds. We restrict ourselves to a presentation of histograms for equity characteristics and R-squared. The histograms for other explanatory variables can be found in Appendix 1, part C. Similar results hold for HY bonds. The analysis shows that all of the considered spread determinants show a consistent sign and significance across the samples. In particular, equity volatility coefficient is consistently estimated with a positive value in the region of 57bp, and shows a significant t-statistics with an average of 45. Finally, the histogram for adjusted

R-squared (Figure 18) shows that the chosen determinants consistently explain around 50% of variation in credit spreads.

Figure 17
Distribution of estimate coefficients and t-statistics for equity volatility and market capitalization

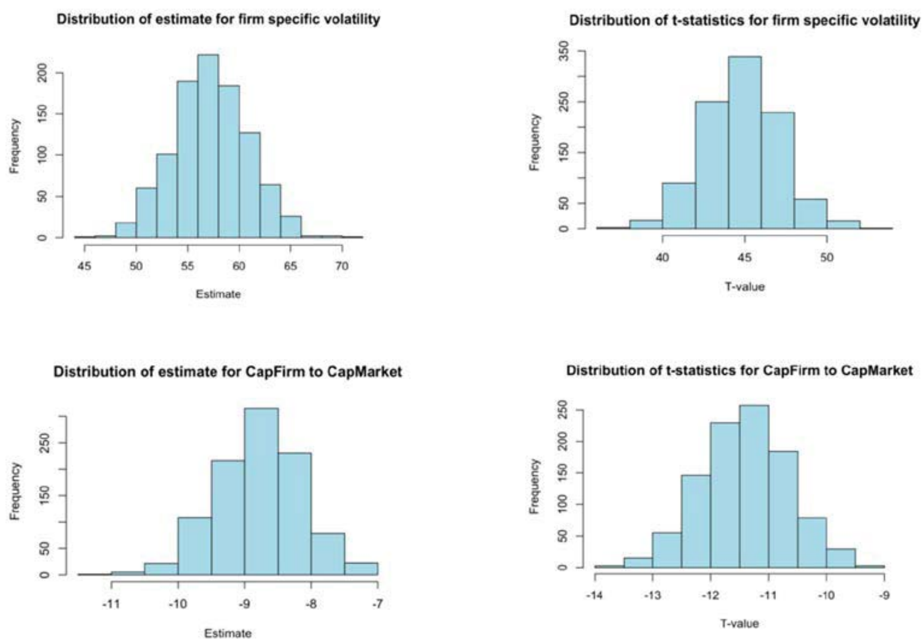
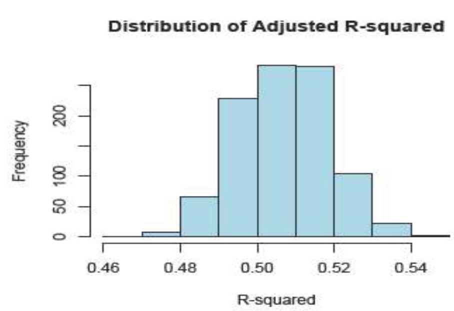


Figure 18
Distribution of explanatory power of regression



DETERMINANTS OF YIELD SPREADS IN THE PERIOD PRECEDING THE CRISIS

In the preceding sections we have studied the impact of various determinants on credit spreads, covering a period between 2003 and 2012. This timeframe included the period of global financial crisis that began in 2007. Following the reasoning and analysis in Chapter 3, as part of our robustness testing, we were interested in testing the validity of our results for the period prior to the financial crisis, corresponding to a stable state of the UK economy. For this purpose, we considered the time period between 2003 and mid-2007, when the average IG yields did not exceed 1%. Table 28 summarizes the results of regressions covering period calm for UK IG corporate bonds. Overall, we see results consistent with the regression covering the entire period (Table 20), although the adjusted R-squared typically falls by about 10%. In addition, all of the coefficients, including equity volatility, remain highly significant and have expected signs. Finally, we note that, adding equity volatility to the regression improves adjusted R-squared by 17%, which suggests that it stays important as determinant of credit spread even during relatively stable times.

Table 28
Determinants of corporate yield spread in the period preceding the crisis

Using panel data between 2003 and 2007 for UK corporate market, we perform regression of corporate bond yield spreads against the list of variables (represented in the first column of the table). Column 2 to 9 represents different configurations of regression (including and excluding some variables). The standard errors of estimated parameters are adjusted using Newey-West method. Associated t-statistics appears in parentheses beneath. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	1	2	3	4	5	6	7	8
STDV (excess RET)(%)		**25.89** (27)		**21.64** (21)		**24.84** (27)		**20.08** (21)
Capital of Firm to Capital of Market (%)		**-6.55** (-10)		**-4.37** (-6.2)		**-6.6** (-11)		**-3.46** (-59)
Downgrade from AA to A			**33.09** (12)	**6.03** (14)			**25.45** (7.2)	**7.25** (19)
Downgrade from AA to BBB			**62.16** (14)	**30.36** (58)			**55.27** (13)	**32.25** (68)
Operating income to sale (%)					**-0.33** (-23)	**-0.21** (-25)	**-0.23** (-20)	**-0.17** (-20)
TD to Capitalization (%)					**0.45** (29)	**0.03** (2.3)	**0.51** (29)	**0.27** (19)
Level Term Structure (%)	**-2.57** (-3.5)	**-3.16** (-2.8)	**-3.62** (-4)	**-3.83** (-3.4)	**-3.61** (-5.1)	**-3.5** (-3.3)	**-4.51** (-5)	**-4.43** (-4.1)
TED Spread (%)	**55.97** (5.6)	**100.97** (8)	**52.01** (4.3)	**90.24** (7.3)	**59.16** (6.1)	**100.29** (8.3)	**54.8** (5)	**89.21** (7.4)
Coupon (%)	**4.78** (54)	**2.41** (30)	**2.28** (24)	**1.34** (15)	**4.22** (47)	**2.38** (31)	**1.74** (19)	**1.19** (13.5)
Years To Maturity	**1.69** (10)	**1.59** (8.4)	**2.03** (11)	**1.98** (10)	**1.63** (9.9)	**1.69** (8.7)	**1.92** (11)	**1.95** (10)
Constant	55 (18)	43 (8.7)	27 (7.2)	36 (22)	61 (20)	49 (11)	36 (9.7)	37 (8.5)
R-squared	**0.14**	**0.29**	**0.31**	**0.38**	**0.18**	**0.3**	**0.34**	**0.39**
Number of transactions	105961	105961	105961	105961	105961	105961	105961	105961

CHECK FOR MULTICOLLINEARITY

In this subsection we investigated the multicollinearity between various explanatory variables. Collinearity of two variables corresponds to a situation where the two variables exhibit a high correlation with each other, and therefore their effect on the dependent variable cannot be decoupled. This leads to large uncertainties in the regression estimation coefficients.

For the analysis of multicollinearity we divided our dataset into two subsets, corresponding to period before QE and after. The QE was a major factor affecting the UK credit market, and had a major effect on various macroeconomic factors. In addition, for the study of multicollinearity, we have included *slope of term structure*. This variable is measured as the difference between yields on benchmark Gilts of 10yrs and 2yrs. Table 29 shows the correlation matrix for our variables for the two periods. The table shows that in the period prior to QE the determinants did not show a significant correlation with each other and with credit spreads. However, following the start of QE, we see a strong correlation of the *slope of term structure* with both *TED spread* (90%) and *level of term structure* (-71%). As a result, in order to avoid the problem of multicollinearity, we have decided not to include the *slope of term structure* variable in our regressions, despite the fact that it has been used in previous literature. The remaining determinants do not show a high level of correlation.

Table 29
Correlation matrix for all variables

Table presents matrix of correlations between the individual determinants of credit spreads and yield spread itself. Correlation matrix is given for periods before and after QE date (March 2009).

Before QE										
	1	2	3	4	5	6	7	8	9	10
1 .Yield Spread	1	0.66	-0.16	-0.08	0.18	-0.11	0.38	0.64	0.02	0.04
2. STDV (excess RET)	0.66	1	-0.1	-0.12	0.12	-0.1	0.55	0.48	0.05	-0.08
3. Capital of Firm to Capital of Market	-0.16	-0.1	1	-0.03	-0.36	0.01	0.04	0.01	-0.22	-0.04
4. Operating income to sale	-0.08	-0.12	-0.03	1	0.45	-0.02	-0.05	-0.03	-0.05	0.22
5. TD to Capitalization	0.18	0.12	-0.36	0.45	1	-0.01	0.14	0.07	0.03	0.25
6. Level Term Structure	-0.11	-0.1	0.01	-0.02	-0.01	1	-0.31	-0.08	-0.03	-0.02
7. Slope Term Structure	0.38	0.55	0.04	-0.05	0.14	-0.31	1	0.49	0.04	0.03

8. TED Spread	0.64	0.48	0.01	-0.03	0.07	-0.08	0.49	1	-0.09	-0.01
9. Coupon	0.02	0.05	-0.22	-0.05	0.03	-0.03	0.04	-0.09	1	-0.15
10.Years To Maturity	0.04	-0.08	-0.04	0.22	0.25	-0.02	0.03	-0.01	-0.15	1
After QE										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. Yield Spread	1	0.54	-0.29	-0.15	0.07	-0.07	-0.2	0.33	0.33	-0.17
2. STDV (excess RET)	0.54	1	-0.12	-0.21	0.1	0.18	-0.06	0.27	0.02	-0.03
3. Capital of Firm to Capital of Market	-0.29	-0.12	1	0.04	-0.28	-0.03	-0.03	0	-0.21	0.06
4. Operating income to sale	-0.15	-0.21	0.04	1	0	-0.01	0.04	-0.05	-0.02	-0.04
5. TD to Capitalization	0.07	0.1	-0.28	0	1	0.04	-0.02	0.08	-0.06	0.11
6. Level Term Structure	-0.07	0.18	-0.03	-0.01	0.04	1	0.9	-0.54	0.02	0.01
7. Slope Term Structure	-0.2	-0.06	-0.03	0.04	-0.02	0.9	1	-0.71	0.02	0
8. TED Spread	0.33	0.27	0	-0.05	0.08	-0.54	-0.71	1	-0.02	0.02
9. Coupon	0.33	0.02	-0.21	-0.02	-0.06	0.02	0.02	-0.02	1	-0.07
10. Years To Maturity	-0.17	-0.03	0.06	-0.04	0.11	0.01	0	0.02	-0.07	1

ALTERNATIVE PROXIES OF CREDIT SPREADS

In this subsection, following the path of analysis of US market, we report on the analysis of determinants of credit spreads for UK corporate using alternative proxies of credit risk. We look at two measures, namely Par Asset Swap spread (ASW) and Credit Default Swap spread (CDS).

Par asset swap spreads

As discussed previously in Section 3.5.3, the appropriate measure of credit risk strongly depends on the choice of risk free rate proxy. The bond yield spread considered up to this point was a spread over the UK treasury rate. The par asset swap spread, on the other hand, is a measure of spread over LIBOR, and is widely used in the industry. Table 30 presents the results multiple regressions using the ASW as a measure of credit spreads (we refer the reader to Section 3.5.3 for further motivations for this analysis). The results of this analysis are consistent with our previous findings in this chapter and mirror the results from Chapter 3. It is worth noting that, in comparison with regressions using bond yield spreads, the sensitivity to *TED spread* is smaller while sensitivity to the *Treasury level* is higher. This fact is a direct reflection of considering a spread over LIBOR in contrast to spread over treasury.

Table 30
Structural Model Determinants of Asset swap spread for UK corporate bond market

Using panel data between 2003 and 2012 for UK corporate bond market, we regress asset swap spread for IG and HY bonds against the list of variables (represented in the first column of the table). Columns 2 to 5 present regressions for IG group and column 6 to 9 for HY. The standard errors of estimated parameters are adjusted using Newy-West method and Driscoll and Kraay method for panel regression. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	IG				HY			
	Pooled OLS	Pooled OLS	Fixed Effect	Random Effect	Pooled OLS	Pooled OLS	Fixed Effect	Random Effect
STDV (excess return) (%)	**58.46** (33.6)	**56.13** (33)	**55.66** (7.5)	**55.54** (7.5)	**98.82** (17.2)	**95.17** (17.2)	**99.95** (8.5)	**100.63** (8.4)
Capital of Firm to Capital of Market (%)	**-10.09** (-33.9)	**-4.86** (-22.8)	-9.4 (-1.4)	-9.19 (-1.4)	**-1088.8** (-7.5)	**-654.12** (-5.3)	-253.82 (-1.1)	-245.27 (-1.1)
Downgrade from AA to A		**-26.68** (-2.2)		-58.76 (-1.6)				
Downgrade from AA to BBB		**19.43** (17)		-31.11 (-0.8)				
Downgrade from BB to B						**31.21** (3)		54.02 (1.6)
Operating-income to sale (%)		**-0.09** (-12.3)	0.03 (0.1)	0.02 (0.04)		**-2.45** (-4.4)	**-8.3** (-3.3)	**-7.19** (-3.3)
TD to capitalization (%)		**0.94** (28.3)	**4.07** (7.9)	**4.06** (7.9)		**1.97** (3.5)	5.56 (2)	5.98 (2.4)
Level Term Structure (%)	**-51.89** (-41.2)	**-51.57** (-40.8)	**-21.77** (-8.8)	**-22.18** (-9)	**-148.9** (-13)	**-160.5** (-14.4)	**-98.04** (-4.2)	**-98.93** (-4.4)
TED Spread (%)	**90.47** (23.9)	**88.32** (24)	**59.61** (12.7)	**59.74** (12.8)	**68.68** (3.7)	**70.72** (3.7)	41.74 (1.5)	42.33 (1.5)
Coupon (%)	**19.44** (29.6)	**16.25** (27.9)		15.91 (1.9)	19.61 (2.7)	26.7 (3.6)		-13.39 (-0.5)
Years To Maturity	**1.31** (27.2)	**1.72** (38.5)	**-9.24** (-8.1)	**-9.04** (-8)	0.16 (0.2)	0.3 (0.2)	**-19.94** (-3.5)	**-18.76** (-3.5)
Constant	**95.36** (12.2)	**92.01** (12.5)		**37** (0.5)	**694.89** (9.3)	**623.09** (8.2)		**737.17** (2.7)
Number of transactions	223179	223179	223179	223179	10305	10305	10305	10305
R-squared	**0.5**	**0.53**	**0.64**	**0.64**	**0.79**	**0.8**	**0.82**	**0.82**

CDS spreads

An alternative measure of credit spread is given by the CDS spread. The CDS instrument and the corresponding spread were introduced in Chapter 1. In general, the corporate bonds and CDSs are traded in different markets. Although, there is an arbitrage argument that relating the relative pricing of credit risk in these markets, the relation holds only approximately (more on this in Chapter 5). For this reason, it is interesting to consider the determinants of credit spreads using CDS spreads as proxy, thereby in effect studying a different credit risk market (see Section 3.5.3 of Chapter 3 for more details). For the purpose of this study, the daily CDS spread data was obtained from MarkIt for the period from 2003 to 2011. We restricted our analysis to CDSs with modified restructuring clauses (MR) and five-years contracts, since these are the most liquid contracts (Blanco, Brennan, & Marsh, 2005), (Norden & Weber, 2009). Figure 19 shows the aggregate CDS spreads (5yr maturity) for different credit ratings. Overall, the behaviour of CDS spreads is quite similar to those of corresponding corporate bond yield spreads (see Figure 15), though the maximum is reached at a slightly lower level for CDS spreads. This already serves as an indication that the credit risks are not priced equivalently in the bond and CDS markets, particularly during the time of the financial crisis.

The Table 31 presents the results of regressions using CDS spreads as proxies of credit spreads. Firstly we note that, overall, the results are consistent with findings for bond yield spreads. The explanatory power of the regressions is comparable to the results with bond yield spreads and ASW. This is in contrast to our finding for the US market, where the explanatory power for CDS spreads was lower than the equivalent for bond spreads and ASW.

Figure 19

Aggregated CDS spreads (5yr maturity) for different rating groups (AA, A, BBB), 2003 to 2012 (in percent).

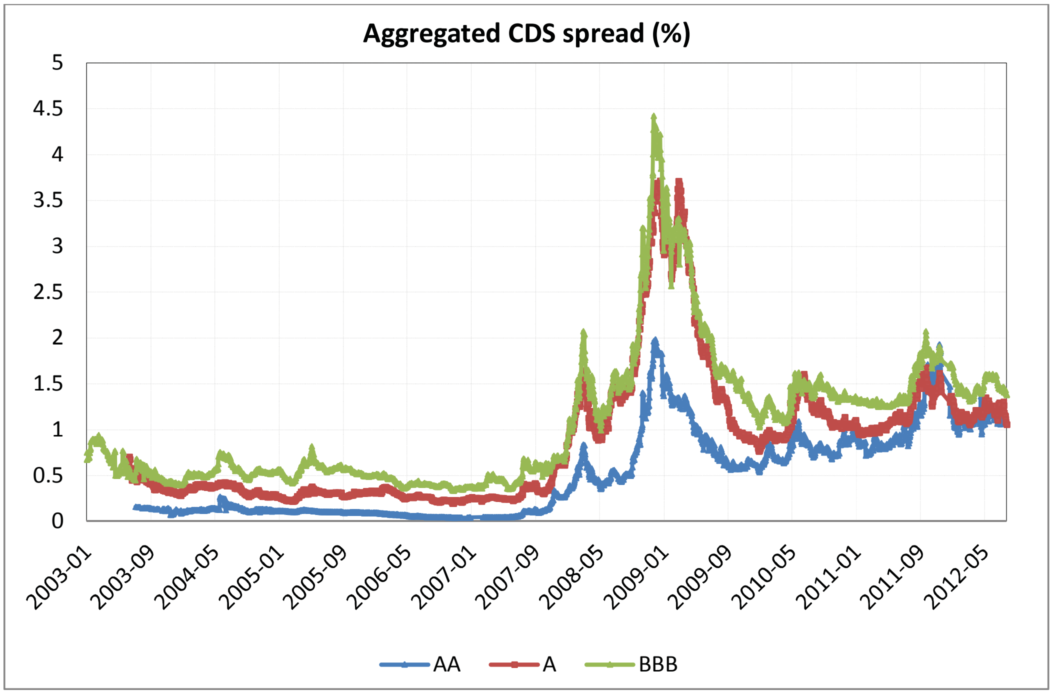


Table 31
Structural Model Determinants of CDS spreads for Investment Grade Entities

Using panel data between 2003 and 2012 for UK CDS market, we regress CDS spread (with 5 years maturity as most often traded) against the list of the variables which is determinants of UK corporate yield spreads. Columns 2 to 9 present results of pooled OLS approach, while last column presents results of panel approach. The standard errors of estimated parameters are adjusted using Newy-West method and Driscoll and Kraay method for panel data. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	Pooled OLS								**Fixed Effect**
STDV of excess return (%)		**52.35** (21)		**52.92** (20)		**46.16** (29)		**46.88** (32)	**38.01** (21)
Capital Firm to Capital Market (%)		**-9.14** (-19)		**-8.67** (-13)		**-6.43** (-15)		**-4.91** (-20)	**-6.84** (-14)
Downgrade from AA to A			**-32.47** (-18)	**15.98** (7.7)			**-4.22** (-4)	**21.89** (14)	**4.22** (1.34)
Downgrade from AA to BBB			20.22 (35)	**18.49** (25)			**26.51** (30)	**25.99** (30)	**26.5** (14)
Operating income to sale (%)					**-0.61** (-20)	**-0.41** (-15)	**-0.57** (-20)	**-0.38** (-16)	**-0.29** (-15)
TD to capitalization (%)					**1.43** (18)	**0.96** (18)	**1.61** (19)	**1.29** (21)	**4.98** (19)
Level of Term Structure (%)	**-37.13** (-14)	**-34.16** (-22)	**-38.68** (-14)	**-34.2** (-21)	**-34.62** (-23)	**-32.53** (-30)	**-35.72** (-22)	**-32.53** (-23)	**-31.53** (-14)
TED Spread (%)	**121.12** (17)	**78.41** (18)	**120.17** (16)	**78.11** (18)	**115** (16)	**79.58** (21)	**114.09** (19)	**78.31** (16)	**71.16** (10)
Intercept	**207** (17)	**141** (18)	**206** (16)	**130** (16)	**179** (10)	**126** (23)	**165** (17)	**102** (27)	**99.83** (25)
Number of transactions	83449	83449	83449	83449	83449	83449	83449	83449	83390
R-squared	**0.29**	**0.44**	**0.3**	**0.45**	**0.37**	**0.47**	**0.38**	**0.49**	**0.61**

4.4 COMPARISON OF SPREAD DETERMINANTS IN US AND UK MARKETS

One of the main purposes of our investigation of the UK corporate bond market was to compare and contrast it with the US market. For this reason, we dedicate the current section to a comparative summary of our findings for the two markets.

Table 32 summarizes the results of our benchmark regressions for the US and UK corporate bond markets, for IG and HY bond categories. It is worth noting that the sensitivities to equity volatility are very close for the two markets, hovering around

60bp for IG bonds and 110bp for HY bonds. We note that the magnitude of the sensitivity to equity volatility obtained in our work is 3 times smaller than reported previously (Campbell & Taksler, 2003). We observe a similar pattern for sensitivities to accounting variables, bond specific characteristics and market capitalization. A noticeable difference between the two sets is the coefficient for the credit rating dummy (A), which changes sign to negative in one of our regressions for UK (column 5). This effect was analyzed in Section 3.5.2, and was shown to arise in the aftermath Lehman's collapse. Another noticeable difference between the UK and US markets is the magnitude of sensitivity to TED spread. The comparison shows that UK IG corporate bond yields are in general much more sensitive to variations in TED spread than the US IG ones. This effect is much less pronounced for the HY category. Another noteworthy difference between the two markets is the difference in explanatory power of the chosen determinants for the two markets. For IG bonds, the explanatory power (measured by the adjusted R-squared) is nearly 10% higher for the US market than for the UK (columns 2 and 5, respectively). On the other hand, for HY bonds we find a diametrically opposite picture, with adjusted R-squared larger by 10% for the UK markets than for US.

Going beyond the results summarized in Table 32 , we note that, for both the markets after Lehman's collapse the explanatory power of determinants falls for financial sector, while improves for the non-financial sector. In case of both the markets, this is explained by the post-Lehman expectations that financial sector companies will not be allowed to default by their respective governments (US and UK) due to the associated systemic risks. Another effect found for both, US and UK markets, was that coefficient for years to maturity changed sign after Lehman's collapse. This indicates that, in both the markets, during the height of the financial crisis, short term debt was seen to be more risky than long term debt. Overall, we see that the determinants suggested by Merton's structural model explain over half of the variation in corporate bond yield spreads for US and UK markets. This is further supported by the investigation of the interaction effect for the two markets, which gives results consistent with Merton's model.

Table 32
Comparative table of yield spread determinants for US and UK corporate bond markets

Using panel data between 2003 and 2011 for UK and US corporate bond market, we regress corporate bond yield spreads against the list of variables (represented in the first column of the table). Estimate coefficients are presented separately for investment grade bonds (AA, A, BBB) and high yield bonds (BB, B). The standard errors of estimated parameters are adjusted using Newy-West method. Associated t-statistics appear in parentheses beneath. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 0.1 percent level (>3.09)).

	US			UK			US	UK
	IG			IG			HY	HY
Variables	Reg1	Reg2	Reg3	Reg1	Reg2	Reg3	Reg4	Reg4
STDV (excess RET) (%)	**66.04** (71)	**70.1** (79)		**57.03** (34)	**60.24** (33)		**106.66** (55)	**146.2** (17)
Capital Firm to Capital Market (%)	**-7.18** (-23)	**-47.99** (-61)		**-8.78** (-35)	**-14.1** (-38)		**-620.5** (-28)	**-692.8** (-5)
Downgrade from AA to A	**11.97** (29)		**23.29** (42)	**-25.72** (-22)		**40.57** (40)		
Downgrade from AA to BBB	**59.55** (63)		**78.6** (73)	**19.72** (21)		**85.63** (53)		
Downgrade from BB to B							**74.38** (35)	**42.88** (3.2)
Operating income to sale (%)	**-0.16** (-11)			**-0.16** (-19)			**-0.19** (-6)	**-3.14** (-4.2)
TD to Capitalization (%)	**1.53** (27)			**1.01** (27)			**4.67** (56)	1.74 (2.1)
Level Term Structure (%)	**-39.19** (-39)	**-40.37** (-67)	**-56.12** (-42)	**-26.59** (-35)	**-27.1** (-34)	**-28.23** (-19)	**-112.0** (-52)	**-162.6** (-12)
TED Spread (%)	**71.27** (25)	**69.38** (28)	**94.48** (23)	**115.34** (32)	**118.08** (30)	**160.9** (24)	**104.68** (13)	**117.09** (4.2)
Coupon (%)	**12** (60)	**17.94** (73)	**21.69** (63)	**10.82** (26)	**13.99** (28)	**13.39** (26)	**23.04** (56)	21.13 (2.1)
Years To Maturity	**0.94** (10)	**0.6** (21)	**0.28** (7)	**0.29** (5.7)	-0.1 (-1.9)	**0.44** (7.3)	**0.18** (1.8)	2.65 (1.7)
Number of transactions	1248893	1248893	1248893	235540	235540	235540	267557	10409
R-squared	**0.62**	**0.57**	**0.41**	**0.51**	**0.47**	**0.36**	**0.71**	**0.81**

4.5 CONCLUSION

The purpose of the current work was to contribute to the relatively small empirical literature on determinants of credit spreads for bond markets outside the US. In the current chapter we analyzed main determinants of credit spread in the UK corporate bond market (2003 to2012), in particular the relation between yield spread and equity volatility. The work investigated the relation between the equity and bond markets, as well as looked at the empirical validation of predictions of Merton's structural model.

To the best of our knowledge, this work is the first one to examine determinants of UK corporate bond yield spreads covering the period of the recent financial crisis.

We find that factors suggested by Merton's model explain 51% of corporate yield spread variation for IG bonds and 81% for HY bonds. We find evidence that equity volatility is an important determinant of corporate bond spreads, in line with previous research (Campbell & Taksler, 2003), (Landschoot, 2004) and consistent with our results for the US corporate bond market (Chapter 3). However, as in the case of the US market, the size of the estimate coefficients is 3 times smaller than reported in Campbell and Taksler (2003). Analyzing the interaction effect, we find that the capital structure of a company affects the strength of the volatility effect. In addition, our results show that HY bonds are more sensitive to the determinants than the IG bonds. Both these findings are consistent with the predictions of structural models.

Our results show that equity volatility is not the only important factor driving credit spreads up during financial crisis. We report significant effect on spreads from falling confidence of investors (measured by TED spread). This effect is much stronger than was reported in previous literature (Campbell & Taksler, 2003). We show that, during the financial crisis, credit spreads became more sensitive to TED spread. As a result, falling investor confidence and high equity volatility become the main drivers of the rising credit spreads between 2007 and 2012. We have shown that credit rating variables explain as much of credit spreads as accounting variables. Thereby, credit ratings taken together with accounting variables does not significantly increase the adjusted R-squared over an analysis considering accounting variables alone. Looking at the other determinants, we see that treasury rate level and coupon size show expected sings, consistent with Longstaff and Schwartz (1995) and Longstaff (2002).

Examining the effect of Lehman's bankruptcy, we show that the explanatory power of our determinants falls slightly falls (2-3%) for financial companies, but significantly improves (16%) for non-financials. This supports our previous findings from US corporate market. We conclude that this is effect was a reflection of the market perception that large financial companies were not going to be allowed to default by the UK government.

Focusing on the period of financial crisis, we looked at the impact of quantitative easing on the credit spreads. We found evidence of statistically significant negative relation between corporate spreads and (weekly) quantity of asset purchased variable characterizing QE. Thus, we found evidence that an increase in QE was responsible for a fall in the credit spreads. These findings are consistent with results reported in Joyce, Lasaosa, Stevens and Tong (2011).

Finally, we verified the robustness and stability of our results to inclusion of fixed effect, random sub-sampling, non-linear effects, over different time periods (economically stable period, post-Lehman period, period of QE), as well as using alternative measures of credit spread.

CHAPTER 5
DETERMINANTS OF CDS-BOND BASIS DURING 2005-2011

5.1 INTRODUCTION

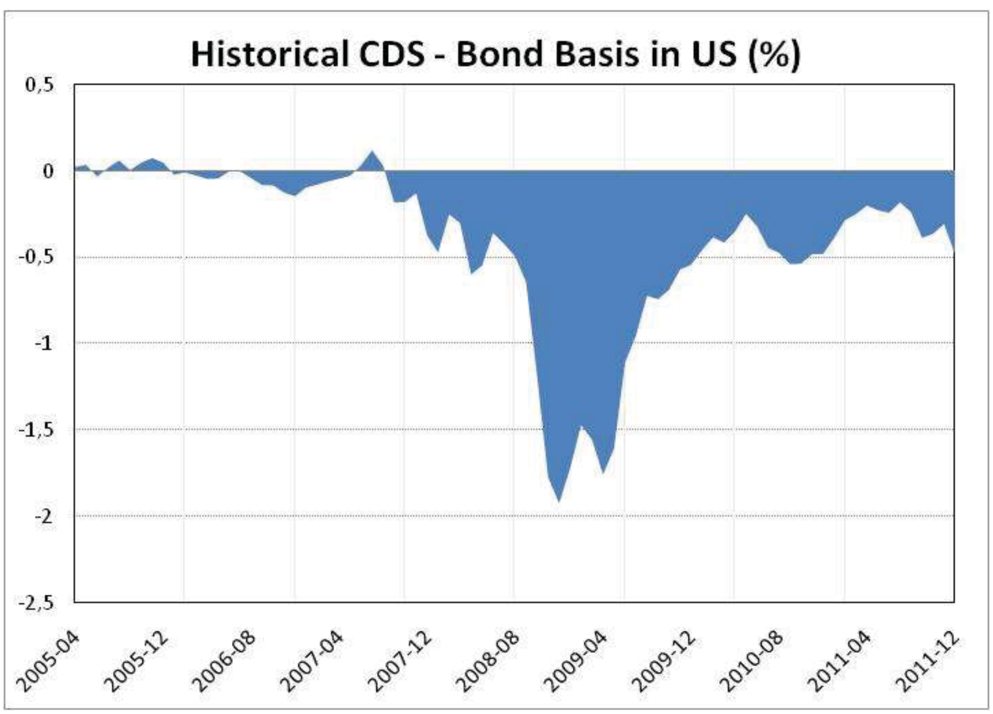
Credit derivatives and structured credit instruments significantly reshaped the corporate credit markets over past two decades. Initially they were created to help protect lenders from the credit risk of the corporations and sovereigns to whom they lent. Gradually they became asset class in their own right (Mahadevan, Musfeldt, & Naraparaju, 2011). The most standard credit derivative product is the Credit Default Swap (CDS). A single name CDS is a contract between the seller and the buyer of protection against the risk of default on a set of debt obligations issued by a specified reference entity. An explanation of the mechanics of the CDS contract and a general overview of the CDS markets was provided in Chapter 1.

From the beginnings of the CDS market in mid-1990s, one of the most basic valuation measures has involved comparing a corporate bond with a CDS contract. This measure is known as the CDS-Bond basis (CBB), and is the difference between the CDS spread and the corresponding corporate bond yield spread (measured relative to a particular benchmark). Since the CDS contract and the corresponding reference bond bear the same level of credit risk, the CBB should be close to zero according to the Law of One Price (no-arbitrage argument). However, market data shows (see Figure 20) that during the financial crisis the basis was significantly negative. This phenomenon has raised a lot of questions that are of interest for both, academia and the industry. In particular, there has been significant interest in understanding the question of what drove the basis into negative territory and what factors are responsible for its persistence.

The anomaly of the negative CBB suggest that the relationship between the bond and CDS markets is much more complicated than looks at first glance based on a simplistic no-arbitrage argument. This complex relation led many to treat basis trade as an investment strategy with an opportunity to earn a carry (Elisade, Doctor, & Saltuk, 2009), (Mahadevan, Musfeldt, & Naraparaju, 2011), (Bai & Collin-Dufresne, 2013). However, in practice, investors face many risks and costs in realizing profit from basis trades. In order to identify these factors, we study the persistence of the negative CBB from a theoretical perspective. Through an analysis of a negative basis trade, we identify funding costs (of collateralized and uncollateralized borrowing), collateral quality, liquidity (in CDS and bond markets), volatility of the basis and counterparty risk as the main factors that explain the persistence of the negative basis. We proceed to empirically investigate the impact on the basis from the various economic and firm specific variables that capture these risk and cost factors.

Figure 20
CDS-Bond basis in US corporate credit market.

Monthly aggregated CDS-Bond basis for IG companies in US for period between 2005 and 2011



We conduct an empirical study of the dynamics of the CBB, for US corporates covering the period between 2005 and 2011, and study the factors that affect it. The period of study includes three relatively distinct market environments: (1) a relatively stable period for the US market (2005-2007), (2) the period of the financial crisis (2007-2009), and (3) the post-crisis/European sovereign crisis period (2009-2011). For our analysis we use a large dataset of Bond and CDS daily prices for US corporates provided by MarkIt. We work with a panel dataset covering more than 420 different companies and 10 different sectors. Our work contributes to a limited but growing literature on the CDS-Bond Basis (Bai & Collin-Dufresne, 2013), (Fontana, 2010), (Augustin, 2012). In this regard, our work considers a broader dataset than previous literature, over a longer and newer time period, as well as investigates some of the factors not considered previously. In addition, we consider a range of econometric methods to validate the robustness of our findings.

In our analysis, we look at CBB for the two broad investment categories, namely investment grade (IG) and high-yield (HY). Overall, we find that for IG group, the chosen factors explain 36% of the variation in CBB, while for HY group this number is smaller at 20%. In addition, when focusing on the period of financial crisis, we divide our dataset further into financial and non-financial sector categories. We look at the dynamics of the CBB and its sensitivity to the various factors for the categories identified above before and after the collapse of Lehman Brothers'. We found that, prior to Lehman bankruptcy, the variation in basis was mostly explained by funding cost, counterparty risk and basis volatility. However, in the post-Lehman period, funding cost along with collateral quality and illiquidity of the bond market became the dominant explanatory factors for the CBB, with counterparty risk losing its economic significance. An important finding was that counterparty risk lost its economic significance as a determinant of the CBB after the collapse of Lehman. This finding is in line with Arora, Gandhi and Longstaff (2012), who argue that the impact of counterparty risk diminished after Lehman's demise due to rise in collateralizations in CDS markets. An additional reason for the diminishing sensitivity of CBB to counterparty risk was the systematic bailouts of a number of CDS sellers (e.g. AIG, CIT Group, The Bear Stearns Companies Inc, The Goldman Sachs Group, Citigroup Inc and others). These bailouts were a signal to the market that large systemically important financial organizations, which include the major CDS dealers, will not be allowed to fail. Another finding in this work, is the difference in dynamics for low rated bonds (B and below) compared to the bonds belonging to other credit ratings. These low rated bonds had a highly positive CBB at the peak of the financial crisis, when bonds corresponding to all of the other credit ratings had highly negative basis. We explain this phenomenon by very low level of liquidity in CDS market for credit rated B and below, as there was limited CDS protection available in the market for credits with high probability of default.

The remainder of this chapter is organized as follows. We begin in Section 2 with a review of literature on CBB and related topics. Following this, in Section 3, we give a more formal definition of the CBB, and walk the reader through its historical behaviour. In Section 4, we introduce the negative basis trade, and use it to identify the various factors that could hold the CBB in negative territory. We proceed to explain and analyze the individual factors, and comment on their expected effect on the basis. In Section 5, we give an overview on data sourcing, and various data manipulation and cleaning procedures. In this section we provide the descriptive statistics for our final dataset, and highlight some other key aspects about our dataset. In Section 6, we describe the empirical methodology and present the main results of our analysis. In addition, in this section, we report on the results of a range of robustness tests that were done to confirm the validity of our results. Finally, we conclude with a summary of our findings in Section 7.

5.2 REVIEW OF THE RELATED LITERATURE

As we mentioned above, the academic literature on the relation between CDS and bond is currently quite limited. However, there is a natural dividing line between the early works and the more recent ones. Earlier works were primarily focused on trying to explain the small but positive basis, which had persisted through the first half of the 2000s Blanco, Brennan and Marsh (2005), De Wit (2006), Norden and Weber (2009), Hull, Predescu and White (2004), Nashikkar, Subrahmanyam and Mahanti (2011) and Zhu (2004). The early works analyzes the relationships between credit default swap and corporate bond spreads in a pre-crisis period. The main conclusion of these works was that although arbitrage between the bond and CDS markets held quite well, there was scope for a small positive basis due to certain small differences between the contracts as well as some other technical reasons (Blanco, Brennan, & Marsh, 2005), (De Wit, 2006). The factors such as cheapest-to-deliver option of a CDS and difficulties in short selling bonds were identified as the main drivers of a positive basis. The picture changed dramatically with the advent of the financial crisis, when the basis was driven deep into the negative territory. This fact was the driver behind a renewed wave of research interest that focused on explaining the negative basis observed in the market in the second half of 2000s of Fontana (2010), Garleanu and Pedersen (2011), Augustin (2012), Gou and Bhanot (2010), Kim, Li and Zhang (2011), Arora, Gandhi and Longstaff (2012), Bai and Collin-Dufresne (2013) and Wang (2013). These works have focused on identifying various firm specific, market specific and macroeconomic factors that could explain the persistence of the negative basis. Below, we discuss the above mentioned works in more detail.

Blanco, Brennan and Marsh (2005) analyzed the time series properties of credit default swap prices in conjunction with matching bond credit spread data between 2001 and 2002 in the framework of structural models. Authors concluded that the theoretical arbitrage relationship linking CDS prices to bond credit spreads holds well on average for most of the companies. They showed that the cheapest-to delivery option inherent in a CDS contract drives its price higher than the true price of credit risk. On the other hand, bond credit spread understates the true credit risk in the presence of repo costs. Both these reasons imply that, in normal conditions, CDS-Bond basis is expected to be slightly positive on average. The authors also found that the bond credit spreads appear to react more to the market-wide variables such as changes in interest rate, slope of the yield curve. On the other hand, CDS prices react more to firm-specific factors such as the stock prices and volatility.

Zhu (2004) analyzes the CBB and its determinants using a sample of 24 entities (US and Europe) for a period between 1999 and 2002. The main considered determinants included lagged basis spreads, change in credit spreads, credit rating, contractual arrangements, liquidity factors (bid-ask spreads) as well as macroeconomic factors (treasury rate, stock market indices). The author concluded that market inefficiency exist in both the markets, and that credit factors are important in generating a non-zero CBB. Author found that most of the CBB could be explained by credit rating events, changes in credit conditions and dynamic adjustment of the two spreads. On the other hand, contract terms, liquidity and short sale restrictions had only a limited impact on CBB.

Hull, Predescu and White (2004) analyzes the impact of rating announcements on the pricing of CDSs, covering period between 1998 and 2002. In addition, they examine the validity of the theoretical relationship between credit default swap spreads and bond yield spreads. Authors conclude that the theoretical relationship between credit default spread and bond yield spread holds fairly well and they were able to use it to estimate the benchmark five-year risk free rate used by participants in credit default swap market. Authors build two types of analyses to study the relationship between the credit default swap and rating announcements. The first one examined CDS changes conditional on ratings announcements and reveals that reviews for downgrades contain significant information. The second type of analysis examined ratings announcements conditional on credit spread level and credit spread changes. Authors find that credit spread changes or credit spread levels provide helpful information in estimating the probability of negative credit rating changes. The results for positive rating events were less significant than results for negative rating event.

Jan De Wit (2006) studies the long-run equilibrium relationships between the two markets covering period between 2004 and 2005. The author argued that the positive CDS-bond basis was driven by contract specifications (such as CDS cheapest to deliver option and CDS restructuring clauses) and technical aspects (such as difficulties in shorting cash bonds). Author argued that shorting the cash market tend to be difficult, as the bond needs to be sourced in a fairly illiquid and short-dated repo market in which bonds additionally might trade on special, making it expensive to borrow the bond.

Nashikkar, Subrahmanyam and Mahanti (2011) analyze CDS-bond basis as difference between the CDS spread of the issuer and the par-equivalent CDS spread of the bond (the spread of hypothetical CDS contract that has same default probability and recovery rate as implied by the price of the bond). Authors examined the role of liquidity factor measured using a recently developed latent liquidity measure (weighted average turnover of funds holding the bond). Authors analyse determinants of basis including latent liquidity, liquidity in the CDS market, firm specific effects (leverage, current ratio, tangible assets) and other bond characteristics. Their results show that CDS liquidity along with CDS volatility have higher explanatory power for the basis than bond-specific liquidity. Higher volatility in the CDS market makes a bond cheaper relative to the CDS contract. Authors find that firm-specific variables have strong explanatory power for the basis. This finding implies that either some of these variables affect the basis through other channels such as liquidity, or that credit risk of the bond is not fully captured in the price of the CDS because of the frictions that exist between the two markets.

Garleanu and Pedersen (2011) introduced a theoretical dynamic general-equilibrium model where leveraged constraints could generate a pricing difference between two securities with nearly identical cash flows. The model consider group of risk-averse and risk-tolerant agents. Each risk-tolerant investor (banks or financial sector) uses leverage, but is subject to margin requirements. This type of investors can fund all the margins on position with uncollateralized loan. Risk-averse investors may be constrained in their trading of derivatives and cannot borrow uncollateralized. In this framework they show how negative shocks to fundamentals could lead to bases (price gaps between securities with identical cash-flows but different margins). They proceed to empirically test and validate the predictions of the proposed model using the CBB. In relation to the CBB, their model predicts a covariance between the basis and LIBOR – general collateral (GC) repo rate spread as well as with tightness of credit standards.

Fontana (2011) conducted an empirical analysis of the behaviour of CBB based on the time-series variation in the average basis using cointegration techniques for a sample of US IG companies. The work focused on studying the phenomenon of negative basis. The author showed that the financial sector had a more pronounced negative CBB in comparison to other sectors. The author also pointed out that, for lower rated entities, the negative basis is typically larger. The author considered several variables that could explain the CBB, including: Libor-OIS as an indicator of counterparty risk and funding liquidity risk; VIX as a measure of liquidity and risk premia in financial market; OIS-T-bill capturing the flight to quality phenomena and corporate bond market liquidity deterioration; as well as bid-ask spread of CDSs as a measure of liquidity in the CDS market. The Author applied Engel-Granger two step estimation approach using dummies for the crisis period. The results showed that LIBOR-OIS, OIS- T-bill, VIX and bid-ask spread were the main determinants of the basis during the crisis.

Gou and Bhanot (2010) analyzed a sample of CDS prices and corporate bond yield spreads for period between 2008 and 2009. Authors focused on different types of liquidity and their role in explaining deviations of CBB from zero. Funding liquidity variables were separated into three categories: arbitrageur's capital availability/volatility (VIX index); arbitrageurs' funding – shadow cost of capital (Libor – T-bill spread, Repo – Libor Spread); and arbitrageurs' funding risk in rollover (Repo-rate Volatility). The asset specific liquidity factors considered included short term stock volatility, long term stock volatility, bond credit rating, bond trading volume, bond bid ask yield spread. Other risk factors studied were the stock return, HML, SMB, term spread. The authors showed that asset-specific liquidity explained the significant chunk of the negative CBB during the crisis.

Augustin (2012) analyzed the behaviour of CDS-bond basis and factors that drive the basis in crisis time. Author calculated the basis based on non-parametric methodology, directly from observed CDS quotes and transaction process in corporate bond market. The author worked on determining the basis, based on asset-specific liquidity, general market and funding liquidity, counterparty risk and collateral quality (Credit rating) as well as some additional controls, capturing firm-specific characteristics and the overall economic environment (slope, level of term structure, default risk premium and the sign of the basis dummy). The results identified various types of liquidity as important determinants of the basis.

Kim, Li and Zhang (2011) empirically analyzed the relationship between prices of CDS and cash corporate bonds between 2001 and 2008. The authors focused on potential impacts of the basis arbitrage trade on the pricing of cash corporate bonds. Authors construct a new risk factor based on the basis level (due to the basis arbitrage activity) for corporate bond returns. Based on Fama-MacBeth regression they find that the basis level is negatively related to future returns of the individual bonds. Authors demonstrate that after controlling for all systematic risk and liquidity factors the basis factor still carries significant positive risk premium during normal market conditions. They provide some evidence for the breakdown of normal pricing relation in the corporate bond market during 2007 and 2008.

Bai, Collin-Dufresne (2013) analyzed cross-sectional variation in individual firms' CBBs for large sample of individual firms during the 2007-2009 financial crisis. The authors conducted a Fama-MacBeth cross-sectional regressions to identify the impact of factors driving the CBB. The considered factors included bond liquidity, funding cost, flight to quality, collateral quality and counterparty risk. The results show that, these factors explain a significant fraction of cross-sectional variation in the CBB (35%). In the pre-Lehman period the main determinants are funding risk, collateral quality and counterparty risk. However, in post-Lehman phase the main determinants are bond liquidity as well as market and funding liquidity. The authors find evidence that counterparty risk does not play a significant role in driving the basis in the post-Lehman phase.

Overall, although there is a clearer picture emerging about the nature of the negative basis and its main drivers, there is currently a significant scope for further investigations. There is a growing consensus about the importance various forms liquidity in explaining the persistence of the non trivial basis. However, there is considerable uncertainty on the precise quantitative contribution of these factors. In addition, there are several other firm-specific and macroeconomic factors whose effect on the basis has not yet to be properly analyzed. For example, the effect of counterparty credit risk is not yet fully understood, with differing views being expressed. For this reason, there is a need for further empirical investigations using broader datasets and more refined analysis techniques. The current chapter aims to contribute to the small but growing body of empirical literature investigating the behaviour of CDS-bond basis.

5.3 CDS-BOND BASIS

The CDS contract enables a counterparty (protection buyer) to transfer its credit risk to another counterparty (protection seller). For a description of the mechanics of a CDS contract and an overview of the CDS market we refer the reader to Chapter 1. From the point of view of the protection buyer, the CDS contract allowed to hedge the credit risk on a long bond position. On the other hand, the CDS gave an opportunity to the seller of protection to gain exposure to the underlying credit synthetically. Since, in essence both, bonds and CDSs, provide an exposure to credit risk, there has been significant interest in comparing the prices of credit risk in the two markets (Credit Derivatives Insights Handbook 2010, Morgan Stanley).

A corporate bond and CDS written on this bond are essentially two instruments holding the same credit risk of a reference entity, with only difference that corporate bond is funded investment and CDS is unfunded. Theoretically, the synthetic (CDS) and cash credit markets should price credit risk equally. The CDS-Bond basis is a measure of the discrepancy between the risks priced in the bond and CDS markets. The CBB is defined as the difference between the credit default swap spread (CDS) and bond credit spread (CS) for particular reference entity at time t with a similar maturity:

$$Basis_{i,t} = CDS_{i,t} - CS_{i,t} \tag{10}$$

This definition is motivated by a simple arbitrage argument. Consider an investor who holds a corporate bond together with a CDS protection on the issuer of the corporate bond. In the event of default of the bond issuer, the investor will be able to cover any losses on the corporate bond by the protection payments on the CDS. Therefore, the position of the investor is economically equivalent to holding a risk free bond. For this reason, using the law of one price, it follows that the return on the investor's portfolio should be equal to the return on a risk-free bond. The return on the investors' portfolio consisting of a corporate bond and CDS protection is $R_{inv} = R_{rf} + CS - CDS$, where $R_{rf} + CS$ is the yield earned on the corporate bond, and $-CDS$ is the protection premium paid on the CDS. Thus, requiring the return on the portfolio to be equal to return on risk-free bond (i.e. $R_{inv} = R_{rf}$), it follows that $Basis \equiv CDS - CS = 0$. It is important to note that the presented arbitrage argument holds only approximately. The main reason for this is that, in the event of default, the losses on a non-par bond position are not exactly offset by the CDS protection payment. We will return to this topic in the following section where we consider a negative basis arbitrage trade.

An important aspect of Equation (10), that requires further clarification, is the precise definition of the bond credit spread CS. There are several definitions of bond credit spread currently used in the academic research and industry (Elisade, Doctor, & Saltuk, 2009). The main ones include bond yield spread above benchmark treasury rate of comparable maturity, par asset swap spread (ASW) and the Z-spread.

The bond yield spread above benchmark treasury measures the credit spread as the difference between the yield of a corporate bond and the yield of an nearest (in terms of maturity) on-the-run government bond. This measure of credit spread is widely used in corporate bond research, and was the one that we adopted in Chapters 2 and 3. This spread measure, in effect, measures credit spread relative to a risk free rate proxied by the yield on government treasury bonds.

Another measure of bond credit spread is the par asset swap spread. A par asset swap, introduced in Chapter 1, is a way to transform a fixed coupon bond into a floating rate bond. The par asset swap spread is the spread over LIBOR that a bond will pay for an initial exchange of par. An asset swap allows an investor to take an exposure to the credit risk of a bond, while not being exposed to the interest rate risk. For this reason this measure is considered a good proxy of credit spread risk. Moreover, as we shall show in the next section, an asset swap is a natural instrument for the purposes of realizing a negative arbitrage trade. Finally, from a historical perspective, in the early days of the CDS market, the par asset swap spread served as a pricing benchmark for

CDSs. For these reasons, par asset swap spread serves as a natural measure for credit spread of corporate bonds. In the current work we shall primarily use this measure for our theoretical and empirical studies.

Finally, the Z-spread is measured as the parallel shift applied to the zero curve in order to equate the bond price to the present value of the cash flow. The zero curve typically used in practice is the LIBOR curve. Thus, the Z-spread can be thought of as the flat spread that needs to be added to the risk-free rate in order to capture the riskiness of a corporate bond. The advantage of Z-spread is its intuitive simplicity. One the other hand, a drawback is that, although Z-spread takes into account the term structure of interest rates, it nonetheless assumes a flat term structure for credit spreads. Furthermore, in contrast to par asset swap spread, Z-spread is not traded and requires additional calculations. To test the robustness of our results, which were obtained using ASW, we repeated our analysis using Z-spreads as a proxy for bond credit spreads.

Let us turn to a discussion of the historical behaviour of the CDS-bond basis. We see from Figure 20 that in the early days of CDS market, the CDSs generally traded wider than cash bonds. The average basis typically stayed in the slightly positive territory of 5-10bp before 2007. The existence of a positive basis was generally associated with broader scope of credit events and cheapest-to-deliver optionality inbuilt into the CDS contracts. However, starting from 2007, the basis traded primarily in the negative territory, plummeting to unprecedented levels (-250bp for IG ratings) in the wake of Lehman's collapse.

From a point of view of arbitrage, it is typically easier to take advantage of a negative basis than a positive one. In order to profit from a positive basis, an investor needs to be short on bond yield and long on the CDS premium. This would involve short selling a corporate bond and simultaneously selling CDS protection on underlying issuer. The difficulty with repo of corporate bonds for the purpose of short selling as well as regulatory capital on selling CDS protection make this difficult to realize in practice (Elisade, Doctor, & Saltuk, 2009). On the other hand, to profit from a negative basis, one would need to be long on bond yield and short on the CDS premium. This would require an investor to buy the corporate bond and a corresponding CDS protection. In order to lock in a profit, an investor would typically buy the corporate bond, funding the purchase it in the repo market and the uncollateralized LIBOR market, and simultaneously enter into a CDS agreement as a protection buyer. The investor would then use the coupon payments received on the bond in order to pay the CDS premium and interest accrued on the funding debt. In order to hedge the interest rate risk inherent in a bond, the investor may also enter into an asset swap with a derivatives dealer. Overall, the investor will earn a carry on this trade if the basis large enough to cover the funding costs and transaction costs for the investor. Many players treat the negative basis trades as an investment strategy with an opportunity to arbitrage pricing and earn a profit for taking on specific "basis" risk (Elisade, Doctor, & Saltuk, 2009). The presence of arbitrageurs should in principle drive the basis back to zero. However, various limits of arbitrage, including funding costs, transaction costs and risks hamper the narrowing of the basis. It is the purpose of the current work to analyze these factors in detail and give a quantitative estimate of their effects and relative importance.

In the next section we shall analyze the negative basis trade in detail, outlining a practical approach to realizing it. As a result, we will explicitly uncover the various costs, market frictions and risks associated with a negative basis trade which will serve as our theoretical determinants for explaining the persistence of negative basis.

In this section, we shall proceed by constructing a negative-basis arbitrage trading strategy, which, in an ideal setting, would lead an investor to a risk-less profit opportunity with zero initial investment (the proverbial "free-lunch"). However, the various market frictions, funding constraints and risks, which we describe below, will limit the profit opportunities for the investor. The existence of these factors and their amplitudes will thereby serve to explain the persistence of the negative basis in the recent times.

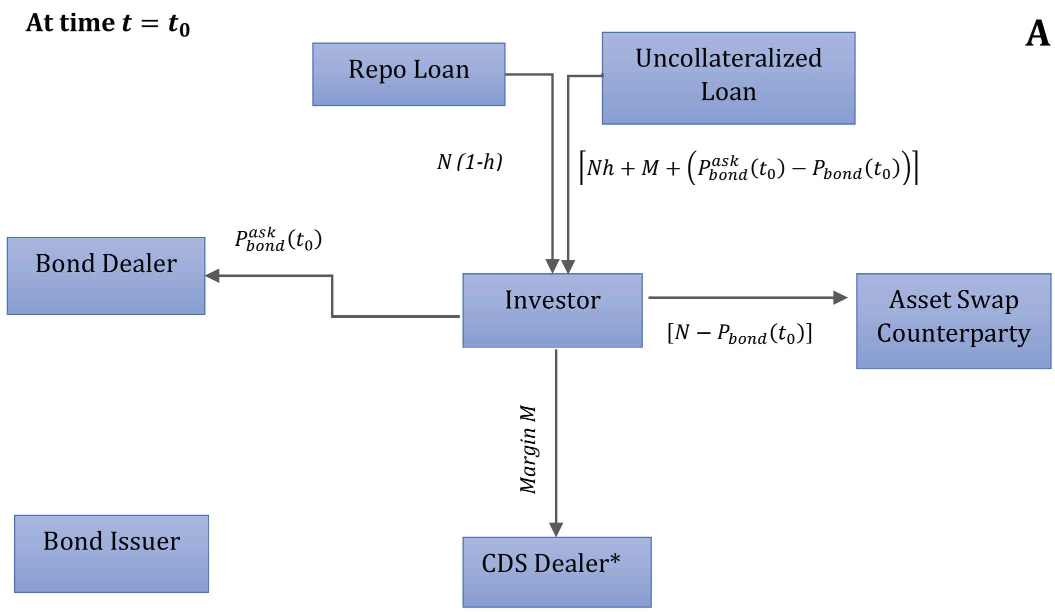
The idea of a negative basis trade directly stems from the definition of the CDS-Bond Basis (see Equation (10). The negative basis implies that CDS < CS, essentially implying that an investor should take a position so as to short the CDS spread payment (CDS) and long the Credit Spread (CS) from a bond (buy low, sell high). A straightforward way to achieve this is by going long the bond as well as long the CDS protection. However, this strategy will be exposed to interest rate risk, inherent in the corporate bond. In order to avoid exposure to interest rate risk, an investor can simultaneously enter into an asset swap on the underlying bond.

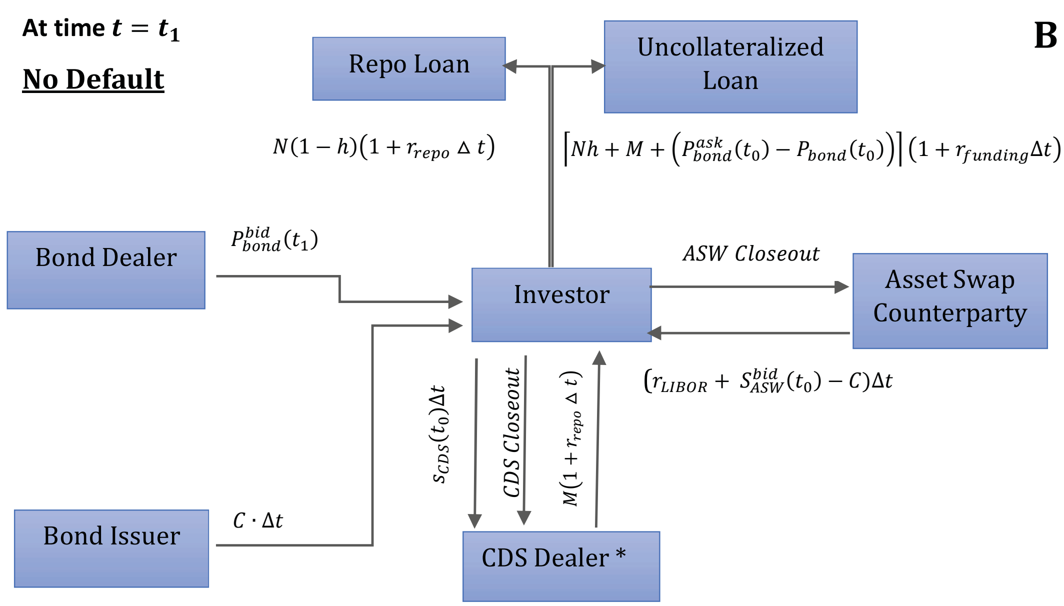
A Par Asset Swap is an over the counter (OTC) derivative transaction, whereby the coupons on an underlying bond are exchanged for floating rate coupons (typically referencing LIBOR) plus a fixed spread known as the Asset Par Swap Spread. The main idea of a Par Asset Swap is that it transforms a fixed coupon bond into a floating rate bond, thereby allowing an investor to avoid interest rate risk while maintaining an exposure to bond's credit risk. We refer the reader to Chapter 1 for an explanation of the precise mechanics of this swap. The swap is characterized by a rate known as the par asset swap spread, which is the premium over LIBOR that is exchanged in return for the bond coupons on an initial investment of par. This rate is determined from the price of the underlying bond and its coupon characteristics, and as was discussed previously, serves as a good proxy for the credit risk of the underlying bond.

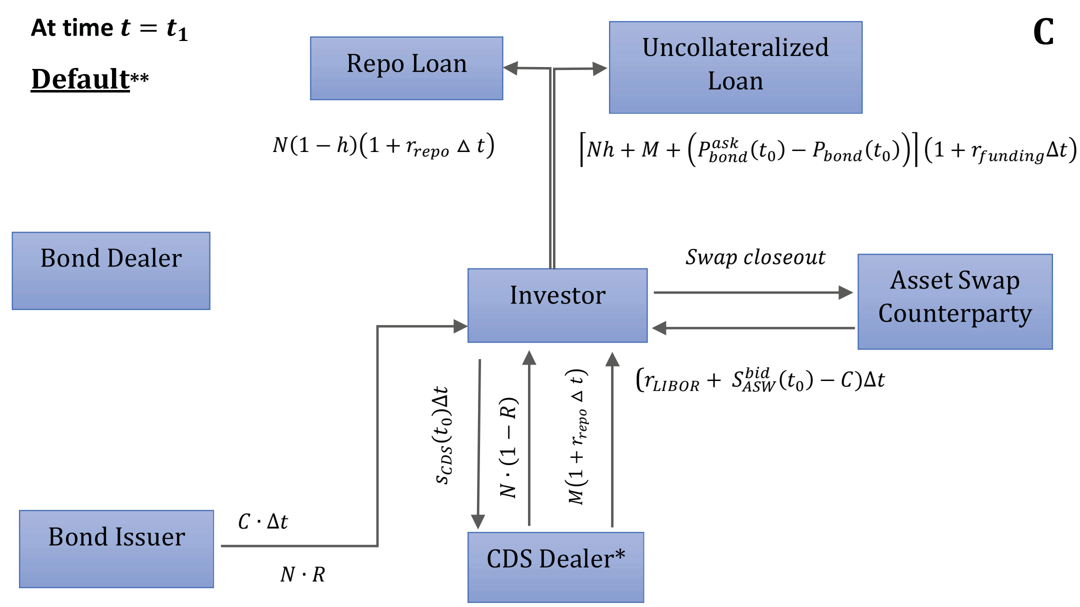
The negative basis trading strategy involves a long position in a bond, CDS protection, a Par Asset Swap and a loan to fund the transaction. The strategy is shown schematically in Figure 21. At inception, an investor takes out a par loan (repo and uncollateralized loans) which is used to buy a bond and enter into a par asset swap contract. Simultaneously, the investor enters into a CDS contract as a protection buyer. The purpose of the CDS protection is to hedge the investor against two types of related credit risks. Firstly, the risk of increasing credit spreads (more probably, smaller losses), and secondly the risk of outright default of the bond (less probable, higher losses). On the other hand, the purpose of the asset swap is to hedge the interest rate risk, making the investment strategy not sensitive to movements in the interest rates. At the time of close-out, the investor sells back the bond in the market, and pays back the loan with accrued interest. At the same time, the investor closes out his par asset swap and CDS contracts by entering into corresponding offsetting trades. In an idealized scenario, with no funding and bid-ask spreads, assuming the basis remains constant, the investor walks away with a riskless profit proportional to $N|BASIS| \vartriangle t$, in the event that the bond does not default in the interim. On the other hand, this strategy also ensures that, in the event of bond default, the CDS contract protects against any potential credit losses on the bond. As we shall see below, this seeming arbitrage opportunity only holds under the unrealistic assumptions of absence of funding/bid-ask spreads and constancy of basis.

Figure 21
Negative basis trading strategy cash flow diagrams

The diagram A shows cash flow at initial moment of time t_0 . The diagram B and C show cash flow for strategy at time t_1 in case of no default and default scenario, correspondingly. The origin and value of the individual cashflows is explained in detail in the main text and Appendix 3.







* For simplicity in the diagram we assume that margin is deposited only to the CDS seller.

** For simplicity we assume that default (if it happens) happens at time t_1, after coupon payment.

Let us proceed to analyze the details of this trading strategy. We shall consider an investor who is able to trade corporate bonds at bid and ask prices set by dealers, thereby encountering transaction costs. We shall assume that an investor has an ability to fund his bond purchase partially in the repo market, using the bond as collateral. The remaining funds are obtained in the uncollateralized LIBOR market. In general, repo markets offer loans at lower rates than LIBOR markets due to collateralized nature of lending. However, these markets typically require a haircut on the collateral, and for this reason, an investor will not be able to obtain full funding, required to buy the bond, in the repo market. The investor will also need to hold funds in the margin account in order to enter into an OTC derivative positions, this margin account will typically pay interest equal to the repo market rate. Finally, the investor has access to the OTC derivatives markets, where he has an ability to enter and close out positions in CDSs and asset swaps. The investor will face transaction costs in the derivatives market in the form of bid and ask quotes on the corresponding CDS and ASW spreads. We shall consider the position of an investor over a short time horizon, between the date of trade inception t_0 and the date t_1 when the investor closes out his/her positions.

For convenience, the reader is referred to Table 33 for a summary of the main notations used in the formulas below.

Table 33
Table of notations

Notations	Explanation
$\boldsymbol{P\&L(t_i)}$	Net cash flow at time t_i.
N, C	Notional and Coupon rate of the bond.
$\boldsymbol{P_{bond}^{bid/ask}(t_i)}$	Bid/ask price of the bond at time t_i.
$\boldsymbol{P_{bond}(t_0)}$	Mid-price of the bond at t_0.
M, m	Payment into margin account for derivatives. $M = mN$.
$\boldsymbol{h}$	Haircut in the repo market.
$\boldsymbol{S_{ASW}(t_i)}$	Mid spread on par asset swap and CDS at time t_i.
$\boldsymbol{S_{ASW}^{bid/ask}(t_i), S_{CDS}^{bid/ask}(t_i)}$	Bid/ask spread on par asset swap and CDS at time t_i.
$\boldsymbol{BAS_{bond/CDS/ASW}}$	Bid-Ask spread for bond, CDS and Par Asset Swap. We assume that BAS does not change from t_0 to t_1.
$\boldsymbol{r_{LIBOR}, r_{repo}, r_{funding}}$	Interest rates: LIBOR rate, Repo rate, and investor's uncollateralized funding rate. These rates are set at t_0.
$\boldsymbol{PV01(t_i)}$	Market price at time t_i, of a risk free annuity with payments on bond coupon dates.
$\boldsymbol{RPV01(t_i)}$	Market price at timet_i, of a risky annuity with payments on bond coupon dates. The risky annuity stops payments in the event of bond default.
$\boldsymbol{BASIS(t_i)}$	CDS-bond basis at time t_i.
$\boldsymbol{\triangle BASIS}$	Change in basis between t_0 and t_1.
$\boldsymbol{\sigma_{BASIS}^2}$	Variance of the basis.
$\boldsymbol{R}$	Bond recovery rate upon default. Recovery rate is assumed known and constant.

At inception time t_0, the investor buys the corporate bond, and enters into a par asset swap contract on the bond with a derivatives dealer. At the same time, the investor enters into a CDS contract with CDS dealer as a protection buyer. The investor partially funds his position by borrowing in the repo market, pledging the bond as collateral. The remaining funds are borrowed in the form of an uncollateralized loan. Thus, the net cash flow at trade inception is zero, i.e. $P\&L(t_0) = 0$. However, in order to keep track of the various terms, it is convenient to expand the expression for the cash flow at inception

$$P\&L(t_0) = -P_{bond}^{ask}(t_0) - [N - P_{bond}(t_0)] - M + N(1-h) + \left[Nh + M + \left(P_{bond}^{ask}(t_0) - P_{bond}(t_0)\right)\right] \tag{11}$$

In the above expression, the term $-P_{bond}^{ask}(t_0)$ corresponds to the cash paid out for the purchase of the bond. The term $-[N - P_{bond}(t_0)]$ corresponds to the initial cashflow associated with the par asset swap. The term $-M$ is the payment made into the derivatives margin account. Quantity $+N(1-h)$ represents the cashflow from the repo loan. Finally, $+\left[Nh + M + \left(P_{bond}^{ask}(t_0) - P_{bond}(t_0)\right)\right]$ represents the cashflow from the uncollateralized loan. As a result of the transactions at time t_0, the investor has a long position in the underlying bond, a CDS protection struck at the prevailing ask spread $S_{CDS}^{ask}(t_0)$, as well as a par asset swap struck at the bid spread $S_{ASW}^{bid}(t_0)$. Finally, we note that, expression (11) does not contain cashflows associated with the CDS contract, since a CDS contract assumes no exchange of cash at inception.

We shall assume that at time t_1 the investor closes out his position in bond and derivatives, and at the same time pays back on the repo and uncollateralized loans. The resulting net cashflow represents the total profit/loss made by the investor. In order to keep our presentation simple, below we provide the final results of our calculations. We refer the reader to Appendix 3 for a detailed derivation of these results as well as the discussion about the various assumption and limits of their application.

Let us firstly assume that the bond has not defaulted by time t_1. In this case, the investor sells off his bond in the market, closes out his positions in CDS and asset swap, and pays dues on his loans. The net cashflow at time t_1 is given by

$$\begin{aligned} P\&L_{no\ default}(t_1) = {} & -N\Delta t\left[(h+m-1)\left(r_{LIBOR} - r_{repo}\right) + (h+m)\left(r_{funding} - r_{LIBOR}\right) + BASIS(t_0)\right] \\ & -N\left[BAS_{bond}\left(1 + \frac{1}{2} r_{funding}\Delta t\right) + BAS_{CDS}\left(RPVO1(t_1) + \frac{1}{2}\Delta t\right) + BAS_{ASW}\left(PVO1(t_1) + \frac{1}{2}\Delta t\right)\right] \\ & +N \cdot PVO1(t_1) \cdot \Delta BASIS\,. \end{aligned} \tag{12}$$

The various terms in this expression have a direct interpretation. The first line represents the carry of the negative basis trade. In the first line, the terms proportional to $(r_{LIBOR} - r_{repo})$ and $(r_{funding} - r_{LIBOR})$ represent the net funding cost, while the term proportional to $BASIS(t_0)$ is the carry earned on negative basis. The second line presents the total losses due to market frictions. This line represents the losses incurred on bid-ask-spreads in the process of opening and closing out of the bond and derivatives positions. Finally, the last term, proportional to $\Delta BASIS$, represents the risk associated with the change in basis between time t_0 and time t_1. This term can be either positive, negative or zero.

In order to gain intuition into the result in equation (12), it is instructive to look at this expression in a simplistic scenario. Let us consider a situation with no bid-ask spreads, a single rate for borrowing and lending, and a constant CDS-bond basis (i.e. $BAS_{bond,CDS,PAS} = 0$, $r_{repo} = r_{LIBOR} = r_{funding}$, $\vartriangle BASIS = 0$). In addition, for the moment, let us ignore the possibility of default. In this case, the profit and loss is given by expression (12), which simplifies to:

$$P\&L_{simple\ scn}(t_1) = -N \vartriangle t \cdot BASIS.$$

Thus, in this case, as might be expected, there is a riskless profit proportional to the (negative) basis that can be obtained using this strategy. On the other hand, if one assumes that there is no-arbitrage available in the market, one would conclude that in the absence of funding costs and market frictions, the basis cannot stay at a persistent negative value. Furthermore, one can look at expression (12), in the presence of bid-ask spreads ($BAS_{bond,CDS,PAS} \neq 0$) and/or funding costs ($r_{repo} \neq r_{LIBOR} \neq r_{funding}$). In these cases, we see that a negative basis can persist without allowing for arbitrage.

Let us now consider the case when the underlying bond defaults by time t_1, when investor closes out his position. In Appendix 3 we show that the resulting profit/loss stays practically unchanged. Therefore, we have

$$P\&L_{default}(t_1) \approx P\&L_{no\ default}(t_1)\,. \tag{13}$$

This equality is a reflection of our hedging strategy using a CDS, whereby the losses on bond default are covered by protection payment on the CDS. However, as explained in Appendix 3, the hedge is not perfect due to the persistence of asset swap in the event of a default. As a result, equation (13) holds true only approximately. In what follows we shall neglect this small mismatch in hedging, and will assume that equation (13) holds exactly. As a result, we shall drop the subscripts "no default"/"default" in notation for $P\&L$ below.

Returning to expression (12), the expression can be schematically presented in the form

$$P\&L(t_1) = Profit + Risk$$

Where

$$\begin{aligned} Profit = & -N\Delta t\left[(h+m-1)\left(r_{LIBOR}-r_{repo}\right)+(h+m)\left(r_{funding}-r_{LIBOR}\right)+BASIS(t_0)\right] \\ & -N\left[BAS_{bond}\left(1+\frac{1}{2}r_{funding}\Delta t\right)+BAS_{CDS}\left(RPVO1(t_1)+\frac{1}{2}\Delta t\right)+BAS_{ASW}\left(PVO1(t_1)+\frac{1}{2}\Delta t\right)\right] \\ Risk = & \ N\cdot PVO1(t_1)\cdot \Delta BASIS \end{aligned} \tag{14}$$

In the above expressions, we have decomposed the profit/loss earnings on the negative basis trade into a component corresponding to expected earnings (*Profit*), and a risky component whose value is unknown initially (*Risk*). At this point, we shall make an assumption that the profit of a negative basis trade is directly proportional to the risks in this trade. This assumption can be viewed as a reflection of the standard result in the Capital Asset Pricing Model (CAPM) (Pennacchi, 2008), whereby the risk premium on a portfolio is directly proportional to its risk and the degree of risk aversion of a representative investor

$$ExcessReturn_{\Pi} = \bar{A}\sigma_{\Pi}^2$$

Where $\mathrm{ExcessReturn}_{\Pi}$ is the return on a portfolio in excess of the risk free rate, $\overline{\mathrm{A}}$ is the coefficient of risk aversion, and σ_{Π}^{2} is the variance of the portfolio (the measure of it's risk). We shall adopt a simplified approach, and shall ignore the effects of possible covariance of the basis risk with the general market risk. Thus, our assumption translates into the following expression for the negative basis trade:

$$Profit = \bar{A}_{nbt}\sigma_{BASIS}^{2} \tag{15}$$

In the above expression $\sigma_{\mathrm{BASIS}}^{2}$ is the variance of the basis, which is the main risk identified for negative basis trades. The term $\overline{\mathrm{A}}_{\mathrm{nbt}}$ is a proportionality coefficient, which serves as the measure of risk aversion for the negative basis trades.

Using expression (14) and straight forward algebra we can rewrite expression (15) as follows:

$$BASIS(t_0) \ = \ -\left[(h+m-1)\left(r_{LIBOR}-r_{repo}\right)+(h+m)\left(r_{funding}-r_{LIBOR}\right)\right]$$
$$-\frac{1}{\Delta t}\left[BAS_{bond}\left(1+\frac{1}{2}r_{funding}\Delta t\right)+BAS_{CDS}\left(RPVO1+\frac{1}{2}\Delta t\right)+BAS_{ASW}\left(PVO1+\ \frac{1}{2}\Delta t\right)\right]\ -\ \left(\frac{\bar{A}_{nbt}}{N\Delta t}\right)\sigma_{BASIS}^{2} \tag{16}$$

The above expression determines the breakeven level of negative basis that can hold in the market without leading to arbitrage opportunities. The functional dependency of the CDS-bond basis in the above expression can be schematically presented in the form:

$$BASIS \ = \ f\left(r_{repo}, r_{LIBOR}, r_{funding},\ \sigma_{BASIS}^{2}, BAS_{bond}, BAS_{CDS}, BAS_{ASW}, h, m\right) \tag{17}$$

Based on relation (17) we can conclude that the factors that explain a negative basis are as follows:

1. Funding cost, as measured by benchmark Libor rate and Repo rate.
2. Worsening collateral quality of the bond, which can be reflected in increase of haircut (h).

3. Illiquidity in derivatives and Bond markets, as measured by the bid ask spread of CDS, ASW and Bonds.
4. The volatility of the basis σ^2_{BASIS}.
5. In addition to factors that have been explicitly captured in expression (16), in our analysis we shall also consider the impact of counterparty risk.

The impact of the factors entering the expression above is schematically presented in the table below:

Factors		Movement of Basis
Funding Cost	↑	Basis ↓
Collateral Quality	↓	Basis ↓
Liquidity of CDS & Bond markets	↓	Basis ↓
Volatility of Basis	↑	Basis ↓
Counterparty Risk	↑	Basis ↓

We note that our analysis was based on a no-arbitrage argument. In this framework, the persistence of the negative basis was explained by various market frictions, including funding costs and bid-ask spreads, as well as risks that preclude an investor from taking an advantage of the negative basis. In this framework, the observed negative basis was at a level that would preclude any practical possibilities of arbitrage. An alternative framework for explaining negative basis was adapted by Garleanu and Pedersen (2011), who approached the problem from a fundamental perspective of asset pricing theory. The authors considered a model with funded and unfunded assets, and showed how a basis could arise as a result of funding liquidity shocks. It is worth pointing out that their theoretical approach led to analogous factors for the determinants of the negative basis. In the remainder of this section, we look at the various factors that we have identified in more detail.

5.4.1 FUNDING LIQUIDITY

A key determinant of basis is the funding liquidity. Funding liquidity contain two aspects, namely funding cost and funding availability. In order to implement a negative basis trade an investor needs funding, which is primarily borrowed in the repo market. The remainder of the funding, which is equal to the haircut value of the repo bonds, is obtained from investor's capital base. An increase in the haircut leads to using more investor capital (Brunnremeier, 2009), (Fontana, 2010). Capital is typically obtained through uncollateralized borrowing in the market. The cost of capital (i.e. uncollateralized borrowing) is therefore a critical determinant of discrepancies between price of bond which are funded investment and CDS which are unfunded investments, thereby affecting the CBB. During the financial crisis the cost of capital dramatically increased. As a result it become relatively expensive to buy bond in comparison with taking short positions on CDSs.

Following the literature, we proxy funding cost using Libor-OIS spread, which is the difference between interbank 3-month borrowing and overnight borrowing rate. This measure reflects short term banking credit risk and interbank liquidity. Widening of the Libor-OIS spread shows a lack of funding liquidity in the market. We expect that the higher the funding cost the less aggressively an arbitrageur will invest in the basis trade, as the basis will become more negative in trades where his funding cost increase. Therefore, we expect that an increase in funding cost will be associated with a more negative basis.

5.4.2 COLLATERAL QUALITY

From our analysis of the negative basis trade, we observe that the deterioration in collateral quality should negatively affect the basis. The deterioration of collateral quality leads to an increase in haircut (h) in repo markets. As a result, larger fraction of funds would be borrowed in the Libor market, at higher rate than repo borrowing. A rising haircut reduces the amount of leverage available to the arbitrageur. Therefore, deterioration of collateral quality leads to an increase in the cost of funding and makes the basis trade less profitable. For this reason, we expect bonds with higher haircuts to be less attractive for basis trades, and as a result allow for more negative basis.

Bond haircuts are not directly observed in the market. For this reason, we proxy collateral quality using firm characteristics that are correlated with expected haircuts. In order to proxy individual collateral quality of the bonds we include average credit rating in our regression. With deterioration of credit rating we expect that collateral quality of the bonds deteriorate as well, and so expect a negative effect on basis. In addition, as an additional proxy of collateral quality we include a company specific characteristic, firm specific volatility. Increase of firm specific volatility reflects an increase in riskiness of a company. This increase in riskiness should be reflected in decrease of collateral quality of its bonds (higher haircut h), and as a result increase of funding cost. For this reason, we expect firm specific volatility to have a negative effect on basis.

5.4.3 ILLIQUIDITY IN CDS AND BOND MARKETS

Our analysis of the arbitrage trading strategy shows that asset specific liquidity factor can explain a negative basis. Intuitively, if bond and CDS market deteriorate in liquidity the negative basis trade becomes more costly to implement. In order to capture asset specific liquidity (liquidity of individual bonds) we use a modified version of Amihud's measure (Amihud, 2002). This measure was widely used in corporate bond research, but is relatively new for basis research ((Augustin, 2012), (Wang, 2013)). The Amihud measure captures liquidity risk. Intuitively, if liquidity deteriorates in the bond market (increase in Amihud measure), it reflected in bond yields by a higher liquidity premium and as a result bond spread increase. We expect that asset-specific illiquidity has a negative impact on the basis.

Augustin (2012) argues that, despite the fact that this measure is calculated at bond level, it should also reflect liquidity in the CDS market since investors trade off the cash and the synthetic market and turn to the CDS market if bonds become too expensive (when liquidity premia are high). Fontana (2010) showed that liquidity in the bond and CDS market are positively cross-correlated.

5.4.4 MARKET LIQUIDITY RISK

Market liquidity risk is another important factor affecting the basis. We proxy market liquidity as difference between 3-month general collateral repo rate and 3-month Treasury bill rate (RepoGC-T-bill). If the rate on repurchase agreement is low relative to the other market rate, the underlying collateral is relatively valuable and the borrower does not have to pay much interest for using the cash funds. However, if repo rate is relatively high it signals a relative abundance of collateral and borrower has to pay a higher interest rate in order to obtain cash funds.

According to Bai, Collin-Dufresne (2013), 3-month general collateral repo rate minus 3-month Treasury bill rate measure captures a flight-to-quality liquidity component, where widening of this spread reflect the attitude of investor to owning a 3-month Treasury bill paying a lower yield, than an overnight loan fully collateralized by the same Treasury. We expect that with higher market liquidity risk the arbitrageur would be less attracted to investing in a negative basis trade. As a result RepoGC-T-bill should have a negative effect on the basis.

5.4.5 VOLATILITY OF BASIS

Our theoretical analysis of the P&L function for a negative basis trade reveals that volatility of the basis risk can be an important determinant of the basis. A higher volatility of the basis would lead an arbitrageur to demand additional premium for assuming the risk associated with losses due to further widening of the basis. For this reason, an arbitrageur would avoid entering a negative basis trade, unless the profit opportunity was sufficient to compensate for the risk. Therefore, one can expect that basis volatility would have a negative effect on the basis. This factor has not been previously studied in the literature, but naturally arises when one carefully considers a negative basis arbitrage trade.

5.4.6 COUNTERPARTY RISK

The failure of Bears Sterns, Lehman Brothers and AIG highlighted the importance of accounting for the counterparty risk in derivative transactions. In our context for the CDS position in the negative basis trade, the counterparty risk is the risk that protection seller would fail to pay the protect buyer in case of default of the underlying. Counterparty risk typically makes CDS protection less valuable, and therefore lowers the CDS spread. For this reason, one can expect a negative effect of counterparty risk on basis. Counterparty risk, as factor of explaining negative basis, was previously analyzed in Bai, Collin-Dufresne (2013), Augustin (2012), Fontana (2010), Wang (2013). However, these works did not come a firm and consistent conclusion on the role of counterparty credit risk in explaining the basis. The major problem in measuring the contribution of counterparty risk is that the CDS market is an OTC market, which makes the identification of counterparties to transactions tricky. Furthermore, the transactions are often carried out under netting and collateral agreements, which further complicates the analysis.

For the purpose of analyzing the effect of counterparty risk on CBB, we construct an intuitive measure, a weighted CDS index, characterizing the credit riskiness of the major CDS dealers. Intuitively, the higher the CDS index of major CDS dealers, the larger is the probability of CDS dealer defaulting on its obligations. This would lead to a decrease in the price of CDS protection, and therefore should lead to a decrease in the CDS-bond basis. For this reason, we expect a negative coefficient for counterparty risk variable in our regression.

5.5 DATA

The data we used in our analysis of the CDS-bond basis came from different sources. We collected data on CDS spreads and corporate bond yields from the MarkIt Group. MarkIt is a provider of comprehensive global financial data, and is becoming extensively employed in academic literature as a result of its high quality standards. The MarkIt dataset used for the current research contained daily firm level data on corporate bond and CDS spreads for the period from January 2003 to August 2013. The corresponding equity returns were obtained from Center for Research in Security Prices (CRSP) database. In order to collect the information on trading volume for each corporate bond we used Trade Reporting and Compliance Engine (TRACE) database. This database captures and disseminates consolidated information on secondary market transactions in publicly traded securities, in particular, covering all over-the counter market activity in corporate bonds. We collected accounting firm specific data from the COMPUSTAT database. The data was cleaned to remove obvious data outliers and erroneous data points. A major technical challenge was to merge the data from different data sources. For this purpose we used a matching scheme based on CUSIP/ISIN identifiers to track an issuer/specific-bond issue across our datasets.

As a result of the extensive data restrictions, cleaning, and merging of data between various data sources we were forced to ignore almost half of our initial dataset. However, we were still left with a significantly large dataset to work with. Overall, we were left with 506,279 daily CBB observations spanning a period between January 2005 and December 2011, containing data on 403 unique US issuers. The dataset contained data on investment grade (IG) and high yield (HY) US companies, with bonds and CDSs denominated in US dollars. In what follows, we give a detailed description of the various data that was used in our analysis.

CREDIT DEFAULT SWAP SPREADS

We collected the single-name credit default swap data from MarkIt. The dataset contained the following information: identifier (entity code, tier, CUSIP), currency, documentation clause, default swap spread curve for different maturities, recovery rates. MarkIt receives contributed pricing (quotes) from CDS market makers (22 global banks) and publishes daily consensus pricing on approximately 2650 individual entities and 3000 entity-tiers. MarkIt applies rigorous data cleaning tests to each curve in order to provide an independent, accurate and reliable pricing data. To maintain data quality, MarkIt subjects all quotes to a series of tests and cleans data accordingly, which checks for stale data, outliers, flat CDS term structure inconsistent across data contributors, and consistency of quotes across documentation clauses. MarkIt calculates a composite price, which a mathematical average of all contributed prices and spread data for a given instrument type, entity, tier, maturity, currency, and restructuring type. In order to form a composite, MarkIt requires at least 3 distinct contributors submitting curves of which at least 2 pass all data cleaning tests. Our original dataset provides daily CDS prices in different currencies and different type of restructuring clauses. For the purpose of this work we included only CDS quotes written on US entities and denominated in US dollars. We have also restricted our analysis to CDSs on Senior Unsecured Debt (Tier SNRFOR). We further restrict analysis to MR (modified restructuring) clauses CDS contracts since they are most popularly traded (and most liquid) in US.

CORPORATE BOND DATA

The corporate bond data was also obtained from MarkIt. The dataset contained information on bond price, identifier (CUSIP, ISIN), coupon rate, issuing date, maturity date, composite Z-spread and composite par asset swap spread. We imposed several restrictions on the sample of bonds for our analysis. Firstly, we exclude unrated bonds. Secondly, all samples were restricted to fixed coupon bonds denominated in US dollars. Thirdly, the corporate bonds with non-standard features such as callable, puttable, sinking finds, convertible and/or structured were excluded from the analysis. Fourthly, we restricted ourselves to just bonds corresponding to senior unsecured debt (SNRFOR). The main motivation for this restriction is that the yield spread on collateral secured bonds reflects mainly creditworthiness of the collateral rather than the creditworthiness of the issuer (Campbell & Taksler, 2003). In order to avoid issues with data imprecision, we restricted our analysis to composite data points (i.e. a prices obtained after averaging and cleaning contributions from several sources). Finally, in order to reduce the number of data error related outliers in the data, we eliminated the top and bottom 1% of spreads. As a characteristic of bond credit spread we considered two measures from bond dataset. The first and the main measure for credit spread was the composite par asset swap spread. In addition, we also looked at the Z-spread as a measure of bond credit spread. Z-spread is calculated iteratively by shifting the LIBOR curve (a proxy of risk-free curve) up or down until the present value of the cash flows of the bond using the shifted curve equals the market price of the bond. Our Markit dataset contained composite prices for both of these quantities.

Another bond specific characteristic used in our analysis is the credit rating. This information was obtained from the MarkIt dataset. The MarkIt credit rating is constructed as average of Moody's and S&P ratings adjusted to the seniority of the instrument and rounded to not include "+" and "-". Following the standard procedure in literature Campbell and Taksler (2003), Elton, Gruber, Agrawal and Mann (2001), , we eliminate AAA bonds from our data set due various apparent issues with their spreads. In addition, we eliminate all credit ratings lower than B (CCC and NR) since this data seems to contain a lot of noise and outliers. The resulting bond dataset consisted of bond data corresponding to ten business-sector categories (Industrial, Utilities, Financials, Technology, Consumer Goods, Healthcare, Consumer Services, Telecommunications, Services, Basic Materials, Energy) and five rating categories (Aa, A, Baa, Ba, B).

CDS-BOND BASIS

As we were previously discussed in Section 5.3, the CDS-bond basis, for a particular bond, is defined as the difference between a CDS premium for a protection with maturity corresponding to the bond's maturity and the bond's par asset swap spread (ASW). The MarkIt CDS dataset contained CDS spreads for a set of discrete maturities in the range from 6 month to 30 years. In order to obtain the CDS spread corresponding to a required maturity, we interpolated the MarkIt CDS curve using a cubic spline in Matlab. We used the interpolated CDS spread in conjunction with the ASW to calculate the basis for each bond as

$$Basis_{i,t} = CDS_{i,t} - ASW_{i,t}$$

As mentioned previously, for the purposes of a robustness check, we also calculate CDS-Bond basis using the Z-spread instead of ASW.

EQUITY MARKET DATA

To construct the collateral quality characteristic, we calculated the firm specific volatility. Firm specific volatility measure, by construction, is free from market volatility effect, and as a result represents the riskiness of company, independent of the overall movement of market. We collected the stock price and market index (CRSP value-weighted index) data form CRSP database. In line with Campbell and Taksler (2003) as a characteristic of equity volatility we use standard deviation of daily excess return relative to CRSP value-weighted index for each firm's equity over the 180 days before the bond transaction date.

$$\sigma = \sqrt{\frac{1}{180}\sum_{i=1}^{180}(R_i^{excess} - \mu)^2} \ ; \qquad \text{where } \mu = \frac{1}{180}\sum_{i=1}^{180} R_i^{excess}$$

Where R^{excess} is the daily excess return relative CRSP value-weighted index, and μ is its mean over 180 days. An important practical issue was to identify whether the stock was traded constantly during the period of volatility calculation. Since any gaps in trading of a stock would lead to sudden jumps in price which will cause spurious jumps in volatility. For this reason, we put restrictions on calculation of the standard deviation for returns to not exceed 120 days gaps in trading.

COUNTERPARTY RISK

As discussed in the previous section, the CDSs are traded is an OTC market with the information on exact nature of counterparties unknown. However, according to the Federal Reseve Bank dealer list for 2009[3], most of the CDS sellers are big investment banks and insurance companies. For this reason, it is natural to assume that a measure of credit worthiness of these main CDS dealers can serve as a measure of the counterparty risk in the CDS market. In order to capture counterparty as a factor, we constructed a proxy based on representative CDS issuers using the list of primary dealers published by the Federal Reserve Bank of New York in July 2009 (Bai & Collin-Dufresne, 2013). We introduce US CDS sellers Index measure as:

$$CDSIndex_t = \frac{\sum_{i=1}^{N} CDS_{i,t} \times Capitalization_{i,t}}{\sum_{i=1}^{N} Capitalization_{i,t}}$$

$$Capitalization_{i,t} = Price\ of\ stocks_{i,t} \times Total\ Number\ of\ Shares\ Outstanding_{i,t}$$

[3] Source: Federal Reserve Bank of New York.
http://www.newyorkfed.org/markets/pridealers_current.html

where N is number of major CDS dealers from the list of Fed primary dealers provided in Appendix 2, part A. The daily composite CDS prices for the individual dealers was taken from our MarkIt CDS dataset. The annual stock price data and total number of shares outstanding for the list of dealers was collected from the CRSP database and Datastream, respectively. We used fixed annual weights for each dealer.

MARKET LIQUIDITY RISK AND FUNDING COSTS

The liquidity risk was proxied by flight-to-quality liquidity component, measured as spread between 3-month general collateral repo rate collateralized by treasury and 3-month Treasury Bill rate.

$$Market\ liquidity = Repo_{GC} - Treasury\ Bill_{3M}$$

The measure was constructed using daily rates of 3-month T-Bill and Repo General Collateral (Treasury) obtained from Board of Governors of the Federal Reserve System (Federal Reserve Economic Data).

The funding cost was proxied by LIBOR-OIS spread

$$Funding\ cost\ measure_t = LIBOR_t - OIS_t$$

The Daily rates for 3-month Libor and overnight index swap (OIS) came from Federal Reserve Bank in St. Louis and Bloomberg, respectively.

BOND LIQUIDITY

The bond liquidity was measured using Amihud measure. This measure is calculated, for individual company *i* on day *t*, as :

$$Amihud_{i,t} = \frac{r_{i,t}}{Vol_{i,t}}$$

Where $r_{i,t}$ is weighted average return for i-th issuer at day t, and $Vol_{i,t}$ is total trading volume on day t in millions of US dollars. Since, Amihud measure is typically a small value, in our analysis, we multiply the Amihud measure by a factor of 100 million. The Amihud measure gives an indication of an impact of trade volume on price change. An increase in Amihud measure indicates higher bond illiquidity. To calculate the Amihud measure we collected bond transaction data, including prices and trading volume, from TRACE database. We restrict our dataset to include at least two different trades for a given bond on a given day. This restriction is crucial for calculation of weighted average price (depending on volume of trade) for each issuer over the day t.

VOLATILITY OF BASIS

The volatility of the basis was constructed using the historical time series for the basis for individual firms.

$$\sigma_{i,t}^{Basis} = \sqrt{\frac{1}{N_t}\sum_{k_t=1}^{N_t}\left(Basis_{i,k_t} - \mu_{i,t}^{Basis}\right)^2}, \quad \text{where} \quad \mu_{i,t}^{Basis} = \frac{1}{N_t}\sum_{k_t=1}^{N_t} Basis_{i,k_t}.$$

Where N_t corresponds to the averaging period. In our work we considered periods of 3 month and 6 month. The results for the two periods did not have any significant differences. For this reason, we present our results for 3 months averaging period only.

SUMMARY STATISTICS

Table 34 presents the summary statistics for our final CDS-bond basis dataset for 2005 -2011. The biggest number of transactions came from A and BBB rated companies' data. In terms of time periods, 2005 had the smallest number of observations (54,877), while

2011 had the largest with the double the number of data points (108,826). We note that AAA rating contains only a limited number of data points, restricted to the Energy and Healthcare sectors. This was another reason for excluding this rating category from our analysis.

The various sector types are overall well represented in our dataset; with biggest number of transactions belong to Consumer Goods (86,837), Consumer Services (86,485) and Financial (83,949) sectors and smallest number belonging to Utilities (24,393). We note that telecommunication services and basis materials sectors are not represented within AA ratings, while financial sector is not represented in B rating category in our dataset.

Panel C reports averages of basis for each credit rating category at particular year represented in basis points (bp). We note that, the CBB stays positive for most of the credit ratings from 2005 to 2007 (excluding A and BB rated companies in 2006). During the period of financial crisis, between 2008 and 2009, the basis fell significantly in to negative territory across most of the credit rating categories. For example, for AAA companies the averaged basis fell to -36bp, for A companies it fell to -54bp and for BBB companies the fall was -50bp. However, summary statistics shows that for B rated companies' (belonging to HY rating category) the averaged basis stayed significantly positive during the crisis period (149pb and 158bp). These firms seem to show a somewhat peculiar and highly volatile dynamic of the basis, staying positive before and during Lehman collapse. By 2011, the level of negative basis started to narrow across all rating categories, reaching almost zero for AAA ratings and a level of 21 bp for A ratings.

Figure 22 graphs the historic behaviour of the averaged basis for various rating categories. The figure shows that the rating fluctuated around zero across all rating groups for the period between 2005 and March 2007. From March 2007 to Jan 2008, the average basis started moving down into the negative area, at the same time showing several jumps from negative to positive territory (most clearly seen for AA and A ratings). Starting from September 2008, corresponding to Lehman bankruptcy, we observe a deep fall of basis into the negative territory. The size of this fall depends on credit rating of company. For AA rated companies the basis falls on average to -100bp, for A ratings the fall is -180bp, BBB rated companies fall to -260bp, and BB ratings fall to almost -340bp. For all of the rating groups, basis stood strongly negative at least until the end of 2009. However, starting from March 2009, the basis changes trend from falling to a slight increase. Since May 2009 we observe a slow climbing of the basis back to the zero level. The basis has not however reached the zero level by December 2011. Figure 23 shows the historical behaviour of basis for companies corresponding to B and CCC ratings. We note that the behaviour of the basis for these categories is very different from the other groups. We see that, during the financial crisis, the average basis for B and CCC ratings was significantly positive, a picture diametrically opposite other rating categories considered above. A feasible explanations of this phenomenon, is that there is very limited liquidity for these low rated issuers in the CDS market.

Figure 24 compare behaviour of the CBB for Financial and Non-financial sector companies. It is interesting to note that the Basis for financials fluctuates around zero level, with a few jumps into the positive territory, in period between October 2007 and March 2008. At the same time, for this period, the basis of non-financials was already significantly negative. In the aftermath of the Lehman collapse, in October 2008, the basis of financial companies was above zero (around 50bp), while the basis of non-financials was below zero (-50bp). Another important observation is that the basis for non-financial companies reached a minimum level of -260bp, while for financials the minimum was -200bp.

Finally, we have tested for the presence of multicollinearity in our explanatory variables in order to avoid potential issues in regressions. Table 35 reports the correlation matrix, containing Pearson correlation coefficients, for variables that proxy funding cost, collateral quality, bond liquidity, basis volatility, counterparty risk and aggregate liquidity risk. Table 35 shows absence of any problem with high correlation.

Table 34
Summary Statistics of CDS – Bond basis

The tables provide descriptive statistics of CDS-bond basis over the period between 2005 and 2011. Panel A and Panel B report number of transactions we have for different credit rating and year together with different sector category. Panel C presents average CDS-bond basis according to firm's credit rating and year. The average basis is given in basis points.

Panel A

Year	AAA	AA	A	BBB	BB	B	Total
2005	577	4,415	20,450	19,868	6,362	3,205	54,877
2006	614	4,788	25,893	21,987	7,346	3,422	64,050
2007	756	4,926	24,844	18,708	5,125	3,529	57,888
2008	1,702	4,308	27,188	19,049	4,610	2,756	59,613
2009	1,933	4,402	35,265	30,489	7,161	2,098	81,348
2010	1,381	4,864	36,275	33,776	10,008	1,607	87,911
2011	1,173	7,086	46,029	42,897	9,916	1,725	108,826

Panel B

Sector	AAA	AA	A	BBB	BB	B	Total
Industrials	N/A	4,809	18,733	15,529	2,988	90	42,149
Utilities	N/A	46	5,142	14,383	4,291	531	24,393
Financials	N/A	4,560	68,047	10,927	415	N/A	83,949
Technology	N/A	2,212	19,961	10,154	1,528	2,056	35,911
Consumer Goods	N/A	4,327	22,453	38,505	12,698	8,854	86,837
Healthcare	4,697	980	25,807	7,186	110	2,741	41,521
Consumer Services	N/A	17,076	12,490	46,426	7,031	3,462	86,485
Telecommunications Services	N/A	N/A	25,660	2,030	5,872	206	33,768
Basic Materials	N/A	N/A	8,666	21,006	6,722	3	36,397
Energy	3,439	779	8,985	20,628	8,873	399	43,103

Panel C

Year	AAA	AA	A	BBB	BB	B
2005	14,05	10,68	6,17	13,51	4,53	29,15
2006	10,53	4,64	-0,67	12,93	-7,72	52,5
2007	3,81	4,21	0,34	4,92	4,73	90,93
2008	-35,48	-18,52	-53,87	-49,2	-60,24	149,36
2009	-74,24	-17,66	-84,71	-120,43	-131,32	157,97
2010	-33,6	-12,35	-34,64	-49	-91,68	-29,34
2011	-0,52	-6,25	-21,29	-40,14	-66,84	52,04

Table 35
Correlation Matrix for CDS –Bond basis determinants

The table reports the correlation values for variables that proxies funding cost, collateral quality, bond liquidity, basis volatility, credit curve slope, term structure slope, counterparty risk, aggregate liquidity risk. The correlation matrix is calculated using whole subsample between 2005 and 2011.

	SD (firm specific volatility)	Daily Amihud	CDS Index	LIBOR-OIS	Repo GC-Treasury	BasisVol6M
SD (firm specific volatility)	1					
Daily Amihud	0.03	1				
CDS Index	0.32	0.001	1			
LIBOR-OIS	0.32	0.04	0.52	1		
Repo GC-Treasury	-0.13	0.03	-0.32	0.3	1	
BasisVol6M	0.44	0.02	0.24	0.27	-0.06	1

Figure 22

Historical aggregate CDS-bond basis for different rating groups for US companies (in percent).

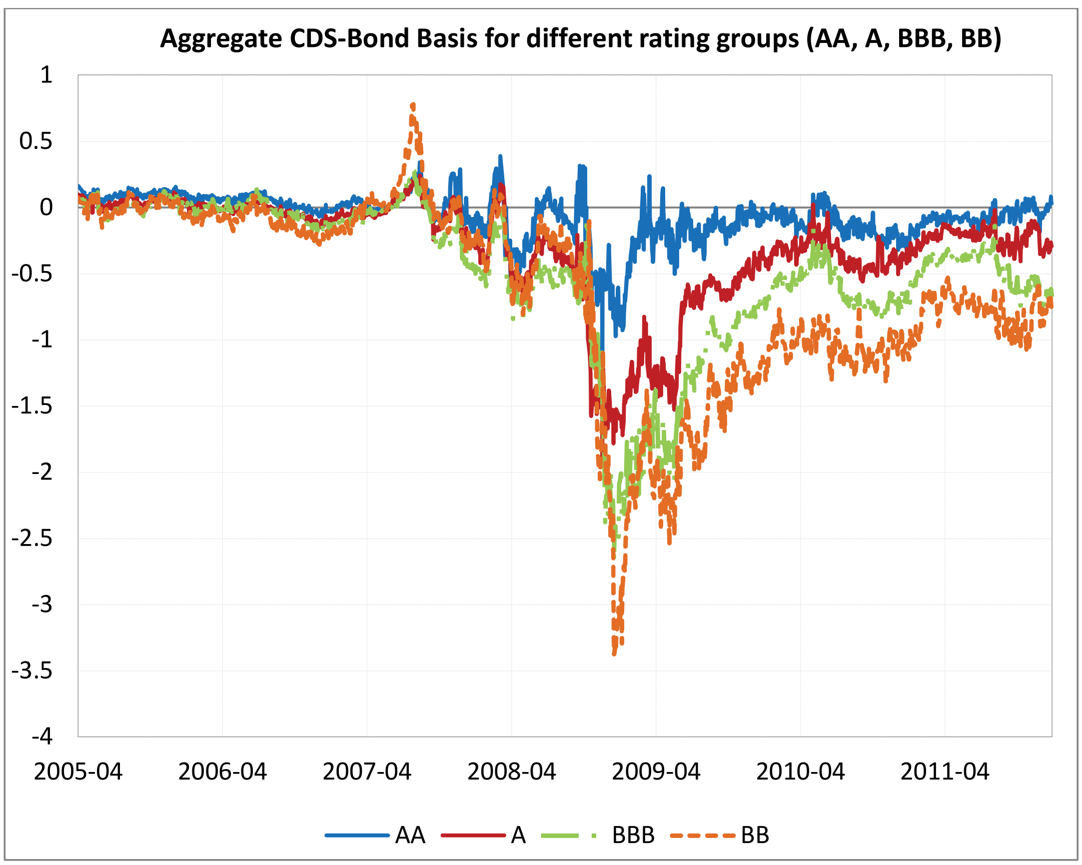
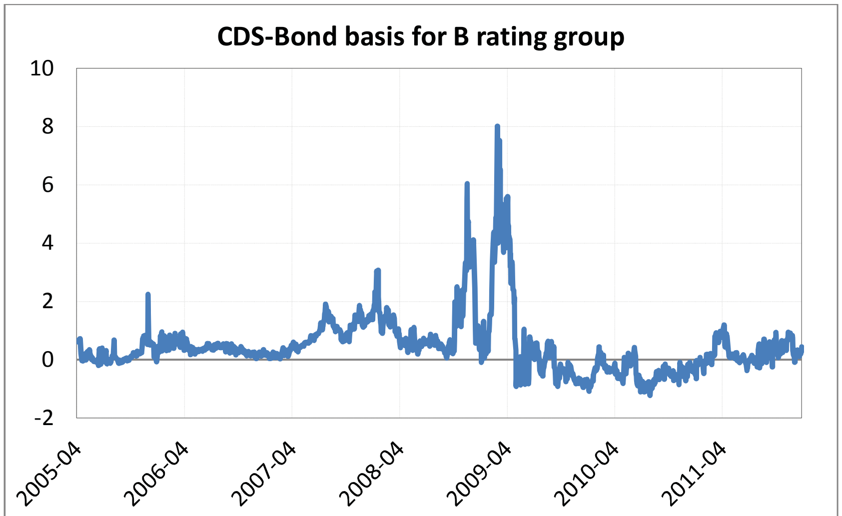


Figure 23

Aggregate CDS-bond basis for low rating bonds (B, CCC) (in percent).



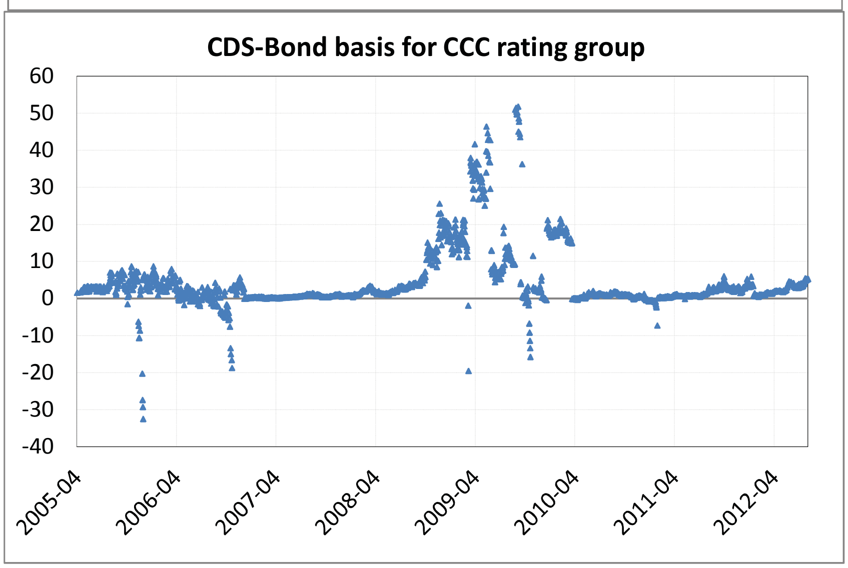
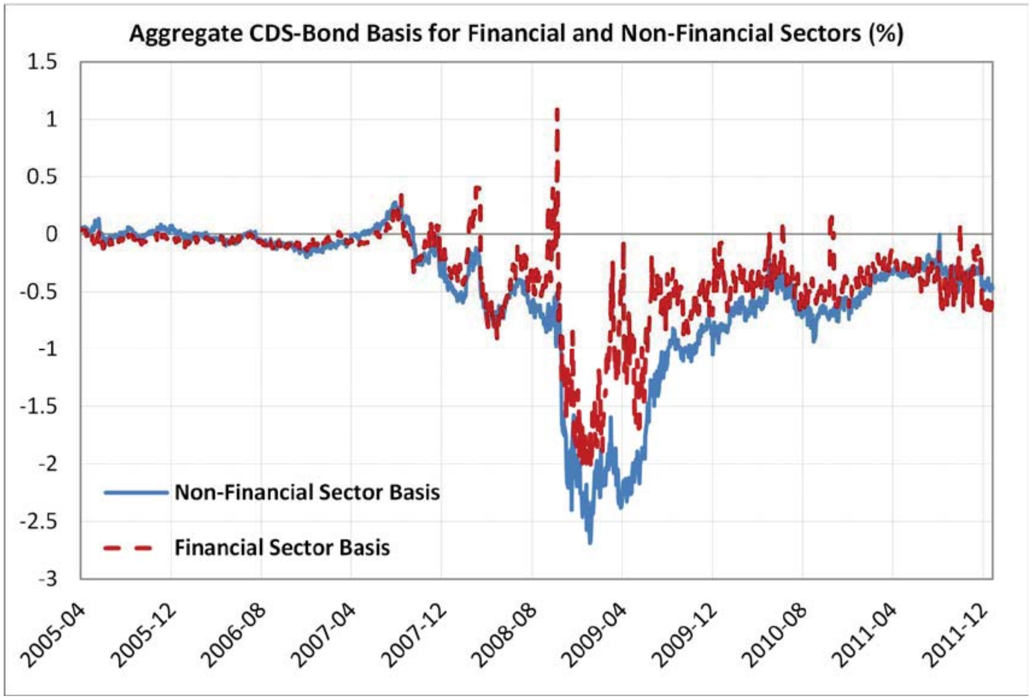


Figure 24

Aggregate CDS-bond basis of financial and non-financial US Companies US Companies (in percent).



5.6 EMPIRICAL ANALYSIS

5.6.1 EMPIRICAL METHODOLOGY

In order to empirically investigate the effect of various factors on the basis we proceed by conducting a regression analysis of the dependency indentified in expression (18). For this purpose we study the cross-sectional determinants of the CBB using the following regression:

$$\begin{aligned} Basis_{i,t} = \alpha_i + \beta_{1,i} STDV_{i,t} + \beta_{2,i} Rating_{i,t} + \beta_{3,i} FC_t + \beta_{4,i} AggLiq_t \\ + \beta_{5,i} BondLiq_{i,t} + \beta_{6,i} CR_t + \beta_{7,i} BasisVol_{i,t} + \varepsilon_t^i \end{aligned} \tag{18}$$

Our expectations about the signature of the estimated coefficients of the above regression are given in the table below.

Variables	Description	Sign Expectation
STDV	Standard deviation of daily excess return relative to CRSP value- weighted index (proxy of collateral quality of bond)	-
Rating	Dummy variable of credit rating (proxy of collateral quality of bond)	-
FC	Funding cost risk. Proxy as LIBOR- OIS.	-
AggLiq	Aggregate liquidity risk, proxy as RepoGC-Treasury(3month)	-
BondLiq	Bond liquidity, proxy as Amihud measure.	-
CR	Counterparty Risk, proxy as CDS seller Index	-
BasisVol	Basis Volatility, proxy as 3 or 6 month standard deviation of basis	-

We estimate the model using the variables in levels. We run a pooled ordinary least square (OLS) regression treating each CBB value as an independent observation. We follow up, by performing panel regressions (Fixed and Random panel estimations), and conducting a Hausman test in order to choose the appropriate approach.

In order to capture the qualitatively different behaviour between IG/HY categories as well as financial/non-financial sectors, we run all our regression analysis individually on each of these subsets. To investigate the CBB during the financial crisis we further separate our dataset into two time periods, divided by the timing of the Lehman Brothers' collapse, and run regressions for the two periods. The pre-Lehman period corresponds to data points prior to August 2008, and post-Lehman period corresponds to data points after October 2008. We study the response of CBB to various determinants in the pre and post Lehman periods separately for financial and non-financial sectors.

In order to mimic the behaviour of arbitrageurs trying to take advantage of negative CBB, we look at our data from a slightly different perspective. An investor looking at negative CBB trading opportunities would typically seek the bond-CDS pairs with the most negative basis. For this reason, one can expect that the explanatory power of our model, that was derived based on a negative basis trading strategy, should improve of the subset of data containing the most negative basis pairs. We test this statement using a procedure identifying top 10% negative CBB data points.

In order to estimate the economic significance of the various determinants of the basis, we use an the Fama-MacBeth approach (Fama & MacBeth, 1973), which is widely used in econometric literature on panel data analysis (Petersen, 2006), (Skoulakis, 2008), (Bai & Collin-Dufresne, 2013). Fama-MacBeth cross-sectional approach is particularly well suited to answer question on relative importance of the various determinants of CBB, as well as the time dynamics of their contribution to CBB.

The Fama-MacBeth procedure consists of a two stage regression process. In the first stage, the first-pass regression, one estimates the sensitivity of CBB to various risk factors, for individual issuers. For this purpose, we perform the following individual regressions for each issuer *i*:

$$Basis_i = \alpha_i + \beta^i_{factors} * Variables^i_t + \epsilon_i \tag{19}$$

Where $Basis_i$ is a *t×1* vector of basis, $Variables^i_t$ is *t×m* matrix of m factors for the issuer *i*, α_i is t×1 vector of intercepts and β^i_{factor} is vector of *1×m* factors estimate coefficients for each individual issuer *i*. Following this, the factors β^i_{factor} are used in the second-pass regression, which consists in a cross sectional regression of the form:

$$Basis^i_t = \alpha_t + \gamma_{t,coll}\beta^i_{coll} + \gamma_{t,libor}\beta^i_{libor} + \gamma_{t,repo}\beta^i_{repo} + \gamma_{t,cp}\beta^i_{cp} + \gamma_{t,liq}\beta^i_{liq} + \gamma_{t,vol}\beta^i_{vol} + e^i_t \tag{20}$$

The coefficients β^i_{factor} serves as an estimate of sensitivity of the basis to the corresponding factor for a given issuer *i*. The coefficients $\gamma_{\mathrm{t,factor}}$ are the time dependent contributions (risk premiums) of the given factor in CBB, and measure the responsiveness of the CBB to the changes in the factor. The time averages of the gamma coefficients γ_{factor} gives an overall magnitude of the effect of the factor on CBB.

5.6.2 RESULTS DISCUSSION

A. NON-FINANCIAL SECTORS ANALYSIS

The estimation results for the non-financial sector are presented in Table 36. The regressions in column 1-3 show that the chosen variables explain 36% of the CBB for the non-financial sector for a period between 2005 -2011. The explanatory power for IG (36%) is significantly higher than for HY (16%).

The standard deviation excess return (firm specific volatility) has a statistically significant negative coefficient for both IG and HY group. This means that an increase in firm specific volatility leads to basis becoming more negative. This is an expected result since firm specific volatility reflects the riskiness of the bond issuer, and as a result the quality of the bond which is used as collateral. With the reduction in the quality of the bond, the collateral haircut requirement rises, forcing the investor to look for additional funding in the LIBOR market. The resulting increase in the funding cost makes the negative basis trade more expensive, thereby leading to widening of negative basis. However, we note that the estimated coefficient for HY bonds is significantly smaller than for IG bonds, perhaps reflecting the relative insensitivity of the already high levels of haircuts required for HY bond repos.

The coefficients for credit rating dummies are significantly negative for IG group. This implies that CDS spreads fall slower than the bond credit spreads as we move from higher ratings to lower ones. This result is also consistent with our expectations. The rating dummy is a natural proxy for the credit quality of the bond, which serves as collateral in the repo transaction. For this reason, rating dummy is a proxy for collateral quality. As in the case of firm specific volatility proxy, one sees that the basis widens when collateral quality drops as a result of moving from a higher rated bond to a lower rated. On the other hand, for HY bonds, we see a positive coefficient for the rating change from BB to B, implying a narrowing of the basis. This fact is in line with our analysis of behaviour of CBB for B rating bonds in Section 5.5 (see Figure 23), and is possibly a result of illiquidity of CDS market for B rated issuers.

The estimated coefficients for the LIBOR-OIS spread are significantly negative for both IG and HY groups. These results are in line with results presented in earlier works Fontana (2010), Bai & Collin-Dufresne (2013), Garleanu and Pedersen (2011)). A rise in the LIBOR-OIS spread is an indication of funding squeeze in the market for uncollateralized debt, i.e. the interbank money market. Therefore, the results show the expected widening of the negative basis with increasing funding illiquidity. As the funding costs increase, arbitrageurs require wider negative basis to profitably exploit negative basis trades. We note that the results show that in general IG bonds are more sensitive to LIBOR-OIS than HY bonds. This finding suggests that for HY bonds, where the basis are already quite wide, funding liquidity plays less of a role in arbitrage decisions. Finally, we note that LIBOR-OIS along with capturing funding costs also captures the general market perception of counterparty risk. This is because any increase in counterparty risk of major derivatives dealers (large investment banks) will naturally be reflected in the unwillingness of these major banks to lend to each other in the LIBOR market. We see a confirmation of this point in the 52% correlation between LIBOR-OIS and CDS-index in Table 39.

The Repo(GC)-Treasury factor measures the impact of flight to quality on the basis. During the financial crisis there was a significant movement of capital from risky corporate bonds to the (virtually) risk-free treasury bonds. This flight to quality affects the funding costs in the repo market, and thereby should affect the profitability of negative basis arbitrage trades. Therefore, Repo(GC)-Treasury serves as a measure of market liquidity risk and a proxy of funding cost (Bai, Collin-Dufresne 2013). Our regressions show a small negative coefficient for IG bonds and a small positive coefficient for HY, however the results show a relatively small t-statistic and are therefore deemed statistically insignificant.

The regressions consistently show a negative sign for the CDS-index coefficient. An increase in the CDS-index reflects a higher market perceived probability of default for the major CDS dealers. Assuming a non-negative correlation between the default of the underlying reference entity and the CDS dealer, this translates into an increase in counterparty risk. For this reason, the CDS-index coefficient reflects the sensitivity of basis to counterparty risk. Our results show that with increase in counterparty risk there is a tendency of negative basis to widen. Our conclusions are in line with recent literature. Bai, Collin-Dufresne (2013) found that counterparty risk becomes negatively significant during the crisis period (2007-2009). Arora, Gandhi and Longstaff (2012) found strong evidence that counterparty credit risk is priced in the CDS market. A similar negative effect of counterparty risk on basis was found by Augustin (2012).

The Amihud measure serves as a proxy for bond illiquidity. An increase in this measure shows an increase in price sensitivity of a bond to its trading volume. The regression coefficients for Amihud measure across our regressions have an expected negative sign, but are mostly not statistically significant. Our result shows inconclusive evidence for the effect of bond illiquidity on CBB. Although this result can be interpreted as a lack of sensitivity of CBB to bond illiquidity, our result could be a reflection of the fact that Amihud measure is not a suitable proxy for bond illiquidity.

Finally, turning to volatility of the basis as a determinant of CBB, we see that for IG bonds we see a significant negative coefficient. This implies that an increase in basis volatility is associated with widening of the negative basis. This is an expected result, since an increase in basis volatility leads to an increased risk for the negative basis arbitrageur, requiring additional risk premium in terms of wider negative basis to compensate for this risk. On the other hand, for HY bonds, the sensitivity of CBB to basis volatility has a significant positive sign. This finding is an artefact of the unusual behaviour of B rated issuers (positive bond basis during 2008-2009) highlighted in our discussion of descriptive statistics.

Our results show that explanatory power of the factors is different for IG and HY groups. The explanatory power of our determinants is significantly smaller for HY bonds (20%). This result is related to the behaviour of the basis for B rated issuers during crisis. In order to validate this assumption, we performed a regression analysis for BB rated issuers, and results showed coefficients and explanatory power in line with results for IG sector.

Following the analysis of the sensitivity of CBB to the various factors, it is interesting to look at the actual contribution of these factors to CBB over the period of our study. For this purpose we decompose the variance of the CBB into contributions from each of the factors. This is obtained by multiplying the standard deviation individual variables with the corresponding estimate coefficient in Table 36. The results are given in Table 37. Columns 2 and 5 represent standard deviations of each factor for IG and HY categories. Columns 3 and 6 report the contribution each factor to changes in basis. Columns 4 and 7 report relative contribution effect, obtained by dividing the effect for individual factors effect standard deviation of CBB.

The results in Table 37 show that for IG bonds, firm specific volatility has the largest contribution to the basis, contributing approximately 21bp to the variation of basis. A significant portion of the IG basis is explained LIBOR-OIS spread (15bp) and CDS-index (17bp). Basis volatility explains almost 5bp in CBB. The main factors for HY bonds are firm specific volatility (17bp), CDS-index (48bp) and basis volatility (69bp). We note that, for both IG and HY bonds, Repo(GC)-Treasury and Amihud measure do not significantly contribute to the basis. These results support our previous findings on the importance of funding cost, collateral quality, counterparty risk and basis volatility in determining the basis.

Table 36
Determinants of CDS-Bond basis for non-financial sectors between 2005 and 2011

Using panel data between 2005 and 2011 for non-financial sectors, we regress CDS-bond basis (calculated with asset swap spread) against the list of variables below. Table reports results of Panel estimation approaches (Fixed and Random effect) and Pooled OLS approach. Table compares results of different approaches for IG and HY companies. The standard errors of estimated parameters are adjusted using Newey –West method (Newey & West, 1987) and Driscoll and Kraay method (Driscoll & Kraay, 1998) for panel data. Associated t-statistics appear in parentheses beneath. Estimate coefficients are given in basis points (bp). Significant coefficients are market in bold (the significance is set at 1 percent level (>2.33)).

	IG				HY			
	Fixed effect (within)	Random effect	Pooled OLS	Pooled OLS	Fixed effect (within)	Random effect	Pooled OLS	Pooled OLS
STDV(excessRET) (%)	**-30.46** (-14)	**-30.48** (-13.3)	**-25** (-11)	**-28.03** (-12)	**-13.08** (-2)	**-13.47** (-2)	-3.43 (-0.6)	-1.8 (-0.3)
Downgrade From AA to A		-13.25 (-0.5)	**-18.46** (-4)	**-17.21** (-4)				
Downgrade From AA to BBB		-38.58 (-1.5)	**-38.61** (-7.9)	**-35.42** (-7.3)				
Downgrade From BB to B						**60.32** (3.2)	**74.19** (7.5)	**67.23** (7)
LIBOR-OIS (%)	**-31.49** (-6)	**-31.14** (-6.3)	**-40.03** (-13)		**-24.79** (-2)	**-24.01** (-2)	-8.92 (-0.5)	
Repo GC-Treasury (%)				-3.34 (-1.1)				**11.08** (8)
CDS Index (%)	**-22.86** (-7.6)	**-22.04** (-7.2)	**-19.5** (-14)	**-28.35** (-17)	**-80.84** (-7.1)	**-80.59** (-7.2)	**-65.89** (-9.3)	**-53.42** (-7)
Daily Amihud	-0.03 (-0.18)	-0.05 (-0.11)	**-1.07** (-5.1)	**-1.63** (-7.5)	-0.53 (-0.63)	-0.68 (-0.63)	-0.36 (-0.4)	-0.13 (-0.1)
Basis Volatility (%)	**-30.24** (-2.1)	**-33.6** (-2.1)	**-48.02** (-2)	**-79.14** (-2.8)	**323.08** (3.2)	**323.22** (3.2)	**297.37** (3.7)	**288.56** (3.4)
Intercept		**69.9** (2.8)	**59.72** (14)	**62.15** (15)		**- 18.27** (-3)	**-19.87** (-2.3)	**-47.6** (-5.3)
Total Sum of Squares:	106180	106930			167230	168170		
Residual Sum of Squares	67794	68276			136400	137080		
R-squared fixed (within)	**0.36**		**0.35**	**0.32**	**0.15**		**0.19**	**0.21**
R-squared random		**0.36**				**0.16**		
Number of panels	1524	1524			311	311		
Number of observations	326340	326340	326340	326340	67342	67342	67342	67342

Table 37
CDS-bond basis variation decomposition

Table below reports the decomposition of contributions to the variation in CBB from individual variables. Results are presented in basis points (bp). Columns 2 and 5 represents standard deviations of each variable for IG and HY category. Columns 3 and 6 report effect from each variable for IG and HY category. Columns 4 and 7 report relative contribution from individual factors. In order to calculate the contribution to the basis change due to each variable, we multiply standard deviation of each variable with its estimate coefficient from Table 36 (column 4 and 8).

	IG			HY		
Variable	**SD Variable**	**SD Variable * Estimate Coefficient (bp)**	**Relative Contribution (%)**	**SD Variable**	**SD Variable * Estimate Coefficient (bp)**	**Relative Contribution (%)**
CDS- Bond basis (bp)	73 bp			120 bp		
STDV (excess RET)	0.7	**-21**	28%	1.31	**-17**	14%
LIBOR-OIS	0.37	**-15**	21%	0.35	**-9**	7.5%
Repo GC-Treasury	0.26	**-0.8**	1%	0.27	**3**	2.5%
CDS Index US	0.75	**-17**	23%	0.73	**-48**	40%
Daily Amihud	1.06	**-1.2**	1.6%	1.31	**-0.5**	0.4%
BasisVol3M	0.1	**-4.6**	6%	0.24	**69**	57%

CONSEQUENCES OF LEHMAN BROTHERS' COLLAPSE FOR NON- FINANCIAL SECTOR

The bankruptcy of Lehman Brothers' was a major shock to the financial system that had a strong impact across bond and CDS markets. For this reason we investigated the impact of this event on CBB and its determinants. Table 38 provides a summary of results for non-financial IG issuers for the periods before (Jan 2005 to August 2008) and after (Oct 2008 to December 2011) Lehman's collapse. The table shows a slight increase of explanatory power (R-squared) for determinants after Lehman Collapse. All determinants explain around 23-29% of CBB in the pre-Lehman phase and 31-34% in the post-Lehman phase.

For non-financials, we see an almost 10-fold increase in the sensitivity of the basis to firm specific volatility and credit rating. For both the phases the coefficients are negative and significant. This finding implies that collateral quality increases in important as a determinant of the basis during the height of the financial crisis.

The coefficient for LIBOR-OIS increases in magnitude significantly from -36bp to -62bp between the two phases. We note that in the wake of Lehman's collapse, there was a general deterioration in funding liquidity and an increase in funding liquidity risk across the market. Furthermore, there was a related worsening of counterparty risk in the derivatives market. The increased sensitivity of the basis to LIBOR-OIS shows an increased wariness of the investors to enter negative basis trades with deterioration of funding liquidity in the post-Lehman era. Our results show that funding cost and funding liquidity risk became more prominent as explanatory factors for the basis in the post-Lehman period. This conclusion is different from findings of Bai, Collin-Dufresne (2013), who argue that funding costs lose their power in driving negative basis in the period after crisis. At this point it is worth mentioning that recently it has surfaced that the LIBOR fixings were manipulated by certain banks during the crisis period. The precise impact of this manipulation on pricing of various financial products, including its effect on CBB, is an open avenue for research, but is a difficult enterprise due to lack of information on the precise magnitude of these manipulations.

The sensitivity of basis to the counterparty risk proxy, CDS-Index, fell 3 folds in the period after Lehman's collapse. In the pre-Lehman period the coefficient was -11bp, but dropped to -4bp in the post-Lehman period (Table 38 column 2 and 4). This result supports the view that counterparty risk became less important after Lehman's collapse. There are two arguments to support this view. Firstly, in the aftermath of Lehman's collapse, there was a general perception in the market that big financial institutions (including the major CDS dealers) will not be allowed to fail by the government due to the systemic risk (too-big-to-fail). Secondly, after Lehman's there was a general market move towards collateralization of CDS contracts, which significantly reduces the impact of counterparty risk (Arora, Gandhi, & Longstaff, 2012).

The bond illiquidity measure, Daily Amihud, has a negative effect on basis in both pre and post Lehman periods. We see that the coefficient increases in size almost 6 times in the post Lehman period. However, overall we note that, bond illiquidity has a weak economic impact on the basis. Basis volatility has a significant negative effect on CBB in the periods before and after crisis. We see that, after Lehman's, the regression coefficient falls slightly in size but still remains significantly negative.

To summarize our findings, we note that for non-fnancial sector, our empirical results show that the chosen factors do a good job in explaining the basis variation during the crisis. The main determinants are statistically significant and have an expected sign. Prior to Lehman's collapse the main factors affecting negative basis were funding costs, counterparty risk and basis volatility. However, in the post Lehman period, some of the factors became less important (counterparty risk and basis volatility), while others became more prominent (collateral quality and funding cost).

Table 38
Determinants of CDS-bond basis determinants before and after Lehman Collapse for IG non-financial corporates

Using panel data between 2005 and 2011 for US corporate bond and CDS markets, we regress the CDS-bond basis against the list of variables (presented in the first column of the table). Second and forth column represent pooled OLS regression, 3 and 5th column represents fixed effect panel estimation regression. Regressions were performed for period before Lehman collapse (Jan 2005 to August 2008) and after Lehman Collapse (October 2008 to December 2011). Variables were calculated in percent. Estimate coefficients are represented in basis points (1%=100bp). The standard errors of estimated parameters are adjusted using Newey–West method and Driscoll and Kray method for panel data. T-statistics appears in parentheses. Significant coefficients are market in bold (the significance is set at 1 percent level (>2.33)).

	Before Lehman Collapse		After Lehman Collapse	
	Pooled OLS	**Fixed effect**	**Pooled OLS**	**Fixed effect**
STDV (excess RET) (%)	-2.05 (-1)	**-6.8** (-1.9)	**-25.74** (-10)	**-29.82** (-10)
Downgrade From AA to A	**-5.41** (-3)	**-0.8** (-0.11)	**-31.06** (-5)	**-31.39** (-4)
Downgrade From AA to BBB	**-20.23** (-10)	**-28.7** (-4.9)	**-56.18** (-8)	**-56.0** (-7.2)
LIBOR-OIS (%)	**-36.66** (-16)	**-37.82** (-19)	**-62.18** (-15)	**-49.11** (-15)
CDS Index (%)	**-11.01** (-5)	**-7.6** (-3.5)	**-4.11** (-2)	**-1.09** (-7.2)
Daily Amihud	**-0.35** (-3)	-0.05 (-0.56)	**-2.22** (-5)	-0.11 (-0.4)
Basis Volatility (%)	**-46.8** (-2)	**-19.24** (-2)	-21.37 (-1)	-5.76 (-1)
Intercept	**19.51** (8)	**22.4** (5.2)	**51.03** (8)	**61.03** (9)
Total Sum of Squares:		7942		68685
Residual Sum of Squares		6090.2		45646
R-squared fixed (within)	**0.29**	**0.23**	**0.31**	**0.34**
F- statistic	7844	4968	10680	12144
Number of panels		789		746
Number of observations	130600	130739	192389	192494

Table 39
Table of correlations for explanatory variables for non-financial sectors

This table represents the correlation values of the variables for non-financial sectors. Panel A to Panel C shows how correlation values change in different periods of analysis.

Panel A. Whole period (2005-2011)							
	1	2	3	4	5	6	7
1. Basis (ASW)	1						
2. SD (firm specific volatility)	0.004	1					
3. Daily Amihud	0.01	0.03	1				
4. CDS Index	-0.22	0.32	0.001	1			
5. LIBOR-OIS	-0.14	0.32	0.04	0.51	1		
6. Repo GC-Treasury	0.14	-0.13	0.03	0.32	0.3	1	
7. BasisVol6M	0.37	0.44	0.02	0.24	0.27	0.06	1
Panel B. Before Lehman Collapse (January 2005 – August 2008)							
	1	2	3	4	5	6	7
1. Basis(ASW)	1						
2. SD (firm specific volatility)	-0.26	1					
3. Daily Amihud	-0.03	0.03	1				
4. CDS Index	-0.44	0.41	0.01	1			
5. LIBOR-OIS	-0.47	0.35	0.01	0.84	1		
6. Repo GC-Treasury	-0.22	0.1	0.01	0.37	0.58	1	
7. BasisVol6M	-0.33	0.31	0.02	0.51	0.51	0.25	1
Panel C. After Lehman Collapse (October 2008 – December 2011)							
	1	2	3	4	5	6	7
1. Basis(ASW)	1						
2. SD (firm specific volatility)	-0.41	1					
3. Daily Amihud	-0.06	0.04	1				
4. CDS Index	-0.26	0.19	0.03	1			
5. LIBOR-OIS	-0.43	0.34	0.06	0.56	1		
6. Repo GC-Treasury	0.05	-0.1	-0.02	0.11	0.27	1	
7. BasisVol6M	-0.29	0.45	0.02	0.23	0.39	0.03	1

B. *FINANCIAL SECTOR ANALYSIS*

We now focus on the regression analysis for the financial sector. Our dataset contains 45 IG financial companies with 82,344 daily values for CBB, and only 2 HY financials with 404 data points. For this reason we restrict our analysis of US financial firms to investment grade category. Table 40 reports estimation results for the CBB determinants. The format of the table is analogous to Table 36, with columns 2 and 3 reporting estimation coefficients for panel estimation approach (fixed and random effects), and columns 4 and 5 reporting results for a pooled OLS approach. The panel approach and OLS approaches explain just 6% and 11 % of the CBB. These figures are significantly smaller than the 36% for non-financial sector. Therefore, we note that, for financial sector only a small fraction of the variation in the CBB is explained by our chosen determinants.

Overall, we note that in case of financial sector the explanatory variables show a high level of correlation (see Table 41). This is understandable, since the considered financial companies include the very same companies that act as sellers of CDS protection. There is a tight dependency between the health of the financial sector firms and the health of the CDS dealers.

Firm specific volatility (STDV excess return) coefficient is statistically significant and negative. However, the size of the coefficients is almost 10 times smaller compared to non-financial companies' results. The estimate coefficients for credit rating dummies are negative and statistically significant. The magnitudes of the coefficients are comparable with corresponding values for non-financials. Both these factors are proxies of collateral quality. Our results imply that firm specific volatility for financial firms reduces in role in comparison with rating in determining collateral quality for financial sector bonds. The estimate coefficients for funding cost proxy, LIBOR-OIS spread, have expected negative sign and are statistically significant for all types of regressions. However, the coefficients are typically twice smaller than for non-financial sector. In contrast to the non-financial sector, the alternative proxy of funding cost (RepoGC-Treasury) has a positive sign coefficient. Finally, the CDS-index coefficients are statistically significant and negative as expected, with the sizes of the coefficients comparable to non-financial sector. In analogy with the non-financial sector, the Amihud measure coefficient has an expected negative sign, but is economically and statistically not very significant. The basis volatility regression coefficient is statistically significant, but has an unexpected sign. In contrast with non-financial sector it is positive. The explanation for this positive sign is the high level of correlation of basis volatility with firm specific volatility and funding cost (Table 41). If we run the same regression excluding highly correlated variables we end up with expected negative sign for the basis volatility.

CONSEQUENCES OF LEHMAN BROTHERS' COLLAPSE FOR FINANCIAL SECTOR

In order to study the effect of Lehman collapse on the basis for the financial sector firms, we run separate regression for the pre and post Lehman periods. Tables Table 41 and Table 42 report the correlation matrix for the variables and regression results, correspondingly for the pre and post Lehman periods. We see that, for the financial sector in the pre-Lehman period, CDS-index and LIBOR-OIS are very highly correlated (84%). In addition, the correlation between basis volatility and firm specific volatility is high (73%) during this period. In the post-Lehman period the correlation between these sets of variables falls, but still remains significant. For this reason, one should be careful in drawing economic interpreting from results of the regression for these variables.

The Table 42 reports results of panel and pooled OLS regression in pre-Lehman and post-Lehman periods. Results show that explanatory power, measured by adjusted R-squared, falls from 15% in pre-Lehman phase to 8% in post-Lehman phase. This shows that our set of explanatory variables explains smaller fraction of variations in CBB for financial sector firms in the post-Lehman times. This result is in sharp contrast with the results for non-financial sector, where the power of our explanatory variables improved in the post-Lehman period (from 29% to 31%).

The firm specific volatility shows a fall in size for the estimate coefficients and significance level after Lehman Collapse. The coefficients fall in size almost 10 times. The effect is opposite for non-financial companies. This might be explained by either high correlation of firm specific volatility with basis volatility, or the fact that firm specific volatility is not a good proxy of collateral quality for financial sector firms. On the other hand credit rating dummies coefficients show stable negative sign and are statistical significance for both periods. We note that, in the post-Lehman period, our data does not contain AA rated financial firms, due to the blanket downgrading of financial firms during the crisis. The estimate coefficient for LIBOR-OIS is negative and significant for pre and post periods, and slightly increases in size in the post period. This effect is similar to the one observed for non-financial companies, and shows that the funding cost was one of the main determinants of the negative basis for entire period of observations for both financial and non-financial sectors.

The sensitivity of the basis to CDS-index has a positive sign and fall in size and significance after Lehman. This result seems to be partly an artefact of the high correlation of CDS-index and LIBOR-OIS, since both LIBOR-OIS and CDS-index are proxies of counterparty risk. Some separate analysis required for this two variables. Regressions in columns 4 and 8 in Table 42 report results excluding funding cost. The estimate coefficient of CDS index is negative and stable before and after Lehman event. An analogous issue arises for basis volatility, which in pre-Lehman period correlates with firm specific volatility and CDS-index. Table 42 column 5 and 9 report results of regression excluding correlated variables. The results show that volatility of basis is not significant economically and statistically for financial sector.

Table 40
Determinants of CDS-Bond basis for financial sector between 2005 and 2011

Using panel data between 2005 and 2011 for financial sector, we regress CDS-Bond basis (calculated with asset swap spread) against the list of variables below. Associated t-statistics appear in parentheses. Table reports results of Panel estimation approaches (Fixed and Random effect) and Pooled OLS approach for IG financial US companies. Estimate coefficients are given in basis points. The standard errors of estimated parameters are adjusted using Newey-West method for pooled and Driscoll and Kraay method for panel. Significant coefficients are market in bold (the significance is set at 1 percent level (>2.33)).

	IG	**IG**	**IG**	**IG**
	Fixed effect (within)	Random effect	Pooled OLS	Pooled OLS
STDV(excessRET) (%)	**-3.61** (-2.6)	**-3.59** (-2.5)	**-2.95** (-2)	**-3.01** (-2)
Downgrade From AA to A		**-15.81** (-2.6)	**-20.23** (-6)	**-18.02** (-6)
Downgrade From AA to BBB		**-63.13** (-7.4)	**-40.73** (-6)	**-36.25** (-6)
LIBOR-OIS (%)	**-18.55** (-3.5)	**-18.68** (-3.5)	**-26.64** (-4)	
Repo GC-Treasury (%)				**37.51** (7)
CDS Index (%)	**-13.42** (-3.4)	**-13.47** (-3.5)	**-24.35** (-8)	**-25.64** (-8)
Daily Amihud	0.79 (1.7)	0.76 (1.5)	-1.01 (-0.9)	-0.85 (-1)
Basis Volatility (%)	20.67 (1)	20.9 (1.01)	**52.56** (3)	32.29 (1.8)
Intercept			**23.76** (6)	**11.18** (3)
Total Sum of Squares:	30205	30463		
Residual Sum of Squares	28455	28664		
R-squared fixed (within)	**0.06**		**0.11**	**0.11**
R-squared random		**0.06**		
Number of panels	257	257		
Number of observations	82344	82344	82336	82336

Table 41
Correlations for explanatory variables for financial sector

The table presents the correlation values of the variables for financial sector dataset. Panel A to Panel C show correlation values for different time periods of analysis.

Panel A. Whole period (2005-2011):						
	1	2	3	4	5	6
1. CDS-Bond basis	1					
2. Firm specific volatility	-0.17	1				
3. Amihud measure	0.01	0.02	1			
4. CDS Index	-0.28	0.49	0.01	1		
5. LIBOR- OIS	-0.21	0.43	0.01	0.51	1	
6. BasisVol3M	-0.07	0.53	0.004	0.44	0.5	1
Panel B. Before Lehman collapse (January 2005 – August 2008):						
	1	2	3	4	5	6
1. CDS-Bond basis	1					
2. Firm specific volatility	-0.13	1				
3. Amihud measure	-0.04	-0.005	1			
4. CDS Index	-0.18	0.62	0.004	1		
5. LIBOR- OIS	-0.24	0.57	0.001	0.84	1	
6. BasisVol3M	0.01	0.73	-0.005	0.53	0.54	1
Panel C. After Lehman (October 2008 –December 2011):						
	1	2	3	4	5	6
1. CDS-Bond basis	1					
2. Firm specific volatility	-0.05	1				
3. Amihud measure	0.02	0.02	1			
4. CDS Index	-0.09	0.27	0.02	1		
5. LIBOR- OIS	-0.22	0.42	0.02	0.56	1	
6. BasisVol3M	0.02	0.44	0.01	0.31	0.5	1

Table 42
Estimation results of CDS-bond basis determinants before and after Lehman Collapse for IG Financial sectors

Using panel data between 2005 and 2011 for US corporate bond and CDS markets, we regress CDS-Bond Basis against the list of variables (presented in the first column of the table). Regressions was taken for period before Lehman collapse (Jan 2005 to August 2008) and after Lehman Collapse (October 2008 to December 2011). Column 2 to 5 presents results of pooled OLS and panel approaches before Lehman collapse, column 6 to 9 presents results after Lehman Collapse. Estimate coefficients are represented in basis points (1%=100bp). T-statistics appear in parentheses. The standard errors of estimated parameters are adjusted using Newey-West method and Discoll and Kraay method for panel. Significant coefficients are market in bold (the significance is set at 1 percent level (>2.33)).

	Before Lehman				After Lehman			
	Pooled OLS	Fixed effect	Pooled OLS	Pooled OLS	Pooled OLS	Fixed effect	Pooled OLS	Pooled OLS
STDV(excessRET) (%)	**-10.27** (-2.1)	**-12.96** (-5.2)	**-10.25** (-2)		-0.05 (-0.03)	-1.65 (-1.1)	**-2.55** (-2)	
Downgrade From AA to A	**-14.02** (-4.4)	**-22.33** (-2.2)	**-15.56** (-5.2)	**-17.29** (-6)				
Downgrade From AA to BBB	**-31.59** (-8)	**-45.01** (-3.2)	**-32.19** (-9)	**-33.94** (-9)				
Downgrade From A to BBB					**-21.05** (-2)	**-93.16** (-4.5)	**-18.05** (-2)	-18.59 (-1.6)
LIBOR-OIS (%)	**-43.03** (-8)	**-36.19** (-4)			**-72.16** (-8)	**-46.41** (-6.3)		
CDS Index (%)	9.59 (1.7)	**25.52** (3.5)	**-13.63** (-2.6)		8.72 (1.6)	6.92 (1.9)	**-17.5** (-2.9)	
Daily Amihud	**-0.91** (-3.4)	-0.07 (-0.4)	**-1** (-3.7)	**-0.97** (-3.4)	1.4 (0.8)	0.7 (1.2)	1.33 (0.8)	1.16 (0.8)
Basis Volatility (%)	**99.46** (3.5)	**66.89** (3.1)	**81.71** (3)	-2.57 (-0.1)	**64.18** (3.2)	36.81 (1.5)	27.21 (1.4)	5.22 (0.3)
Intercept	23.37 (4)	22.01 (1.9)	24 (4.3)	12.65 (5)	-51.52 (-6)	-37.81 (-3.4)	-23 (-2.8)	-52.63 (-12)
Total Sum of Squares:		3140				18667		
Residual Sum of Squares		2892				17491		
R-squared fixed (within)	**0.15**	**0.08**	**0.12**	**0.06**	**0.08**	**0.06**	**0.02**	**0.005**
Number of panels		184				184		
Number of observations	39783	39791	39783	39783	41775	41782	41782	41782

C. MOST NEGATIVE BASIS

The estimations so far tested the determinants of CDS-bond basis using the complete dataset, albeit divided into sectors, grades or time-periods. In the current sub-section, we look at the basis from the point of view of potential arbitrageur. In order to profit from negative basis, an arbitrageur would typically identify the most attractive bond-CDS pairs for earning a carry. For this reason, for the purposes of studying the arbitrage determinants of the basis, it is natural to focus on a subset of trades that are most attractive for the purpose. In order to mimic the behaviour of an arbitrageur, for every observation date in our dataset, we restrict our analysis to bond-CDS pairs with a negative CBB lying in top 10% quantile. The resulting dataset consists of bond-CDS pairs, corresponding to the 10% of "most-negative" basis, that are most attractive from the point of view of negative basis arbitrage trading. We constructed these restricted datasets separately for financial/non-financial sectors as well as for IG and HY classes. The results for the regressions on these restricted datasets are presented in Table 43.

We note that the explanatory power of the variables for the top 10% negative basis dataset is significantly higher (60% to 70%) than analogous regressions on full datasets. The coefficient estimates for all of our considered variables, except for Amihud measure, are significant and have expected signs. Like elsewhere in our analysis, Amihud measure, although appearing with predominantly correct sign, is not statistically significant. This confirms our conclusion about Amihud measure not being a significant explanatory factor for the basis.

The negative CBB for non-financial IG group is predominantly explained by firm specific volatility (proxy of bond collateral), Libor-OIS (proxy of funding cost), CDS Index (proxy of counterparty risk) and basis volatility. In contrast, negative CBB for financial IG group is mainly explained by credit ratings (as proxy of collateral), CDS Index and basis volatility, with a smaller contribution from funding cost. The funding cost variable becomes insignificant for financial sector. We note that Repo(GC)-Treasury variable, which is a proxy of market liquidity and partially funding cost, shows an unexpected positive effect on basis. This effect is not statistically significant for IG firms, but is statistically significant for HY category.

Overall, our findings for the most-negative CBB category are consistent with our findings for the complete dataset. We point out that, in line with our expectations, the explanatory power of the factors significantly rises for this subset. The signs, magnitudes and statistical significances of regression coefficients for all of the explanatory variables are consistent with previous findings. This analysis can be viewed as a robustness check for our conclusions on determinants of CDS-bond basis.

Table 43

Estimation results for subset of CDS-bond basis consisting of 10 percent quantile of most negative basis over each day

Using panel data between 2005 and 2011 for financial and non-financial sectors, we build an algorithm to pick 10 percent of most negative basis datapoints for each day. We regress most negative CDS-Bond basis dataset against determinant factors listed below. Associated t-statistics appear in parentheses. Columns 2 to 6 present estimation results for non-financial sector US companies for investment and high yield group. Column 7 and 8 presents estimation results for financial sector investment grade bonds. The standard errors of estimated parameters are adjusted using Newey-West method and Discoll and Kraay method for panel. Estimation coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 1 percent level (>2.33)).

	Non-financial Sector						Financial Sector	
	IG			HY			IG	IG
	Panel	Pooled OLS	Pooled OLS	Panel	Pooled OLS	Pooled OLS	Panel	Pooled OLS
STDV(excessRET) (%)	**-49.06** (-12)	**-40.42** (-20)	**-40.1** (-18)	**-40.16** (-5.9)	**-20.35** (-5)	**-15.13** (-4)	**-26.22** (-5.4)	**-20.7** (-8)
Downgrade From AA to A	-0.55 (-0.08)	**-10.88** (-4)	**-7.66** (-3)				**-149** (-3.9)	**-141.5** (-6)
Downgrade From AA to BBB	0.37 (0.07)	**-11.58** (-6)	**-9.82** (-5)				**-193.4** (-5)	**-183.3** (-7)
Downgrade From BB to B				21.32 (1.7)	**43.75** (6)	**33.16** (6)		
LIBOR-OIS (%)	**-48.93** (-6.7)	**-59.81** (-4)		-38.05 (-1.2)	5.64 (0.2)		-12.93 (-1.5)	-16.6 (-1.2)
Repo GC-Treasury (%)			12.13 (0.9)			**146** (5.4)		
CDS Index (%)	**-58.38** (-17)	**-56.86** (-17)	**-70.67** (-15)	**-81.73** (-4.2)	**-139.15** (-14)	**-126.73** (-14)	**-77.8** (-10)	**-79.1** (-17)
Daily Amihud	0.33 (1.1)	-0.04 (-0.13)	**-0.8** (-3)	0.31 (0.02)	1.15 (0.8)	0.73 (0.5)	-0.003 (-0.02)	-0.2 (-0.7)
Basis Volatility (%)	**-94.41** (-2)	**-92.59** (-5)	**-126.9** (-6)	**-250.8** (-3)	**-173.7** (-4)	**-195.87** (-4)	**-77.07** (-2.5)	**-53.2** (-3)
Intercept	**51.49** (7.5)	**40.53** (10)	**36.41** (6)	**49.36** (2.6)	-0.21 (-0.03)	**-38.45** (-3)	**209.08** (5)	**180.3** (7)
Total Sum of Squares:	22562			7160			5964	
Residual Sum of Squares	7604			2980			1957	
R-squared fixed (within)	**0.66**	**0.68**	**0.64**	**0.58**	**0.68**	**0.71**	**0.67**	**0.7**
Number of panels	646			200			180	
Number of observations	33155	33147	33147	7250	7250	7250	8770	8770

D. CROSS-SECTIONAL FAMA – MACBETH APPROACH

In addition to the previous analysis based on single stage linear regressions, in the current sub-section we present the results of an alternative method based on Fama-MacBeth style cross sectional regressions (Fama & MacBeth, 1973), which is widely used in empirical literature working with panel data (Petersen, 2006), (Skoulakis, 2008), (Bai & Collin-Dufresne, 2013). This approach is better suited to answering the question on quantitative contribution of our factors on CBB, and the time dynamics of this contribution. Instead of answering the question of how sensitive the CBB is to changes in a particular factor, the Fama-MacBeth approach answers the question of how much of the factor's variation is priced in the CBB. This analysis is analogous in spirit to our analysis of the economic significance of the factors, but more robust.

Table 44 reports estimation results for Fama-MacBeth type regression for the CBB on collateral quality, funding cost, counterparty risk, liquidity risk and basis volatility. Table A reports the average values of the factor loadings $\beta^{i}_{factors}$ calculated using first pass regression given by equation (19). Table B reports the time-averages for the "risk-premia" $\gamma_{\mathrm{t,factor}}$ factors, which are obtained as a result of the second-pass regression given by equation (20). Column 1 for both the tables reports results for whole period, while columns 2, 3 and 4 consider the pre-crisis, crisis and the post-crisis periods, correspondingly.

The results of the first pass regression give results consistent with results obtained using OLS and panel regressions. The overall sign and magnitude of the $\beta^{i}_{factors}$ coefficients is consistent with the sign and magnitude of regression coefficients in Table 36 and Table 40. This is expected, both of these quantities measure average sensitivities of CBB to the corresponding factor. The average estimate coefficients of collateral quality, funding cost (LIBOR-OIS) and basis volatility have expected negative signs and are statistically significant. We find Funding cost (Repo-Treasury), liquidity Amihud measure and counterparty risk are not statistically significant. For normal period, when basis was slightly positive, our determinants show an opposite sign and are mostly insignificant. For the crisis time, all of the determinants (except Repo(GC)-Treasury) have an expected negative sign and are statistically significant. In the post crisis period, as basis stays in the negative, we see that all determinants have an expected negative sign and are mostly significant.

The results of second pass regression report γ_{factor} mostly positive and statistically significant for crisis and post-crisis times. This implies that the considered factors are "priced" in the CBB, and are therefore economically significant determinants of the basis during and after the crisis. The results show that adjusted R-squared for the regression covering the whole period is 33%, and rises to 48% during the crisis period.

As we mentioned above, the Fama-MacBeth style analysis allows us to analyze the time dynamics of the CBB and its determinants. In order to visualize the contribution of each factor to the CBB across time, we multiply the time dependent "risk-premia" $\gamma_{\text{t,factor}}$ into the average values of the corresponding factor loadings $\beta_{factors}$ and plot the results as a function of time in Figure 25. For comparison, in Figure 26 we show the behaviour of the total average CBB for the same time period. The individual graphs in Figure 25 clearly show the magnitude and the sign of contribution from various factors to CBB. The figure shows that collateral quality, funding cost (LIBOR-OIS) and basis volatility are the largest contributors to the basis. At the height of the financial crisis, these factors contributed in the order of -42bp, -25bp and -10bp to the basis, correspondingly. On average, over the whole period, these factors contributed -9bp, -3bp and -4bp, correspondingly. We see that Repo(GC)-Treasury and Amihud measure, although giving a contribution with correct expected sign, are not economically significant. At the height of the crisis, these factors only contributed -2bp and -1.2bp, correspondingly to the basis.

Our analysis did not uncover a clear contribution to the CDS-Bond basis from counterparty risk. The results of the first pass regression, for the whole time period between 2005-11, lead to an insignificant coefficient. However, if one restricts to consideration of crisis period, one obtains a significant negative value for the β coefficient. This suggests that during the crisis, counterparty risk did affect the basis. This result is in line with findings of Bai, Collin-Dufresne (2013), who state that counterparty risk became significant only at the end of 2007, and contributed to the basis only in the period after Lehman's collapse. The results of the second pass regression, allow us to quantify the effect of counterparty risk on the basis in the period during the crisis. Counterparty risk contributed -8bp to basis at the height of the crisis, and -1.4bp on average over crisis period.

Finally, in Figure 27 we show the R^2 for the second pass Fama-MacBeth regression. This graph serves as an indication of the power of our factors in explaining CDS-Bond basis over time. For the period before mid-2007 the graph shows that the factors explain less than 10% of CBB. During crisis, this number rises to 60% on average. This finding mirrors our analysis based on OLS and panel regressions, where we saw a significant increase in adjusted R-squared for regressions restricted to post-Lehman period.

Overall, we conclude that findings from the Fama-MacBeth style analysis are consistent with those based on OLS regressions. The negative basis during crisis was mainly driven by funding costs (LIBOR-OIS), collateral quality as well as basis volatility, and to a lesser degree by bond illiquidity. Although our analysis did not uncover a clear contribution from counterparty risk for the analysis of the whole period, a small and negative contribution was uncovered if one restricted analysis to crisis time.

Table 44
Estimation results of cross sectional Fama-MacBeth style regression

The tables A and B present results of Fama-MacBeth regression of CDS-Bond basis on several determinants (collateral quality, funding cost, counterparty risk, liquidity of bonds and basis volatility). In the first-pass regression, one estimates the sensitivity of CBB to various risk factors, for individual issuers:

$$Basis_i = \alpha_i + \beta^i_{factors} * Variables^i_t + \epsilon_i$$

Where $Basis_i$ is a *t×1* vector of basis, $Variables^i_t$ is *t×m* matrix of *m* factors for the issuer *i*, α_i is t×1 vector of intercepts and β^i_{factor} is vector of *1×m* factors estimate coefficients for each individual issuer *i*. Following this, the factors β^i_{factor} are used in the second-pass regression, which consists in a cross sectional regression of the form:

$$Basis^i_t = \alpha_t + \gamma_{t,coll}\beta^i_{coll} + \gamma_{t,libor}\beta^i_{libor} + \gamma_{t,repo}\beta^i_{repo} + \gamma_{t,cp}\beta^i_{cp} + \gamma_{t,liq}\beta^i_{liq} + \gamma_{t,vol}\beta^i_{vol} + e^i_t$$

Where the cross sectional regression runs at daily frequency.

Table A shows results of first stage of Fama-MacBeth regression, which involves a set of regressions equal in number to the number of corporate bonds issued, so it is set of time series regressions of each corporate bond. The table A reports weighted averages of estimates (β) and z-statistics (in parentheses) for different periods in time. Estimate coefficients are given in basis points. Estimated coefficients are in bold scripts if the statistical significance is 5% or below.

Table B reports results of second stage Fama-MacBeth regression, which is a set of regressions equal in number to the number of time periods. The table reports averages of estimates (γ) and standard errors (in parentheses). Estimated coefficients are in bold scripts if the statistical significance is 5% or below.

Table A:

	Whole period	Pre Crisis Period	Crisis Period	Post Crisis Period
Collateral quality	**-30.55** (-6.5)	-3.82 (-0.6)	**-84.62** (-9.3)	**-22.11** (-4.1)
Funding Cost (LIBOR-OIS)	**-13.2** (-2.3)	**27.03** (2.4)	**-43.38** (-9.5)	**-31.83** (-3.5)
Funding Cost (Repo-Tbill)	-3.95 (-0.9)	-0.84 (-0.5)	9.76 (1.7)	**-57.89** (-8.4)
Counterparty Risk	0.59 (0.2)	31.22 (3.9)	**-8.43** (-3.7)	**-3.73** (-2.2)
Liquidity (Daily Amihud)	-3.83 (-0.3)	-3.36 (-0.8)	-3.95 (-0.3)	-3.11 (-0.2)
Basis Volatility	**-63.98** (-4.9)	**-47.22** (-1.9)	**-93.6** (-3.5)	**-56.12** (-3.1)
Number of observation	325369	52152	90522	143159
Number of panels	1372	502	677	967

Table B:

	Whole period	Pre Crisis Period (2005 to July 2007)	Crisis Period (Aug2007 to Sept2009)	Post Crisis Period (Oct2009 to Dec 2011)
Collateral quality	0.28 (0.33)	0.05 (0.27)	**0.58** (0.08)	**0.22** (0.06)
Funding Cost (Libor-OIS)	**0.2** (0.04)	0.02 (0.02)	**0.55** (0.08)	**0.06** (0.03)
Funding Cost (Repo-Tbill)	0.02 (0.05)	-0.002 (0.04)	0.1 (0.08)	0.02 (0.02)
Counterparty Risk (CDS Index)	**0.56** (0.07)	**0.09** (0.02)	**0.92** (0.13)	**0.72** (0.08)
Liquidity (Daily Amihud)	0.01 (0.06)	0.02 (0.06)	0.004 (0.1)	-0.003 (0.03)
Basis Volatility	**0.03** (0.01)	0.002 (0.005)	**0.06** (0.01)	**0.02** (0.01)
R-Square	0.33	0.27	0.48	0.33

Figure 25

Dynamic coefficients in multivariate cross sectional Fama-MacBeth regression. Gamma estimates of each variable ($\gamma_{t,factor}$) are multiplied by beta estimates of variable aggregated across companies (β_{factor}) and plotted in monthly frequency. These graphs represent contribution effect of each explanatory variable on CDS-Bond basis obtained by cross sectional Fama-MacBeth regression. The contribution to the basis is given in percentages and cover period between 2005 and 2011. (Counterparty risk)*(dynamic coefficient) was calculated with average β_{factor} of crisis period to show its contribution.

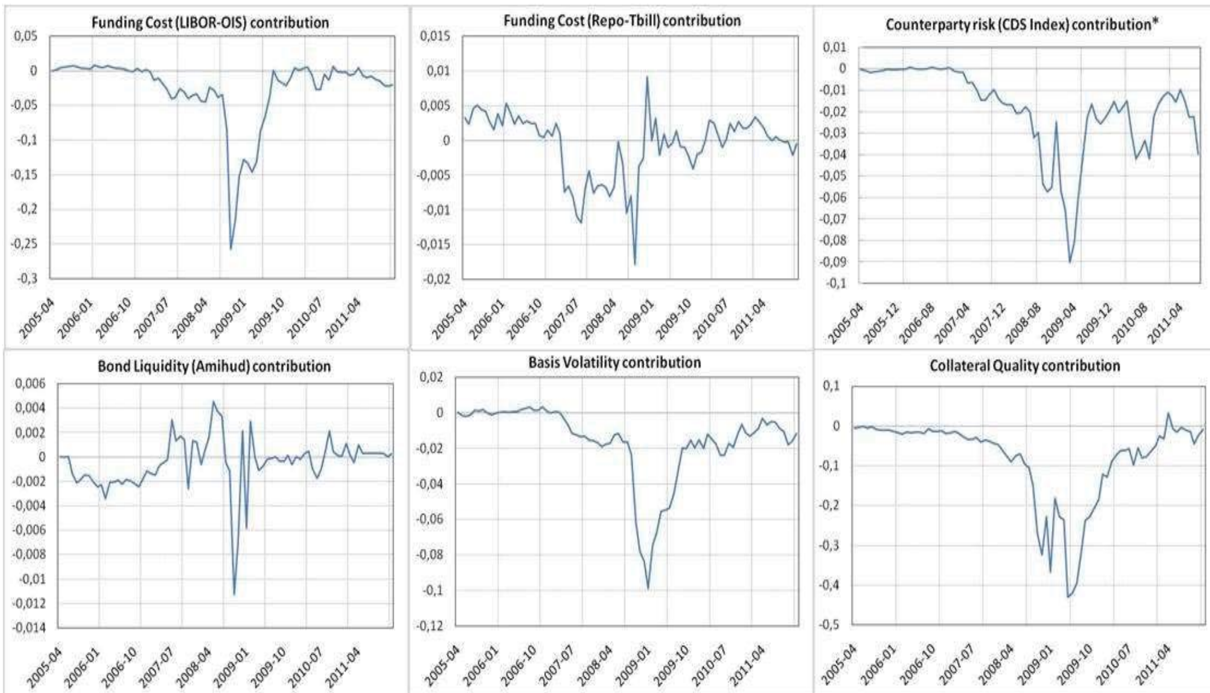


Figure 26

Monthly aggregated CDS-bond basis for period between 2005 and 2011. Visualize what portion of negative basis was explained by determinants factors.

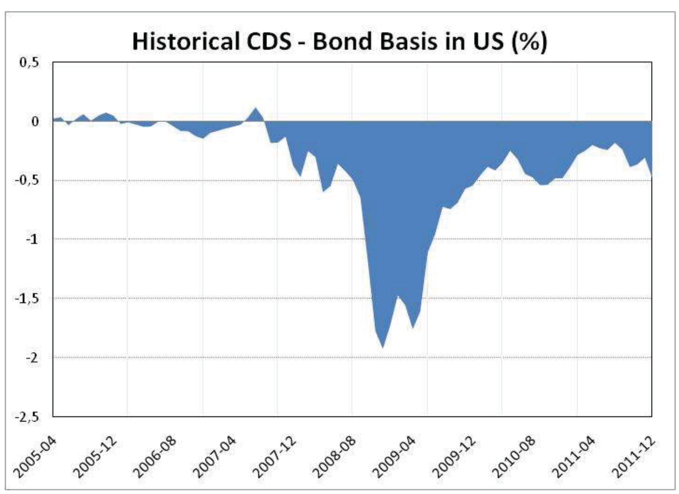
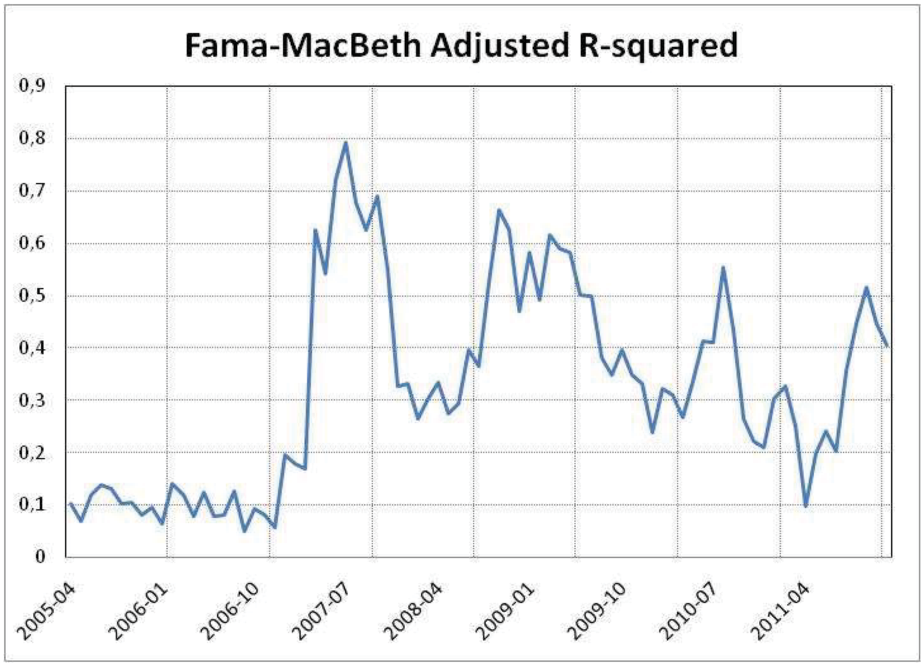


Figure 27

The graph plots Adjusted R-squared obtain from cross sectional Fama-MacBeth regression. R-squared value is reported for monthly frequency. It covers period between 2005 and December 2011.



5.6.3 ROBUSTNESS

In this section we look consider two methods to verify the robustness of our findings. Firstly, we report on regression analysis using an alternative proxy of CDS-bond basis, using Z-spread as a measure of bond credit spread. Secondly, in order to address the possible issues associated with serial autocorrelation in our panel dataset we perform regression analysis on weekly and monthly averaged datasets.

As mentioned previously in Section 5.3, Z-spread is an alternative measure of credit spread for a bond. Intuitively, Z-spread corresponds to the flat credit spread that should be added to the LIBOR curve, in order to equate the discounted bond's cash flow value equal to the observed price of the bond. In order to test the robustness of our results to a different choice of credit spread proxy, we re-ran our regressions using Z-spread. This was simple to implement, since the values for the Z-spread were provided in our MarkIt dataset. Tables Table 45 and Table 46 report the results of the regressions using Z-spreads. We note that the results of the regressions, including signs and magnitudes of coefficients as well as explanatory power of regressions are overall consistent to results obtained using par asset swap spreads (compare with Table 36 and Table 40).

Finally, in order to avoid estimation errors associated with possible serial correlation in our panel data, we looked at time averaged data. We used weekly and monthly aggregations. The results of regressions for a monthly averaging of IG issuers for different sectors are presented in Table 47. Regressions using weekly averaging and/or HY issuers yielded analogous results (results not reported here). Overall, the results for time averaging give signs and magnitude for the regression coefficients consistent with our benchmark regressions (Tables Table 36 and Table 40). Finally, we ran a unit root test, and did not find evidence for stationarity in our panel data.

Table 45
Estimation results for CDS-bond basis calculated with Z-spread for non-financial sectors companies

Using panel data between 2005 and 2011 for non-financial sectors, we regress CDS-bond basis (calculated with Z-spread) against the list of variables below. Associated t-statistics appear in parentheses. The standard errors of estimated parameters are adjusted using Newey-West method and Driscoll and Kraay method for panel data. Table reports results of Panel estimation approaches (Fixed and Random effect) and Pooled OLS approach for IG and HY companies. Significant coefficients are market in bold (the significance is set at 1 percent level (>2.33)).

	IG	IG	IG	HY	HY	HY
	Fixed effect(within)	Random effect	Pooled OLS	Fixed effect (within)	Random effect	Pooled OLS
STDV(excess RET) (%)	**-40.96** (-14)	**-40.87** (-15.3)	**-32.98** (-14)	**-25.59** (-3.3)	**-25.14** (-3.3)	**-12.93** (-2.7)
Downgrade From AA to A		**-12.35** (-2.1)	**-16.56** (-3.4)			
Downgrade From AA to BBB		**-32.84** (-6.5)	**-37.05** (-7.2)			
Downgrade From BB to B					**49.02** (3.1)	**67.18** (8)
LIBOR-OIS (%)	**-44.12** (-7.7)	**-44.55** (-18.5)	**-51.39** (-16)	-15.09 (-1)	**-15.5** (-1)	**-29.66** (-2)
CDS Index (%)	**-18.39** (-5.4)	**-18.07** (-9.5)	**-16.09** (-12)	**-78.45** (-7.2)	**-74.40** (-7.2)	**-63.45** (-10)
Daily Amihud	**-0.43** (-2.4)	**-0.45** (-2.4)	**-1.65** (-6.8)	-1.49 (-1.4)	-1.5 (-1.5)	**-2.42** (-2.1)
Basis Volatility (%)	**-38.31** (-2.5)	**-36.13** (-1.5)	**-57.98** (-2.2)	**193.92** (2.5)	**196.2** (2)	**167.18** (2.4)
Intercept		**75.01** (16)	**69.97** (16)		**41.07** (4)	**10.99** (1.6)
Total Sum of Squares:	133170	134100		92820	93342	
Residual Sum of Squares	78007	78575		72327	72739	
R-squared fixed (within)	**0.41**		**0.4**	**0.2**		**0.18**
R-squared random		**0.4**			**0.2**	
Number of panels	1574	1574		311	311	
Number of observations	326349	326349	326340	65117	65117	67342

Table 46
Estimation results for CDS-bond basis calculated with Z-spread for financial sector companies

Using panel data between 2005 and 2011 for financial sectors, we regress CDS-Bond basis (calculated with Z-spread) against the list of variables below. Associated t-statistics appear in parentheses. The standard errors of estimated parameters are adjusted using Newey-West method and Driscoll and Kraay method for panel data. Table reports results of Panel estimation approaches (Fixed and Random effect) and Pooled OLS approach for IG financial US companies. Significant coefficients are market in bold (the significance is set at 1 percent level (>2.33)).

	IG	IG	IG	IG
	Fixed effect(within)	Random effect	Pooled OLS	Pooled OLS
STDV(excess RET) (%)	**-9.1** (-6.4)	**-9.11** (-6.4)	**-8.43** (-6)	**-8.88** (-6)
Downgrade From AA to A		**-17.39** (-3.4)	**-18.62** (-5)	**-16.74** (-5)
Downgrade From AA to BBB		**-69.28** (-7.3)	**-48.58** (-6)	**-44.11** (-5.4)
LIBOR-OIS (%)	**-32.1** (-6.8)	**-32.23** (-6.8)	**-37.62** (-7)	
Repo GC-Treasury (%)				**26.32** (5)
CDS Index (%)	**-12.57** (-3)	**-12.61** (-3.1)	**-22.17** (-7)	**-26.45** (-7)
Daily Amihud	0.33 (1)	0.24 (0.7)	-0.54 (-0.06)	-0.71 (-0.06)
Basis Volatility (%)	30.5 (1.4)	30.72 (1.4)	**56.18** (3)	30.98 (1.5)
Intercept		**28.03** (8.3)	**31.47** (8)	**21.86** (5)
Total Sum of Squares:	34501	34831		
Residual Sum of Squares	29537	29762		
R-squared fixed (within)	**0.14**		**0.19**	**0.17**
R-squared random		**0.15**		
Number of panels	257	257		
Number of observations	82336	82336	82336	82336

Table 47
Regression results of CDS-bond basis over determinants based on aggregate monthly data

Using aggregated monthly panel data between 2005 and 2011, we regress CDS-bond basis (calculated with asset swap spread) against the list of variables below. Associated t-statistics appear in parentheses. Table reports results of Panel estimation approach and Pooled OLS approach for financial and non-financial sectors. The standard errors of estimated parameters are adjusted using Newey-West method and Driscoll and Kraay method for panel data. Estimate coefficients are given in basis points. Significant coefficients are market in bold (the significance is set at 1 percent level (>2.33)).

	Non-financial Sectors		Financial Sector	
	Panel Estimation	Pooled OLS	Panel Estimation	Pooled OLS
Collateral quality (%)	**-33.09** *(-15)*	**-26.96** *(-16)*	0.12 *(0.19)*	-3.25 *(-1)*
Downgrade From AA to A	**-15.78** *(-3)*	**-18.07** *(-8)*	-7.24 *(-0.45)*	**-9.37** *(-2)*
Downgrade From AA to BBB	**-35.4** *(-7)*	**-39.07** *(-15)*	**-54.85** *(-3.3)*	**-45.1** *(-9)*
Funding Cost (%)	**-25.34** *(-11)*	**-32.8** *(-6)*	**-22.54** *(-7.9)*	**-39.94** *(-3)*
Counterparty Risk Proxy (%)	**-28.2** *(-17)*	**-24.04** *(-11)*	**-28.42** *(-15)*	**-35.96** *(-8)*
Liquidity (Daily Amihud)	-0.09 *(-0.2)*	**-2.14** *(-3)*	**-1.39** *(-1.6)*	**-4.89** *(-2)*
Basis Volatility (%)	**-23.51** *(-2)*	**-47.59** *(-2)*	48.02 *(0.96)*	81.08 *(1.9)*
Intercept	**76.95** *(16)*	**64.19** *(19)*	19.04 *(1)*	**17.2** *(3)*
R-squared	**0.37**	**0.35**	**0.08**	**0.13**
Number of panels	1574		257	
Number of observations	32563	32558	6728	6720

5.7 CONCLUSION

In the current chapter we have empirically analyzed the anomaly of negative CDS-bond basis that has been observed in recent times. In our analysis we used a large and unique dataset on CDS and bond pricing for US corporate, covering a period between 2005 and 2011. This time period included a relatively stable time for the US market (2005- 2007), financial crisis (2007-2009) and post-crisis/European sovereign crisis period (2009-2011). Our total dataset contained around half a million data points, and provided a powerful testing platform for empirically investigate the key determinants of the basis.

In order to identify the key determinants of the basis, we conducted a theoretical analysis of a negative basis arbitrage trading strategy, and identified the various market frictions and risks involved in any practical implementation of this strategy. We showed how presence of these frictions and risks could explain the level of the observed basis. We identified funding cost, collateral quality, liquidity in the bond and derivatives markets, counterparty risk, and volatility of the basis as the main factors affecting the basis. We used the identified factors, in our empirical investigation.

Our analysis revealed a distinct dynamics for the basis for investment grade versus high yield categories, as well as a difference in dynamics between financial and non-financial sectors. For this reason, we investigated these categories individually in detail.

We show that, during the crisis, the negative basis trade for non-financial sector was mainly determined by funding cost, counterparty risk, collateral quality, and in a lower proportion by bond illiquidity and volatility of basis itself. In the post-Lehman period, explanatory power of collateral quality, funding cost and bond illiquidity factors significantly increased, while counterparty risk and basis volatility lose explanatory power. Based on our results, we conclude that in crisis period negative basis trade was mainly determined by availability of funds (funding cost) and market liquidity. This results supports earlier findings Bai & Collin-Dufresne (2013), Fontana (2010), Augustin (2012). We argue that counterparty risk factor lost its power in the crisis period, mainly due to collateralizations of the derivative contracts as well as the market expectation that large financial institutions will not be allowed to fail following the market chaos in wake of Lehman's collapse. Overall, for IG non-financials, our determinants explain 36% in the variation of the basis. Comparing the results between rating grades, we see that our factors typically have a higher explanatory power for IG than for HY category. The picture is different when considering the basis for financial sector firms. In this case, our factors only explain 11% of the basis. We find that the basis for financial companies is typically less sensitive to our chosen determinants, and only shows significant sensitivity to collateral quality and funding cost factors. This finding suggests the presence of other factors, specific to financial sector that affect the basis. An important factor that could affect the basis for financial sector firms is the wrong-way-risk. The analysis of this factor and its impact on the basis is an interesting avenue for future research.

In order to mimic the behaviour of investors looking to profit on the existence of a negative basis, we consider a data subset consisting of CDS-bond pairs corresponding to daily 10% quantiles of the most negative basis. We ran our analysis using this subset, and found that the explanatory power of our variables increased substantially to 70%. This exercise further adds support to robustness of our findings.

In order to estimate the quantitative contribution of our factors to the CDS-bond basis, and investigate the dynamic behaviour of these contributions, we performed a Fama-MacBeth style regression. The analysis confirmed the importance of the collateral quality, funding cost (LIBOR-OIS) and basis volatility as determinants of the basis. The analysis showed that at the height of the financial crisis, these factors contributed -42bp, -25bp and -10bp to the basis, correspondingly. At the same time, Repo(GC)-Treasury and Amihud measure were shown to have insignificant contributions to the basis. The analysis did not reveal a significant contribution from counterparty risk over the whole period. However, when analysis was restricted to the crisis period, regressions revealed that counterparty risk contributes up to -10bp to the basis. Fama-MacBeth analysis showed that our factors explained just 10% of the basis in the period before financial crisis, and 60% during the financial crisis. Overall, the findings of the Fama-MacBeth analysis mirror and complement the findings of the OLS and panel regressions.

Overall, our work has shown that the various considered factors do a fairly good job at explaining the phenomenon of negative basis. However, a large portion of the basis remains unexplained. The situation is particularly acute for financial firms, where just over 10% of the basis is explained by our factors. This leaves large avenues for future research. The effect of wrong way risk, collateralization in OTC markets, contract standardization in CDS markets, impact of recovery rate assumptions on the pricing as well as impact of LIBOR fixing manipulation allegations are just some of the directions for future research.

CHAPTER 6
CONCLUSION

In this thesis, we have looked at several issues related to corporate credit risk. In particular, we have conducted an empirical investigation of the main drivers of credit risk in corporate bond and CDS markets, covering the period of the recent financial crisis. In this regard, we have looked into data on US and UK credit markets. In addition, we have focused in on the analysis of the difference in pricing of credit risk in the bond and CDS markets. Looking at the CDS-bond basis, we addressed the issue of its persistent negative sign during the period of financial crisis.

In Chapters 3 and 4, we focus our attention on the US and UK corporate bond markets, respectively. We have shown that the factors predicted by Merton's structural model of credit risk explain the observed credit yield spreads relatively well over the recent period, including the financial crisis, and explain around 50% of the variations in spreads. We have shown that during the financial crisis, the two main factors driving the yield spreads were equity volatility and macroeconomic investor confidence proxied by the TED spread. Although, equity volatility was found to be an important determinant of the credit spreads, our analysis showed that the sensitivity of spreads to this volatility is 3 times smaller than was reported in previous literature. Our analysis showed that equity volatility plays a greater role in driving spreads than credit ratings. This is an interesting finding, since credit ratings have been designed to reflect the credit riskiness of a company. In fact, we find that credit ratings explain the same portion of spread as accounting variables. These findings serve as evidence that, during the financial crisis, credit ratings did not fully reflect credit riskiness of corporate bonds. In our analysis, we investigated factors driving spreads for both, investment grade bonds and high yield bonds. We found, in line with Merton's model, that the sensitivities to various factors were generally higher for high yield bonds.

In our work we have focused in period of the financial crisis. For this purpose, we investigated the effect on spreads and its determinants of the Lehman Brothers' bankruptcy and quantitative easing (for UK). We have found evidence that the quantitative easing policy significantly reduced the credit spreads, although for an exact quantification one would need to consider the indirect effects of the policy. We find that there was a significant shock in the behaviour of the credit spreads in both the countries as a result of Lehman's collapse. In particular, we show a difference in dynamics of credit spreads for financial and non-financial sectors in post-Lehman period. For non-financials, the effect of determinants increased in magnitude and explanatory power. In contrast, financial sector spreads showed an opposite dynamics, with reduced sensitivities and explanatory power for the determinants. This result is interpreted as evidence for the market view of "too-big-to-fail", when financial firms were seen to be too important systemically to be allowed to fail by the government. In addition, we found empirical evidence that during financial crisis short and medium term debts were seen more risky than long term debt.

Overall, our main findings for the US market were mirrored in our findings for the UK. However, our analysis did show certain differences between the two markets. We found that UK credit spreads were in general much more sensitive to variation in TED spread. We also found that the explanatory power of our determinants for US IG market is 10% higher than for UK IG market, and that the opposite was true for the HY market. In order to verify the robustness our results, we showed that our results and conclusions are consistent and stable to various different econometric techniques and alternative proxies of bond credit risk.

In Chapter 5, we turned our attention to the phenomenon of negative CDS-bond basis during the period of the financial crisis. For the purposes of an empirical analysis, we build a theoretical no-arbitrage model based on a negative basis trade and identify the main factors that explain a negative basis. We identify funding cost, collateral quality, liquidity in the derivatives and bond markets, basis volatility and counterparty risk as the main factors that explain the persistence of the negative basis.

We use the identified factors in an empirical investigation of the dynamics of the CDS-bond basis in the US corporate debt market for a period between 2005 and 2011. Our results show that the chosen variables explain over 35% of the basis for non-financial sector. Overall, the main drivers of the negative basis were funding costs, deteriorating collateral quality and counterparty risk, and to a lesser degree bond market illiquidity and basis volatility. In the post-Lehman period, the effects of funding cost and collateral quality increased, while counterparty risk and basis volatility lost their explanatory power. The somewhat counterintuitive decrease in importance of counterparty risk came about as a result of increased collateralization in the derivatives market, as well as the market's perception of too-big-to-fail perception of the derivative dealers in the aftermath of Lehman's demise. For US financial sector firms, we show that our chosen determinants only explain 11% of the basis over the same period. This fact is an indication that our analysis has not captured certain factors specific to the financial sector. For example, the financial sector is characterized by a high level of correlation between CDS protection seller and the reference entity. This leads to a significant wrong-way-risk component in the counterparty risk of the CDS. The analysis of the impact of wrong way risk on CDS-bond basis of financial and non-financial firms is an important and interesting avenue for future research. Our analysis shows that considered factors explain less of the negative basis for HY rating group than for IG group. We have shown that this is mainly due to the inclusion of B rated bonds within the HY category. We show that B rated bond showed a persistent positive basis during the crisis, and linked this fact to the relative illiquidity of the CDS market in B rated credit.

In order to analyze the economic significance of the various factors, and the dynamics of their contribution over the observation period, we performed a Fama-MacBeth style cross-sectional regression analysis. This analysis supported our earlier findings on the relative importance of funding costs, collateral quality and basis volatility in determining the basis. The analysis showed that at the height of the financial crisis, these factors contributed -42bp, -25bp and -10bp to the basis, correspondingly. The Fama-MacBeth analysis showed that our factors explained just 10% of the basis in the period before financial crisis, and 60% during the financial crisis. Overall, the various regression analysis, including OLS, panel approaches and Fama-MacBeth, showed a consistent picture about the main drivers of the basis.

Athough our analysis has been quite detailed, it has raised new questions that would require future investigation. Although, we have explained a significant part of the variation in credit spreads and CDS-bond basis, there is a significant fraction that remains unexplained. As mentioned above, the picture is particularly critical for financial sector companies. More research is required on theoretical identification of additional driving factors of the spreads and the basis, as well as empirical work to support theory. In particular, we point out the effects of wrong-way-risk on the pricing of CDS, as well as the analysis of recovery rate assumptions in the CDS and bond markets, as two possible promising avenues for research.

7 APPENDIX 1

A. LINKING PROCEDURE FOR DATA FROM DIFFERENT DATA SOURCES

Linking MarkIt and CRSP databases

In order to match companies from MarkIt database with CRSP we used the following approach:

1. We use CUSIP code to identify the company. CUSIP is 8-character alphanumeric code which identifies American financial security. CUSIP serves as the National Securities Identification Number for all products issued from US and Canada. The first 6 characters of this code identify the issuer, while the last 2 characters identify the issue. CUSIP is more reliable than tickers, because they change less over time and they are not reused. CRSP database has a historical track of CUSIPs for all companies and they are not reused with time.
2. Firstly, we cut from the Corporate Bond Total file the columns containing company name and CUSIP code (bond). Then we created an additional column, containing cut CUSIP code (first six characters), which identify the issuer.
3. Following this, we downloaded all Company names and CUSIPs (stocks) for CRSP for their entire database. In analogy with the bond datafile, we created an additional column containing the cut stocks CUSIP (first 6 characters).
4. Next, we matched these two tables in Excel (vlookup) using the 6 character CUSIP from the two datasets, and ended up with the table where for each Short name from MarkIt database we had a name from CRSP with unique CUSIP identifier. The companies that were not identified ether do not issue stocks (only bonds) or their stocks are not traded on NYSE, AMEX, NASDAQ stock exchanges. The unmatched

companies might also have merged or been acquired by other companies, which is difficult to track.

5. As a result of matching I ended up with 1,736 uniquely identified and matched companies between MarkIt and CRSP.

PERMNO number where used in order to find most recent CUSIP and Company name for each matched company, because some companies change their names several times during the life of the company and can be repeated in list of matches. PERMNO is unique five digit permanent identifier assigned by CRSP to each security in file. It neither changes during an issue's trading history, nor is reassigned after an issue ceases trading. According to CRSP, the user may track a security through its entire trading history in CRSP's files with one PERMNO, regardless of name changes or capital structure changes.

We put several restrictions on equity data. Security Status and Share Code variables were used in order to verify the type of shares traded. For the purpose of this analysis we were only interested in Ordinary Common Shares (no certificates or not preferred stocks). After cleaning procedure, all "bad data" lines were deleted from the equity dataset (for example empty or N/A sells instead of returns).

CRSP Value-weighted return (include distributions) was used as a proxy of market. This variable was downloaded with daily frequency from CRSP Stock market indexes for the same period of time (2001-2011). In order to find firm-specific return we took the difference between Stock return and CRSP value-weighted return.

Linking CRSP and COMPUSTAT databases

In order to merge CRSP and COMPUSTAT we used the following approach:

1. Firstly, from the "CRSP-MARKIT" match we took the list of unique PERMNOs, which are the CRSP specific identification numbers for each company.

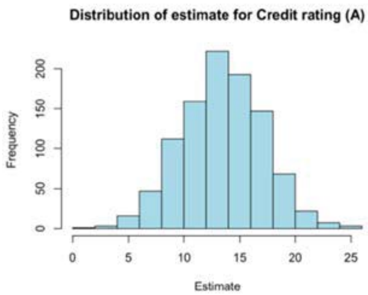
2. Secondly, based on the PERMNO/PERMCO (identification number) list, we downloaded most recent CUSIP and Current Company Name from CRSP-Stock security Files-Stock Header Info. This procedure was necessary due to the fact that CUSIP and Company Name can change during the time of existence of company. CRSP database can identify company based on its old name or CUSIP; however COMPUSTAT can only identify the company following its Current CUSIP and name.
3. Next, we downloaded the entire database of companies from COMPUSTAT for the period (2001-2012).
4. The next step was to link CUSIPs from CRSP and COMPUSTAT. In order to do this, we used the cut (first 6 characters) COMPUSTAT CUSIP (which is a 9 digit numbers) and link it with 6 character CRSP CUSIP (using vlookup function in Excel).
5. Following this procedure, we ended up with 1,038 matched distinct companies in all three databases.

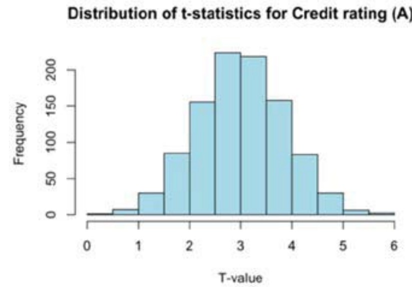
PERMCO is unique permanent identifier assigned by CRSP to all companies with issues on CRSP file. This number is permanent from all securities issued by this company regardless of name changes. It is important to use this identification numbers because CRSP can track the same company even if it changes the name frequently and avoid confusion of different names.

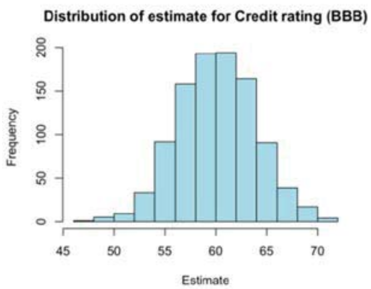
B. RANDOM SAMPLING HISTOGRAMS FOR US MARKET

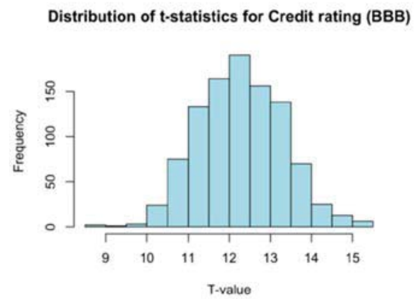
In this subsection of appendix we report details of histograms for all examined dependent variables and its t-statistics for random sampling procedure. The random sampling procedure was explained in Section 3.5.3.

Distribution of estimate coefficients and t-statistics for Credit Rating (A) and Credit rating (BBB)

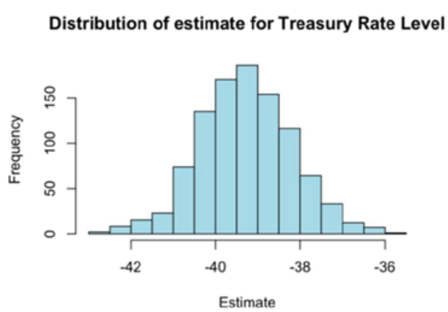


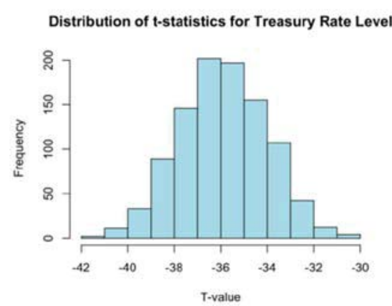


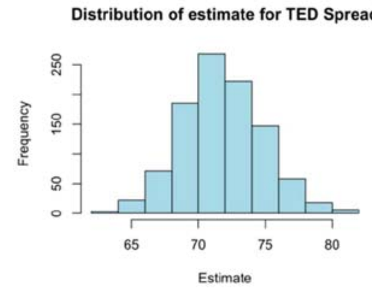


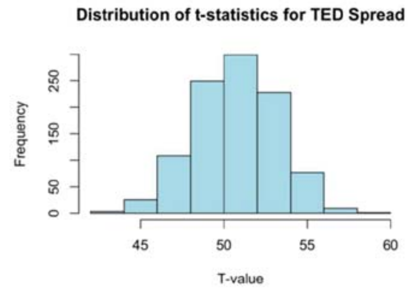


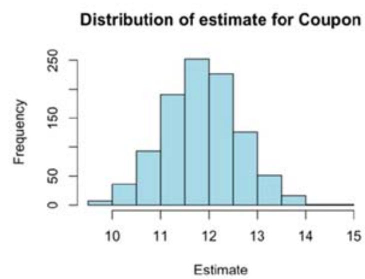
Distribution of estimate coefficients and t-statistics for Treasury Level, Ted spread, Coupon and Years to maturity

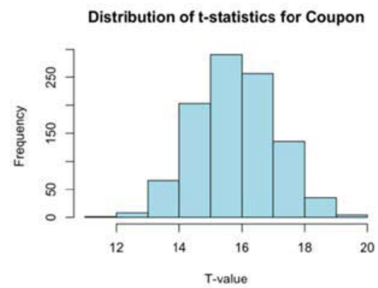


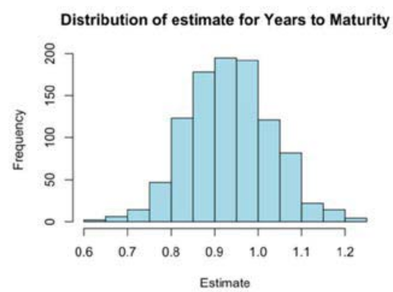


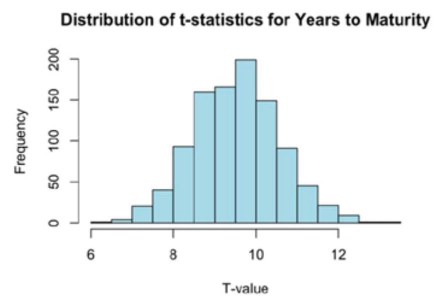




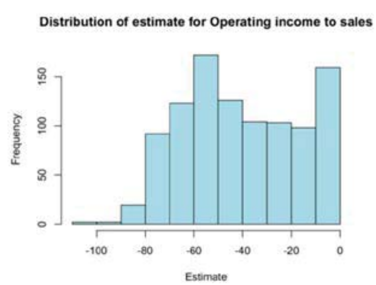


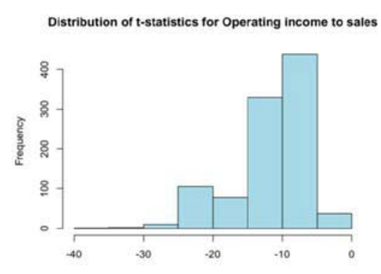


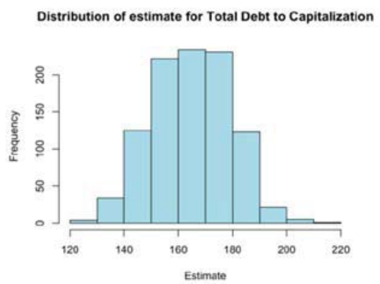


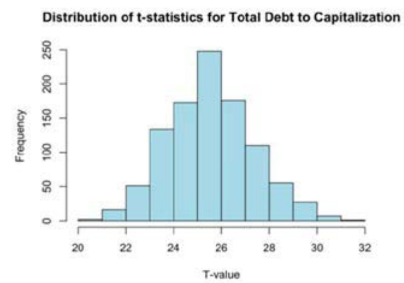


Distribution of estimate coefficients and t-statistics for accounting variables (total debt to capitalization and operating income to sales)





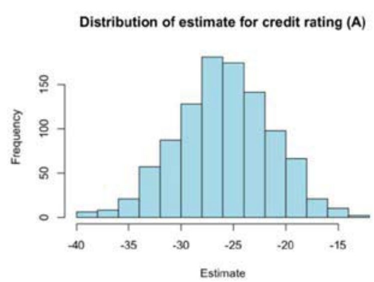


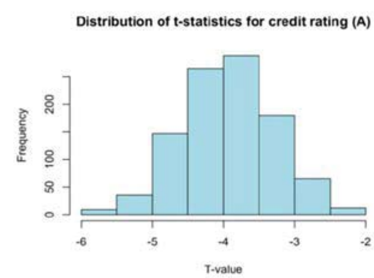


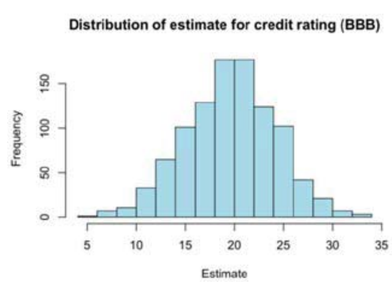
C. RANDOM SAMPLING HISTOGRAMS FOR UK MARKET

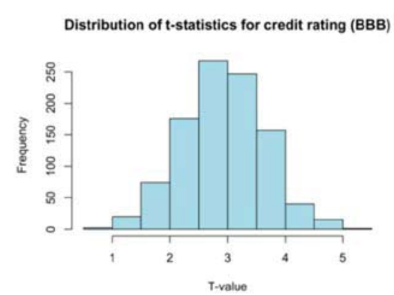
In this subsection of Appendix we present random sampling histograms of estimate coefficients and t-statistics of explanatory variables for UK corporate bond market. The random sub-sampling procedure was explained in Section 4.3.2.

Distribution of estimate coefficients and t-statistics for rating dummy variables (A, BBB)

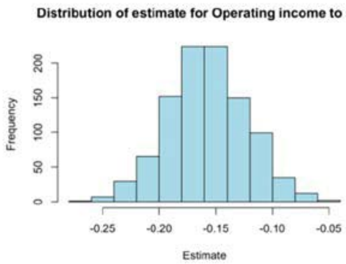


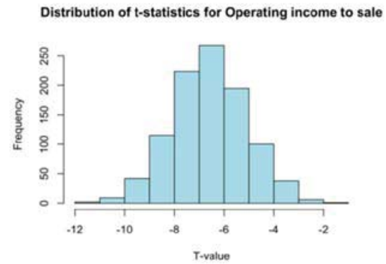


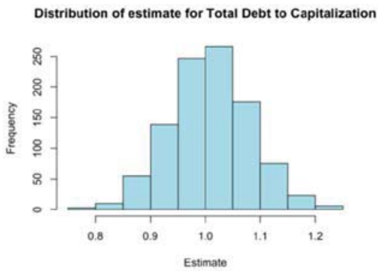


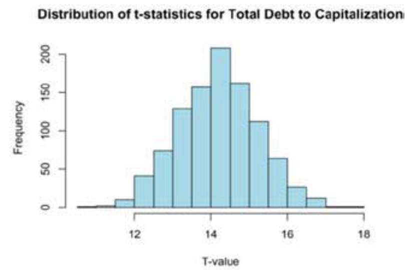


Distribution of estimate coefficients and t-statistics for accounting variables

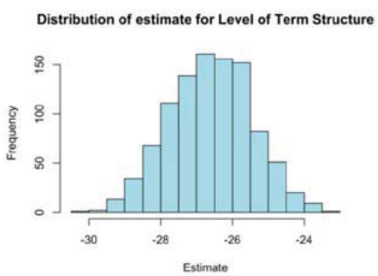


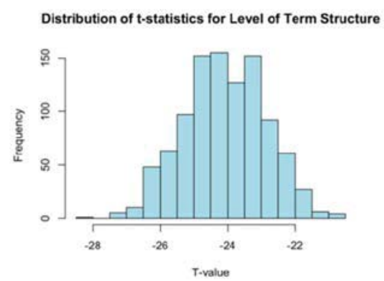


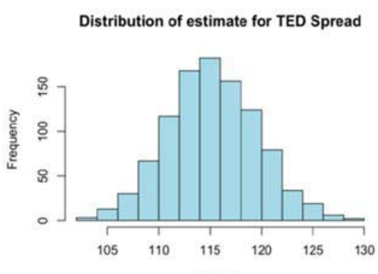


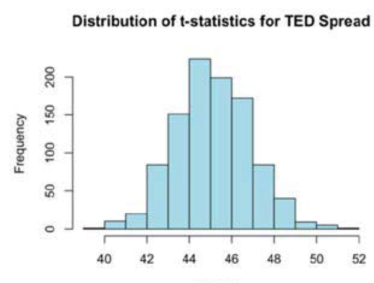


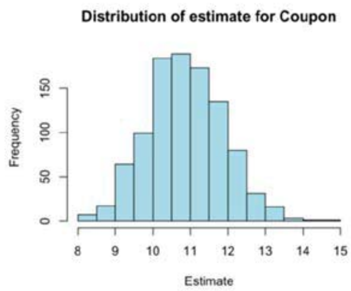
Distribution of estimate coefficients and t-statistics for macro and bond specific variables

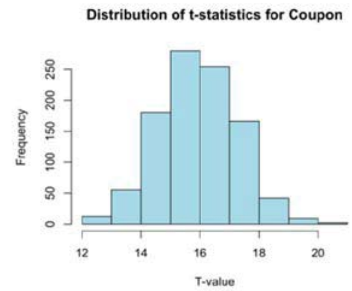


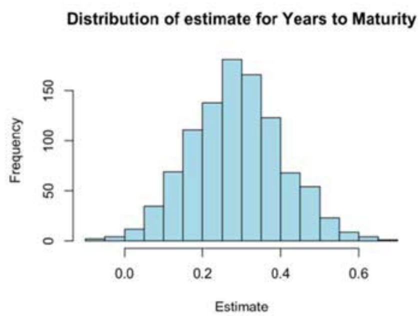


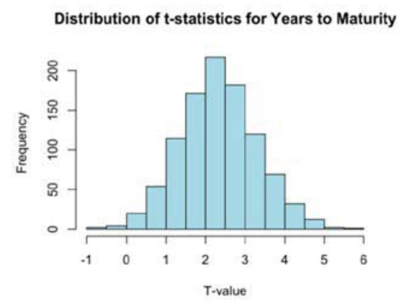





Distribution of estimate for Coupon
Frequency
0
50
100
150
8
9
10
11
12
13
14
15
Estimate


Distribution of t-statistics for Coupon
Frequency
0
50
100
150
200
250
12
14
16
18
20
T-value


Distribution of estimate for Years to Maturity
Frequency
0
50
100
150
0.0
0.2
0.4
0.6
Estimate


Distribution of t-statistics for Years to Maturity
Frequency
0
50
100
150
200
-1
0
1
2
3
4
5
6
T-value

8 APPENDIX 2

LIST OF THE COMPANIES INCLUDED IN CDS INDEX

This is the list of primary dealers from Federal Reserve Bank of New York on July 2009 (Bai & Collin-Dufresne, 2011):

BNP Paribas Securities Corp.
Bank of America Securities LLC
Barclays Capital
Cantor Fitzgerald & Co
Citigroup
Credit Suisse
Daiwa Securities America Inc.
Deutsche Bank
Goldman Sachs
HSBC
Jefferies & Company, Inc.
JP Morgan
Mizuho Securities
Morgan Stanley
Nomura
RBC Capital Markets Corporation
RBS Securities
UBS Securities LLC

9 APPENDIX 3

NEGATIVE BASIS TRADING STRATEGY. MATHEMATICAL DERIVATIONS.

In this appendix we derive the mathematical expressions that were used in Section 5.4. The negative basis trading strategy involves a long position in a bond, CDS protection, a Par Asset Swap and loans to fund the transaction. The strategy is shown schematically in Figure 21. In addition, we refer the reader to Table 33 for a summary of the main notations used in the text.

We shall assume that at time t_0, the investor buys the corporate bond. In order to hedge the credit risk inherent in the bond, the investor buys CDS protection on the underlying entity. In addition, in order to hedge the interest rate risk of the bond, the investor enters into a par asset swap contract with a derivatives dealer. The investor partially funds his position by borrowing in the repo market, pledging the bond as collateral. However, the proceeds from the repo loan are typically not sufficient to fully fund the investment strategy due to the existence of a haircut. For this reason, the remaining funds are borrowed in the form of an uncollateralized loan. Since, we assume that the investor completely funds his strategy with the repo and uncollateralized loan, the net cashflow at time t_0 is zero, i.e. $P\&L(t_0) = 0$. However, in order to keep track of the various terms, it is convenient to expand the expression for the cash flow at inception

$$\begin{aligned} P\&L(t_0) \; &= - P_{bond}^{ask}(t_0) - \; [N - P_{bond}(t_0)] - M \\ &\quad + N(1-h) + \left[Nh + M + \left(P_{bond}^{ask}(t_0) - P_{bond}(t_0)\right)\right] \end{aligned} \tag{21}$$

The terms in this expression have the following interpretation. The terms in the first line show the cash outflows, while the terms in the second line show the cash inflows from borrowing. More specifically, the term $-P_{bond}^{ask}(t_0)$ corresponds to the cash paid out for the purchase of the bond. The term $-[N - P_{bond}(t_0)]$ corresponds to the initial cashflow associated with the par asset swap. The term – M is the payment made into the derivatives margin account. For simplicity, in Figure 21, the margin is only posted to the CDS dealer. In realistic scenario, a separate margin would likely be posted to the asset swap dealer. However, this slight complication does not change our argument in any substance, and we therefore ignore it. Quantity $+N(1-h)$ represents the cash received from the repo loan. Finally, $+\left[Nh+M+\left(P_{bond}^{ask}(t_0)-P_{bond}(t_0)\right)\right]$ represents the cashflow from the uncollateralized loan. As a result of the transactions at time t_0, the investor has a long position in the underlying bond, a CDS protection struck at the prevailing ask spread $S_{CDS}^{ask}(t_0)$, as well as a par asset swap struck at the bid spread $S_{ASW}^{bid}(t_0)$.

We shall assume that at time t_1 the investor closes out his position in bond and derivatives, and at the same time pays back principal and interest on the repo and uncollateralized loans. The resulting net cashflow represents the total profit/loss made by the investor. Let us firstly assume that the bond has not defaulted by time t_1. In this case, in order to close out his positions, the investor sells off his bond in the market, closes out his positions in CDS and asset swap, and pays dues on his loans. The net cashflow at time t_1 is given by

$$\begin{aligned} P\&L_{no\ default}(t_1) = &+ P_{bond}^{bid}(t_1) \\ &- N(1-h)\left(1+r_{repo} \vartriangle t\right) - \left[Nh+M+\left(P_{bond}^{ask}(t_0)-P_{bond}(t_0)\right)\right]\left(1+r_{funding} \vartriangle t\right) \\ &+ M\left(1+r_{repo} \vartriangle t\right) \\ &+ P\&L_{no\ default}^{ASW}(t_1) + P\&L_{no\ default}^{CDS}(t_1) \\ &+ NC_{bond} \vartriangle t + N\left[r_{LIBOR} + S_{ASW}^{bid}(t_0) - C_{bond}\right] \vartriangle t - NS_{CDS}^{ask}(t_0) \vartriangle t \end{aligned} \tag{22}$$

The various terms in this equation have the following origin. $P_{bond}^{bid}(t_1)$ is the cash received from selling the bond in the market. The terms in the second line represent the principal and interest paid out on the loans. In particular, $-N(1-h)\left(1+r_{repo} \vartriangle t\right)$ is principal and interest returned on repo loan at t_1, while $-\left[Nh+M+\left(P_{bond}^{ask}(t_0)-P_{bond}(t_0)\right)\right]\left(1+r_{funding} \vartriangle t\right)$ is the principal and interest paid back on the uncollateralized loan at t_1. The term $M\left(1+r_{repo} \vartriangle t\right)$ is the margin with interest received from the CDS dealer on closeout of the CDS position. We shall assume that the interest rate paid on the margin account is equal to the market repo interest rate r_{repo}. The terms $P\&L^{ASW}_{no\,default}\,(t_1)$ and $P\&L^{CDS}_{no\,default}(t_1)$ represent the closeout prices for the par asset swap and CDS contracts at t_1. We shall look at this terms in detail below. The term $NC_{bond} \vartriangle t$ is the accrued bond coupon payment. The quantity $N\big[r_{LIBOR} + S^{bid}_{ASW}(t_0) - C_{bond}\,\big] \vartriangle t$ is the net accrued payment on the asset swap. Finally, $-NS^{ask}_{CDS}(t_0) \vartriangle t$ represents the accrued protection premium on CDS.

The calculation of closeout prices for the CDS and asset swap contracts involves straight forward but lengthy calculations. We refer the reader to (O'Kane, 2008) for details. The resulting expressions are as follows:

$$
\begin{aligned}
&P\&L^{CDS}_{no\,default}(t_1) = -N \cdot \left[s^{ask}_{CDS}(t_0) - s^{bid}_{CDS}(t_1)\right] \cdot RPVO1(t_1) \\
&P\&L^{ASW}_{no\,default}(t_1) = \,[N - P_{bond}(t_1)] + N \cdot \left[s^{bid}_{ASW}(t_0) - s^{ask}_{ASW}(t_1)\right] \cdot PVO1(t_1)
\end{aligned}
\tag{23}
$$

The quantities $PVO1(t_1)$ and $RPVO1(t_1)$ entering the above expressions are the market prices of a risk-free annuity and a risky annuity, correspondingly. These annuities are assumed to pay a unit cash at the bond coupon days. The difference between the two annuities is that the risky annuity stops payouts if the bond defaults, whereas the risk-free annuity continues payments until the original bond maturity date. The expressions above have a clear intuitive meaning. The P&L on the CDS contract is just the value of the discounted net cash flows from the original contract set at time t_0, and an offsetting contract entered at fair value at time t_1. The bid and ask spreads come into play because an investor is forced to accept the dealers quotes for opening and closing out of the contract. A similar argument holds for the asset swap. The difference in annuities $PVO1(t_1)$ and $RPVO1(t_1)$ arise because CDS premiums expire upon default, whereas asset swap continues to exist until maturity. We note that in derivation of results in expression (23) ignores the effect of counterparty risk inherent in derivatives. The expressions for derivatives pricing become quite complex in the presence of counterparty risk. In our empirical investigations in Chapter 5, we take into account counterparty risk using a simplified factor that is explained in Section 5.4.6.

In order to proceed, we introduce the following notations

$$
\begin{aligned}
&P_{bond}^{bid/ask}(t_i) = P_{bond}(t_i) \mp \frac{1}{2} N \cdot BAS_{bond} \\
&s_{xxx}^{bid/ask}(t_i) = s_{xxx}(t_i) \mp \frac{1}{2} N \cdot BAS_{xxx} \\
&M = m\,N \\
&BASIS(t_i) = s_{CDS}(t_i) - s_{ASW}(t_i) \\
&\Delta BASIS = BASIS(t_1) - BASIS(t_0) \\
&\Delta s_{xxx} = s_{xxx}(t_1) - s_{xxx}(t_0)
\end{aligned}
\tag{24}
$$

Where xxx stands for either CDS or ASW, and t_i refers to either t_0 or t_1. In the above expressions we have assumed that the various bid-ask spreads (BASs) do not change between t_0 and t_1. The quantities $P_{bond}(t_i)$, $s_{CDS/ASW}(t_i)$ are the market mid price and spreads. In addition, we neglect the various roll effects associated with moving from t_0 to t_1 (see (Elisade, Doctor, & Saltuk, 2009) for details).

Substituting expression (23) into expression (22) and taking into account the notations introduced in expression (24), we arrive at

$$
\begin{aligned}
P\&L_{no\ default}(t_1) = {} & -N\Delta t\left[(h+m-1)\left(r_{LIBOR} - r_{repo}\right) + (h+m)\left(r_{funding} - r_{LIBOR}\right) + BASIS(t_0)\right] \\
& -N\left[BAS_{bond}\left(1 + \frac{1}{2} r_{funding}\Delta t\right) + BAS_{CDS}\left(RPVO1(t_1) + \frac{1}{2}\Delta t\right) + BAS_{ASW}\left(PVO1(t_1) + \frac{1}{2}\Delta t\right)\right] \\
& + N \cdot PVO1(t_1) \cdot \Delta BASIS \\
& + N \cdot (RPVO1(t_1) - PVO1(t_1)) \cdot \Delta s_{CDS}
\end{aligned}
\tag{25}
$$

In what follows we shall ignore the last term $+N(RPVO1(t_1) - PVO1(t_1))\Delta s_{CDS}$. This approximation is justified for the following reason. The difference $(RPVO1(t_1) - PVO1(t_1))$ is proportional to the spread level s_{CDS}. For this reason, the product $(RPVO1(t_1) - PVO1(t_1)) \cdot \Delta s_{CDS}$ is quadratic in the spread level s_{CDS}. In our empirical analysis, we limit ourselves to linear regression models that are strictly valid only in the linear approximation for the various factors. In addition, in our empirical research we have restricted ourselves to investment grade and high-yield underlyings. For these cases, the quadratic corrections are typically small, and are much smaller than noises due to the various possible factors that have been left outside the scope of our analysis. Taking into account this approximation, we arrive at our final expression for P&L in the absence of default:

$$\begin{aligned} P\&L_{no\ default}(t_1) = & -N\Delta t\left[(h+m-1)\left(r_{LIBOR} - r_{repo}\right) + (h+m)\left(r_{funding} - r_{LIBOR}\right) + BASIS(t_0)\right] \\ & -N\left[BAS_{bond}\left(1 + \frac{1}{2} r_{funding}\Delta t\right) + BAS_{CDS}\left(RPVO1(t_1) + \frac{1}{2}\Delta t\right) + BAS_{ASW}\left(PVO1(t_1) + \frac{1}{2}\Delta t\right)\right] \\ & +N \cdot PVO1(t_1) \cdot \Delta BASIS \end{aligned} \tag{26}$$

This expression is used in Section 5.4 as equation (12).

Let us now turn to the case when underlying bond has defaulted. For simplicity we shall assume that the default (if it happens) happens at time t_1. In addition, we shall assume that upon default, bond issuer pays up the accrued coupon and the recovery value of the bond. The cashflow at t_1 in the event of default has the form:

$$
\begin{aligned}
P\&L_{default}(t_1) = & + N \cdot R + N \cdot C_{bond} \vartriangle t \\
& + P\&L^{ASW}_{default}(t_1) \\
& + N \cdot (1 - R) \\
& -N \cdot (1 - h)(1 + r_{repo}\Delta t) - \left[Nh + M + \left(P^{ask}_{bond}(t_0) - P_{bond}(t_0)\right)\right](1 + r_{funding} \vartriangle t) \\
& + M(1 + r_{repo} \vartriangle t) \\
& + N\left[r_{LIBOR} + S^{bid}_{ASW}(t_0) - C_{bond}\right] \vartriangle t - NS^{ask}_{CDS}(t_0) \vartriangle t
\end{aligned}
\tag{27}
$$

The terms in the above expression have the following origin. The terms in the first line, $NR + NC_{bond} \vartriangle t$, represent the recovery and the accrued coupon payments on the bond, received following default. $P\&L^{ASW}_{default}(t_1)$ represents the closeout value of the outstanding asset swap. We shall look at this term in detail below. The term $N(1 - R)$ is the protection payment received from the CDS protection seller upon the default of the underlying bond. The remaining terms have the same origin as in expression (22).

The calculation of $P\&L^{ASW}_{default}(t_1)$ once again involves some straight forward but lengthy calculations. Once again, we refer the reader to (O'Kane, 2008) for details. The resulting expressions is as follows:

$$
P\&L^{ASW}_{default}(t_1) = N\left[R_{IRS}(t_1) - \left(C - S^{bid}_{ASW}(t_0)\right)\right] PVO1(t_1) - \frac{1}{2} N \cdot BAS_{ASW} \cdot PVO1(t_1) \tag{28}
$$

In the above expression $R_{IRS}(t_1)$ is the current market fixed swap rate to swap LIBOR payments for the original duration of the bond. We have added a term proportional to BAS_{ASW} to take into account the bid-ask spread encountered by the investor at close out. The above expression can be rewritten in a more convenient, albeit lengthier expression as follows. We note that at contract initiation, the fair asset swap spread $S_{ASW}(t_0)$ is determined by equation (see (O'Kane, 2008)):

$$
N\left(C - S_{ASW}(t_0)\right) PVO1(t_0) + N = NR_{IRS}(t_0) PVO1(t_0) + P_{bond}(t_0) \tag{29}
$$

Using expressions (30) and (25) we rewrite expression (29) as follows:

$$P\&L_{default}^{ASW}(t_1) = N[R_{IRS}(t_1) - R_{IRS}(t_0)]PVO1(t_1) + \left[\frac{N - P_{bond}(t_0)}{PVO1(t_0)}\right]PVO1(t_1) - N \cdot BAS_{ASW}PVO1(t_1) \tag{30}$$

Substituting expression (30) into expression (27) taking into account expression (24) after straight forward algebraic manipulations, we arrive at

$$\begin{aligned} P\&L_{default}(t_1) = & -N\Delta t\left[(h+m-1)\left(r_{LIBOR} - r_{repo}\right) + (h+m)\left(r_{funding} - r_{LIBOR}\right) + BASIS(t_0)\right] \\ & -N\left[BAS_{bond}\left(\frac{1}{2} + \frac{1}{2}r_{funding}\Delta t\right) + BAS_{CDS}\left(\frac{1}{2}\Delta t\right) + BAS_{ASW}\left(PVO1(t_1) + \frac{1}{2}\Delta t\right)\right] \\ & + N[R_{IRS}(t_1) - R_{IRS}(t_0)]PVO1(t_1) + \left[\frac{N - P_{bond}(t_0)}{PVO1(t_0)}\right]PVO1(t_1) \end{aligned} \tag{31}$$

Comparing expressions (26) and (31) we see

$$\begin{aligned} P\&L_{default}(t_1) = & P\&L_{no\ default}^{expected}(t_1) + N[R_{IRS}(t_1) - R_{IRS}(t_0)]PVO1(t_1) + \left[\frac{N - P_{bond}(t_0)}{PVO1(t_0)}\right]PVO1(t_1) \\ & + O(BAS) \end{aligned} \tag{32}$$

Where $P\&L_{no\ default}^{expected}(t_1)$ is given by expression (26) without the basis risk term $N \cdot PVO1(t_1) \cdot \Delta BASIS$. The quantity $O(BAS)$ indicates terms proportional to the various bid-ask spread terms. If one ignores the small mismatches due to bid-ask spreads, the above expression shows that the hedging strategy is perfect if the interest rates have not moved from t_0 to t_1 (i.e. $R_{IRS}(t_1) = R_{IRS}(t_0)$), and the bond was trading initially at par (i.e. $P_{bond}(t_0) = N$). However, in the general case, there is small mismatch in the hedge. It is important to note that this mismatch is significantly smaller than the notional value of the bond. Thus, in the worst case scenario, an investor is exposed to at most a small fraction of the notional value of the bond. The underlying reason for this mismatch is that an asset swap does not extinguish upon the default of the underlying bond. This is in contrast to a CDS, whose premium leg stops following default. For the purpose of our analysis, we shall ignore the mismatch in the hedge, and assume perfect hedging. We therefore assume

$$P\&L_{default}(t_1) \approx P\&L_{no\ default}(t_1)$$

This expression is used in Section 5.4 as equation (13).

In conclusion to this appendix we summarize the main assumptions that were used in derivations above:

- We assume bid-ask spreads for bond prices, CDS spreads and asset swap spreads do not change from t_0 to t_1.
- We assume that the margin account pays interest at the repo rate r_{repo}.
- In the analysis above, we ignore the effects of counterparty risk on CDS and asset swap spreads.
- We ignore terms quadratic in CDS spread. In particular, we neglected the last term in equation (25).
- We have assumed that default, if it occurs, happens at time t_1. At default, the bond pays recovery and the accrued bond coupon.
- We ignore the mismatch in cashflows between no-default and default, and assume $P\&L_{default}(t_1) \approx P\&L_{no\ default}(t_1)$.

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