Sentiment and Volatility in the UK Stock Market

by

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Abstract

This thesis decomposes the UK market volatility into short- and long-run components using the EGARCH component model and examines the cross-sectional prices of the two components. The empirical results suggest that these two components are significantly priced in the cross-section and the negative risk premia are consistent with the existing literature. However, the ICAPM model in this paper using market excess return and two volatility components as state variables is inferior to the traditional three-factor model. Therefore, investor sentiment is augmented to the EGARCH component model to analyse the impacts of sentiment on market excess return and the components of market volatility. Bullish sentiment leads to higher market excess return while bearish sentiment leads to lower excess return. The sentiment-augmented EGARCH component model compares favourably to the original EGARCH component model which does not take investor sentiment into account. The sentiment-affected volatility components are significantly negatively priced in the cross-section.

This paper explores the cross-sectional impacts of market sentiment on stock returns and reveals that the sensitivities of investor sentiment vary monotonically with certain firm characteristics in the cross-section. The analysis suggests that investor sentiments forecast the returns of portfolios that consist of buying stock with high values of a characteristic and selling stock with low values. A sentiment risk factor is constructed to capture the average return differences between stocks most exposed to sentiment and stocks least exposed to sentiment. The two-stage Fama-MacBeth procedure suggests that the sentiment risk factor is significantly priced in the cross-section.

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Chapter 1 Introduction

1.1. Background

The Classical finance revolves around two basic premises:

1) Financial markets are informationally efficient.

2) Market participants are rational.

Rational investors always balance out the capital market price to equal the present fair value of expected future cash flows. In the highly competitive financial market, suboptimal trading behaviours, such as paying attention to signals irrelevant to fundamental values, will be quickly eliminated. However, such theories have shown limitations in finding convincing explanations to long lived “bubbles” and “crashes”. Researchers have found a vast amount of evidence that the markets are not efficient, that people are not rational, and that arbitrage opportunities are limited.

There are some investors who trade on “noise” as if it were information about fundamentals (Black, 1986). Empirical evidence also suggests that the stock market is too volatile to be justified by changes in expectations in dividends. The implication is that investors are not fully rational and stock prices could be affected by factors unrelated to fundamentals (Shiller, 1981; Leroy and Porter, 1981).

There is typically no room for the presence of investor sentiment in classical finance. Since the statement of investor’s ‘animal spirits’ (Keynes, 1936), economists have been trying to understand extreme market fluctuations and price movements that cannot be justified by underlying fundamentals. In recent decades, financial economists have attempted to understand how human psychology influences investors’ financial decisions. This evolution has led to the emergence of a new field of financial research – behavioural finance, which plays a complementary role in understanding the issues that traditional finance fails to explain.

Researchers in behavioural finance base their studies on two alternative assumptions, as summarized by Shleifer and Summers (1990). The first assumption is that some investors are not fully rational and that stock prices are subject to mispricing which does not reflect future cash flows. Subjective valuation is more likely to be influenced by speculative demands originating from varying investor confidence and emotion. The second assumption is that arbitraging against noise investor sentiment is costly, risky and therefore limited. The sentiment of noise traders introduces a systematic risk that is priced and hence affects asset prices in equilibrium. These two critical assumptions are employed in this thesis. Noise traders act in concert on non-fundamental signals and drive prices away from fundamental values. Rational arbitrageurs fail to completely eliminate mispricing due to their risk aversion and limit-to-arbitrage.

DeLong et al. (1990, hereafter, DSSW) formalise the role of investor sentiment in the financial market. In their model, noise traders base their trading decisions on sentiment and risk-averse arbitrageurs encounter limits to arbitrage. Rational arbitrageurs face two types of risks – fundamental risks and noise trader risks. These risks would deter the willingness of arbitrageurs from betting against noise traders and limit the size of the opposite positions, leaving the price deviating from its fundamental value. Furthermore, in real-world trading, there are some other factors that limit arbitrage, such as the length of the arbitrageurs' investment horizon and the ownership of the money used to engage in arbitrage (DSSW, 1990; Shleifer and Summers, 1990).

There is a growing consensus that noise traders are exposed to sentiment and noise trading can generate price movement that shall be priced in asset pricing. Prior research presents a number of proxies for sentiment to use as time-series conditioning variables. There are mainly three measures of investor sentiment in the literature. One approach is directly through economic variables, such as mutual fund flows (Brown et al., 2002), trading volume (Baker and Stein, 2006) and closed-end fund discount (Lemmon and Portniaguina, 2006). Another approach is to use survey data, such as the Association of Individual Investors (AAII) and Investors Intelligence (II) in the US market and consumer confidence in European markets. The last approach is to construct a composite proxy index from the available economic variables. However, empirical research suggests that it is not yet clear how to measure investor sentiment properly.

1.2 Some Characteristics of the UK Stock Market

The existing literature concentrates on exploring the effects of investor sentiment on US stock returns. These papers rely on the notion that retail investors are more vulnerable to sentiment waves and further cause stock prices to deviate from their fundamental values (see, e.g., DeLong et al. (1990), Kumar and Lee (2006)). The analyses implicitly assume that institutional investors are more rational in their trading behaviour whereas retail investors are responsible for the impact of sentiment on stock market. Although institutional investors are subject to restrictions of investment horizon and sources of fund engaged in arbitrage, it is still important to test the robustness of findings from the US market for other markets that are characterised by a different composition of the investor population.

Research on the US market reveals that investor sentiment exhibits cross-sectional effects on individual firms. For example, small firms are more exposed to sentiment. Therefore, it is also interesting to test the impact of investor sentiment on other markets which consist of a different composition of firm characteristics.

Specifically, the UK stock market has some characteristics that might lead to a different reaction of stock returns to investor sentiment. Grout et al. (2009) estimate that 21.2 percent of the US population own shares which means there are 62 million individual shareholders. In contrast, 15.09 percent of the UK population own shares which means there are 9.06 million individual shareholders in the UK. Mayo (2012) reports a similar estimation. Hence, the population of retail investors is lower in the UK than that in the US.

As reported by Blume and Keim (2012), by 2010, the total market value of US common stocks had increased to $17.1 trillion, and institutions had increased their holdings to $11.5 trillion, or 67 percent of all stocks. Davis (2009) reports that retail investors own less than 30% of the stock of US corporations and represent a very small percentage of the US trading volume. However, retail investors are still more active participants in the US market compared to the UK market. The Office for National Statistics (UK) indicates that individuals held 10.7% of the shares listed on the LSE by 2012. That compares with 17.5% held by pension funds, insurance companies and other financial institutions. The proportion of shares held by individuals has declined since 1963 when individuals owned 54% of UK quoted shares in terms of total value. Their percentage holdings reached a record low of 10.2% in 2010 but picked up slightly to 10.7% in 2012. On the other hand, the 'rest of the world', which held just 7% of UK shares in 1963, now own 53.2% of UK quoted shares. The Office for National Statistics finds that about 48% of this is owned by investors in North America, around 26% by European investors and around 10% by investors in Asia. The shares, which are held by foreign investors, presumably would also be mainly held by institutions. In conclusion, despite the fact that both US and UK securities markets are now dominated by institutional investors, retail investors are more active in US stock markets.

The sector allocations of the UK and US stock markets are presented in table 1.1[1]. The financial sector, which consists of general financial, banks, insurance, real estate, etc., is the largest sector in the US market and technology is the second largest sector. The US stock market has more technology companies and the proportion is 22 times larger than that in the UK stock market. However, in the UK stock market, consumer goods sector is the largest sector, the percentage of which is almost three times as big as that in the US stock market. Another distinct difference between the two markets is the basic materials sector, which is comprised of chemicals, mining, industrial metals, forestry and paper. The UK stock market contains more firms in this sector compared to the US stock market.

Table 1.1: Comparison of sector allocation in the US and UK stock markets

Stock Market	US Stock Market	UK Stock Market
Financials	18.55%	11.72%
Technology	16.22%	0.73%
Consumer Services	13.66%	6.24%
Health Care	13.21%	6.01%
Industrials	12.66%	10.62%
Consumer Goods	9.81%	34.45%
Oil and Gas	7.64%	7.45%
Utilities	3.07%	7.79%
Basic Materials	3.05%	11.93%
Telecommunications	2.12%	3.05%

[1]The US market data are taken from :
http://www.djindexes.com/mdsidx/downloads/fact_info/Dow_Jones_US_Total_Stock_Market_Indices_Industry_Indices_Fact_Sheet.pdf
The US market data are calculated from data from:
http://www.lse.co.uk/uk-sectors.asp

Meanwhile, the market turnover of the UK stock market is relatively lower than that of the US stock market. Between 01/01/2004 and 31/12/2013, the daily average trading value was 1.686 billion pounds in the London Stock Exchange whereas the average value was 57.502 billion dollars in the New York Stock Exchange. Furthermore, the aggregate market capitalisation of UK stock markets is much lower compared to US stock markets. As reported by Index Mundi, the value of market capitalisation of listed companies in the US was 18.668 trillion dollars whereas the value of those listed in the UK was 3.019 trillion dollars in 2012. As shown in table 1.2[2], more than 40 percent of US firms have a market value of over 1 billion dollars whereas only 15 percent of UK firms are above this value. In contrast, UK markets have more firms with a market value of less than 1 million dollars which is more than one-half of the proportion in the UK stock markets whereas the US markets only have 19.2 percent of small firms. Therefore, UK stock markets consist of more small firms compared to the US.

Table 1.2: Comparison of the total number and percentage of firms with different market capitalisation in the UK stock market (listed on LSE) and the US stock market (listed on NYSE, NASDAQ, and AMEX) until the end of October, 2014.

		Range of Market Capitalisation in ***billions of dollars***				
		<0.1b	0.1b~1b	1b~10b	10b~100b	>100b
US	No. of Firms	1112	2300	1729	587	62
	Percentage	19.2%	39.7%	29.9%	10.1%	1.1%
UK	No. of Firms	1193	674	273	61	5
	Percentage	54.8%	30.6%	12.4%	2.8%	0.2%

1.3 Motivation

Financial economists have been interested in the risk-return trade-off in the capital market. There are a variety of models that quantify the trade-off between risk and return, including

[2] The lists of companies until October 2014 are provided on the LSE and NASDAQ websites. There are 2,423 UK stocks and 6,673 US stocks. However, there are 230 UK firms and 883 US firms that do not have available market values. Hence, only 2,206 UK firms and 5,790 US firms are included.

the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Model (APT). The CAPM has been criticized for its unrealistic assumptions and has encountered empirical failures, which has led to further theoretical work on the CAPM that refines the models by including more variables in addition to the market risk factor. Merton (1973) extends the CAPM to the intertemporal asset pricing model and shows that risk premia are associated with the conditional variances between asset returns and innovations in the state variables that forecast future investment opportunities. The ICAPM versions of Campbell (1993, 1995) and Chen (2002) suggest that investors are inclined to hedge against changes in future market volatility. Therefore, aggregate volatility is a reasonable state variable that affects agents' investment opportunities and is a systematic risk factor that is priced in the cross-section of stocks.

Measures of volatility implied in option prices are widely believed to be the best available volatility forecast. For example, the VIX index becomes a broadly accepted measure of the market's expectation of US stock market volatility over the next 30-day period. On the other hand, formal models for systems with time-varying volatility have been greatly developed and widely applied in economics and finance, for example, ARCH-type models and stochastic volatility models.

Adrian and Rosenberg (2008) propose the EGARCH component model based on the EARCH and GARCH component models to describe the risk-return relationship. They decompose the aggregate volatility to short- and long-run components depending on the persistent level of volatility. They demonstrate that both the short- and long-run components of the market volatility are priced in the cross-section of the US stock market.

DSSW (1990) have studied the effects of noise trading on equilibrium prices and predict that the direction and the magnitude of changes in sentiment are important elements in asset pricing. The optimism or pessimism of noise traders causes prices to deviate from their intrinsic value, at least in the short run. Furthermore, noise trading occurs contemporaneously across many assets in the market and induces additional variability in returns which is non-diversifiable. Therefore, the DSSW model asserts that sentiment not only influences asset return directly, but also impacts return indirectly through changes in noise traders' misperceptions of the asset's risk.

A voluminous amount of literature has emerged to show the time-series relationship between investor sentiment and stock market returns (Fisher and Statman, 2000; Brown and Cliff, 2005; Schmeling, 2009; Corredor et al. 2013). Motivated by the impacts of sentiment on returns and volatility, it is natural to augment sentiment to the Andrain and Rosenberg (2008) EGARCH component model and examine whether the sentiment-affected volatility, including its short- and long-run components, is priced in the cross-section of the stock market.

Recent literature on investor sentiment sheds more light on the extent to which investor sentiment impacts on individual assets. Empirical studies reveal the diverse impacts of sentiment on individual stocks. Baker and Wurgler (2006) find that stocks that are hard to arbitrage and difficult to value are more vulnerable to waves of investor sentiment. Specifically, small firms, volatile firms, unprofitable firms, firms paying no dividend, firms with less intangible assets, and extremely growing firms are more sensitive to market sentiment. Berger and Turtle (2012) provide statistical evidence of sentiment-prone portfolios and confirm the conjecture of Baker and Wurgler (2006).

Numerous studies exert the predictive power of sentiment on returns of stocks with certain characteristics. Lemmon and Portniaguina (2006) show that consumer confidence forecasts returns of small stocks and stocks with low institutional ownership. However, they fail to detect whether sentiment forecasts value and momentum premium. Studies by Baker and Wurger (2006) and Berger and Turtle (2012) suggest that sentiment has predictive power on firms that are more responsible to market sentiment. Their empirical work suggests that investor sentiment exhibits a cross-sectional influence on individual stock returns.

Motivated by the numerous findings that sentiment has impacts on market return and volatility, this thesis attempts to reveal the relationship between sentiment, risk and returns. Furthermore, following the findings that sentiment exhibits cross-sectional effects on stock returns, this thesis tries to develop a factor based on noise trading risk and examine whether such a sentiment risk factor is priced.

1.4 Objectives and Contributions

1.4.1 Brief Contributions

This thesis makes three major contributions to fill the gap in the existing literature.

First, this thesis attempts to explore the effect of investor sentiment on the UK stock market. The existing literature relating to investor sentiment mainly focuses on the US stock market and the research involving the UK market only studies the UK market as part of the European or global market. To my knowledge, this thesis is the first to examine the cross-sectional impact of investor sentiment on returns of UK stocks. This study focuses on the UK stock market and makes use of a large set of financial and accounting data to examine sentiment effects on stocks with different firm characteristics, such as size, dividend history, profitability, realised volatility, tangibility, and growth opportunity.

Second, this study constructs sentiment-prone portfolios and develops a triple-sort procedure to construct a new risk factor, that is, the sentiment risk factor. The inclusion of the new risk factor improves the performance of the Fama-French 3 factor model. The research reveals that this new risk factor is significantly priced in the framework of the ICAPM model and attenuates the impacts of the traditional risk factors, such as size, value, momentum and liquidity risk factors. The empirical results suggest that the sentiment risk factor is a potential risk factor in asset pricing models, such as the ICAPM model and the arbitrage pricing model.

Meanwhile, this thesis decomposes the market volatility into transitory and permanent components by implementing the EGARCH component model proposed by Adrain and Rosenberg (2008). The study shows that the decomposed volatilities are priced in cross sections in the UK stock market. However, this EGARCH component model does not consider the impact of investor sentiment on market returns and volatility. The DSSW model has presented the influences of noise trading on equilibrium prices. Noise traders acting in concert on non-fundamental signals can introduce a systematic risk that is priced. A handful of research has shown the relationship between investor sentiment and stock returns and volatilities.

Therefore, the last contribution of this study is to improve the EGARCH component model by taking account of investor sentiment. The research demonstrates that investor sentiment has a direct impact on the UK market return and also influences returns indirectly through changes in noise traders' misperception of short- and long-run volatilities. The study further demonstrates that the sentiment-affected short- and long-run volatilities are priced factors in the cross section.

1.4.2 Specific Objectives and Contributions of Each Chapter

The main specific objectives and contributions of each empirical chapter are as follows.

First, this study attempts to fill a gap in the applied literature to investigate the cross-sectional effects of short- and long-run volatility components in the UK stock market. The object of this chapter is threefold. First, the research aims to both determine whether the short- and long-run components of the UK market volatility are priced risk factors and estimate the prices of these two components. Second, it examines the robustness of the volatility component model across sets of portfolios, sub-periods, and model specifications. Third, this study examines the performance of the ICAPM using market risk, short-run volatility and long-run volatility as state variables with comparison to a line of asset pricing models, such as the CAPM and Fama-French 3 factor models. The main findings are that: (i) The short- and long-run components of UK market volatility have significant negative prices in the cross-section; (ii) The volatility component model is robust across sets of portfolios, sub-periods and model specifications; (iii) Although the ICAPM model implemented in this part outperforms the simple CAPM model, it is inferior to FF 3 factor model and Carhart's 4 factor model.

Second, the thesis contributes to the existing literature by investigating the extent to which the impact of investor sentiment has on stock market volatility and returns. The research complements earlier work which shows that sentiment helps to explain the time-series of returns. Previous research has focused on the influence of investor sentiment on the mean of stock returns. The DSSW model states that sentiment has an impact on both stock returns and volatility. It is natural to consider that the decomposed components of market volatility are also related to investor sentiment and this study investigates the impact of investor sentiment on both the market excess returns and the short- and long-run volatility of returns. The objectives are to investigate the influences of sentiment on market returns and decomposed market volatility by applying investor sentiment to the EGARCH component model and further examine the risk prices in the cross-section. The principal findings are that: (i) Investor sentiment is positively related to market returns; (ii) The magnitude of sentiment does not have a significant effect on short- or long-run volatilities. Instead, the sign of sentiment impacts the volatility components. The optimism of previous sentiment leads to an increase in short-run volatility and a decrease in long-run volatility. In contrast, the pessimism of previous sentiment leads to a decrease in short-run volatility but an increase in long-run volatility. Therefore, the overall effect of sentiment on aggregate volatility is ambiguous since the impacts on its components are opposite; (iii) Since short-run volatility is positively related to market returns and long-run volatility is negatively related to market returns, the optimistic sentiment increases market return through short- and long-run volatility and vice versa; (iv) The short- and long-run sentiment-affected volatilities are significantly negatively priced in the cross-section; (v) The ICAPM using market risk and sentiment-affected volatilities outperforms the Fama-French 3 factor model.

Finally, this thesis comprehensively investigates the impacts of investor sentiment on the UK stock market by using a large set of data, including financial and accounting data. Furthermore, the sentiment risk premium is constructed to explain abnormal returns. To my best acknowledge, the existing research relating to the UK market only examines the UK market as part of the international stock market. There is little in-depth research to explore the sentiment effect on stock returns concentrating on the UK stock market. The research of the UK stock market only investigates the impacts of sentiment on the aggregate stock market. None of it looks into the cross-sectional effects of investor sentiment on individual stocks despite the fact that the cross-sectional effects of sentiment have been well examined in the US market. The objective of this part is to study the cross-sectional effects of sentiment on the UK stock market and develop a sentiment risk factor to explain stock returns. The important findings are: (i) Stocks that are vulnerable to sentiment also tend to be hard to value and hard to arbitrage; (ii) Investor sentiment forecasts stocks that are sensitive to sentiment; (iii) The traditional risk factors cannot explain the abnormal returns of sentiment-prone portfolios; (iv) The sentiment risk premium factor, inspired by the construction procedure of the SMB and HML factors of Fama and French (1993), exhibits the explanation power of abnormal returns; (v) The sentiment risk premium has a significant positive price in the cross-section and helps improve the performance of the Fama-French 3 factor model. The pricing ability is robust to the size, value, momentum and liquidity risk premiums.

1.5 Structure of the Thesis

The structure of the remainder of this thesis is as follows.

Chapter 2 describes the EGARCH component model and the framework of the ICAPM model. This chapter investigates the risk-return relationship in the EGARCH component framework. The primary purpose of this chapter is to answer whether the decomposed volatility components are priced in the cross-section of the UK stock market and examine the performance of the ICAPM model using the decomposed volatility components as state variables.

Chapter 3 presents the data available to construct sentiment index and displays the procedure used to measure investor sentiment. After that, at the market level, investor sentiment is augmented to the EGARCH component model as described in DSSW (1990). The sentiment-affected volatilities, both short- and long-run components are obtained. After that, the risk premia of short- and long-run sentiment-affected volatilities are examined in the cross-section. The performance of the ICAPM using sentiment-affected volatilities as state variables is examined as well.

Chapter 4 describes the financial and accounting data used to analyse the cross-sectional effects of investor sentiment on stock returns at the firm level. Portfolios are constructed on the basis of sentiment sensitivities and firm characteristics are calculated to look for the patterns. It then constructs portfolios based on firm characteristics to explore the predictive power of sentiment. The sentiment risk premium is developed from a triple-sort procedure and used to explain the abnormal returns of portfolios. After that, the new risk factor is augmented to the Fama-French 3 factor model.

Chapter 5 summarises the findings of this thesis and outlines possible directions for future research.

Chapter 2 The Cross-sectional Risk Premium of Decomposed Market Volatility in UK Stock Market

2.1 Introduction

The intertemporal capital asset pricing model (ICAPM) by Merton (1973) suggests that when there is stochastic variation in investment opportunities, asset risk premia are not only determined by the covariation of returns with the market return, but are also associated with innovations in the state variables that describe the investment opportunities. Campbell (1993, 1996) points out that empirical implementations of the ICAPM model should not rely on choosing important macroeconomic variables. Instead, in cross-sectional asset pricing studies, the factors in the model should be related to innovations in state variables that forecast future investment opportunities.

There is no doubt that stock market volatility changes over time, but whether or not volatility represents a priced risk factor remains less certain. Campbell (1993, 1996) tests the intertemporal model and shows that investors care about risks both from the market return and from changes in forecasts of future market returns. Time-varying market volatility induces changes in the investment opportunity set by changing the expectation of future market returns, or by changing the risk-return trade off. Ang et al. (2006) set up a standard two-factor pricing kernel with the market return and stochastic volatility as factors. They show that market volatility is a significant cross-sectional asset pricing factor. They demonstrate that the low average returns on stocks with high past sensitivities to aggregate volatility risk cannot be explained by size, book-to-market, liquidity, volume, or momentum effects, which is strong evidence showing that aggregate volatility is a priced risk factor in the cross section of stock returns. They find that innovations in aggregate volatility carry a statistically significant negative price of risk of approximately -1% per annum.

Engle and Lee (1999) developed a new specification of model volatility process based on GARCH. They decompose volatility into permanent and transitory components. Following Engle and Lee (1999), the component GARCH model is applied to numerous economic areas and different countries. Research includes McMillan et al. (2000) on futures markets; Simón and Amalia (2012) on bond markets; Hertog (1994) exploring the US stock market; Zarour and Siriopoulos (2008) investigating the Middle-East stock market; Mansor and Huson Joher (2014) studying the Malaysian stock market.

Adrian and Rosenberg (2008) incorporate the permanent and transitory component model of Engle and Lee (1999) and the EGARCH model of Nelson (1991) and have built up a new specification of volatility dynamics, the EGARCH component model. They decompose the market volatility into short- and long-run components and model the log-volatility of the market portfolio as the sum of a short- and a long-run volatility component. Their approach parsimoniously captures shocks to systematic risk at different horizons. They suggest that the short- and long-run volatility components have negative, highly significant prices of risk which is robust across sets of portfolios, sub-periods, and volatility model specifications. Their three factor model with the market excess return and the two volatility components compares favorably to the benchmark model, the three-factor model of Fama and French (1993, 1996).

The motivation for this chapter stems from the following three important reasons to explore the relationship between volatility components and stock returns:

Firstly, the relationship of return and volatility is a long-standing issue in financial research. Engle and Lee's component structure of volatility extends the rich and complicated dynamics reported by French, Schwert and Stambaugh (1987), Nelson (1989, 1990), and Engle, Bollerslev, and Nelson (1994), among others. This approach parsimoniously captures shocks to systematic risks at different horizons.

Secondly, the idea of decomposing the stock return volatility has been well developed in financial and econometrics literature. Friedman and Laibson (1989) provide empirical evidence supporting a two-component representation of stock price movements. The extreme movements in the stock market cause changes in the transitory component of conditional variance. Muller et al. (1997) relate volatility components to specific trader groups. Volatilities measured with different time resolutions reflect the perceptions and actions of different market agent types. Andersen and Bollerslev (1997) suggest intro-day volatility may contain both short-run and long-run components due to the existence of heterogeneous information flows or heterogeneous market agents. Liesenfeld (2001) reports that the short-run volatility dynamics are directed by the information arrival process, whereas the long-run dynamics are associated with the sensitivity to new information. Schleifer (2000) considers noise trader risks as the main factors affecting the transitory component of stock return volatility.

Thirdly, Campbell (1993) suggests that any variable that forecasts future returns or volatility is a good candidate state variable in the ICAPM model. Chen (2002) and Ang et al. (2006) provide theoretical and empirical evidence that market volatility is a priced factor in the cross-section of stock returns. Adrian and Rosenberg (2008) examine the cross-sectional price of the components of volatility in the US stock market and demonstrate that the short- and long-run volatility components are significantly priced and their volatility components model compares favorably to the traditional CAPM, Fama-French model and several other model specifications.

The motivation for this paper is along these lines. Firstly, there are a growing number of papers dealing with the decomposition of the market volatility into components using Engle and Lee's component GARCH Model. However, to my best knowledge, no studies have examined the cross-sectional effect of the two decomposed components of market volatility, especially on the UK stock market. Contrary to existing empirical studies that simply employ Engle and Lee's component GARCH model to explore the time-series effect of volatility, this thesis attempts to understand the cross-sectional effects of the transitory and permanent components of volatility. Secondly, this chapter implements the EGARCH component framework of Adrian and Rosenberg (2008) together with the simple GARCH component model. The research seeks to investigate whether the decomposed volatilities are significantly priced in the UK stock market and examines the superiority of the ICAPM model using market return and the transitory and permanent components of market volatility compared to the traditional Fama and French model.

To test these, in this chapter, the Adrian and Rosenberg (2008) decomposition of market risk is applied to the UK stock market to investigate the pricing of short- and long-run volatility risk in the cross-section of stock returns. The object of this chapter is threefold: Firstly, the study attempts to both determine whether the short- and long-run components of market volatility are priced risk factors and estimate the prices of these two components. Secondly, Adrian and Rosenberg (2008) report that their three-factor model outperforms the traditional three- factor model of Fama and French (1993, 1996) conducted on the 25 size and book to market portfolio using US stock data. This research tries to examine whether the short- and long-run component model remains superior in the UK stock markets. Thirdly, the study examines the robustness of the volatility component model across sets of portfolios, sub-periods, and model specifications.

The reminder of this article is organised as follows: The literature review is presented in section 2.2. Methodology and data description are presented in section 2.3 and 2.4. Empirical results are reported in section 2.5. The final section offers concluding remarks.

2.2 Literature Review

The most fundamental and best known model in asset-pricing theory is the Capital Asset Pricing Model (CAPM) which is essentially a "single factor" model of portfolio returns. However, the assumption of a single risk factor (market beta) limits the validity of this model and the effects of other risk factors have put this model under criticism. Empirical work presents numerous bodies of evidence that suggest that much of the variation in expected return is unrelated to the market beta. Specifically, in the late 1970s, research began to uncover variables such as size, various price ratios, and momentum that add to the explanation of average returns associated with market beta. For instance, the most prominent contradiction of the CAPM is the size effect of Banz (1981). He indicates that small stocks earn too high average returns provided by their beta estimates while large stocks achieve too low average returns. Statman (1980) indicates that average returns on US stocks are positively related to the ratio of a firm's book value of common equity to its market value (BE/ME).

Fama and French (1992) update and synthesize the evidence on the empirical failures of the

CAPM. In this study, the authors present evidence that beta almost has no explanatory power using average stock returns for NYSE, Amex and the NASDAQ stocks over the period from 1963 to 1990. On the other hand, employing the cross-sectional regression approach, they infer size and book-to-market equity (BE/ME), combined to capture the cross-sectional variation in average stock returns together with the market beta, leverage, and earnings-price (E/P) ratios. Furthermore, the combination of size and book-to-market equity seems to absorb the roles of leverage and E/P in average stock returns, at least during their 1963-1990 sample period.

As a landmark of asset pricing and portfolio management, Fama and French (1993) extend this test using time-series regressions and reach the same conclusion that the traditional CAPM does not account for returns of size and book-to-market sorted portfolios. The tests, together with Fama and French (1992), show that there are common return factors related to size and book-to-market equity that help capture the cross-section of average stock returns in a way that is consistent with multifactor asset-pricing models. Their studies led to the development of the famous Three-Factor Model.

Jegadeesh and Titman (1993) report that short-term returns tend to continue and that stocks with higher returns in the previous 12 months tend to have higher future returns. This momentum effect is left unexplained by the three-factor model. Carhart (1997) constructs a 4-factor model by including a momentum factor to three-factor model to capture the one year momentum anomaly. Using a sample free of survivor bias, Carhart (1997) demonstrates that common factors in stock returns and investment expenses almost completely explain persistence in equity mutual funds' mean and risk-adjusted return. The tests suggest that the 4-factor model can explain sizeable time-series variations and the additional factors could account for much cross-sectional variation in the mean return on stock portfolios. Carhart (1997) stresses that the 4-factor model substantially improves on the average pricing errors of the CAPM and the three-factor model. Overall, the evidence is consistent with market efficiency interpretations of the size, book-to-market, and momentum factors.

Fama and French's three-factor model and Carhart's four-factor model have been widely accepted and employed in empirical analyses. The statistical results seem robust to some extent, especially in the US common stock markets. However, these models suffer from the problem that the factors are not motivated from theory. Fama and French (1996) claim that the success of the three-factor model is fully consistent both with a rational model of returns in which SMB and HML reflect unobserved systematic risk factors, and an irrational model in which they capture the systematic mis-pricing of stocks. However, they also note that the three-factor model has no foundation in finance theory, but is merely a statistical model that summarises the empirical regularities that have been observed in the US stock returns.

In contrast to the lack of theoretical support for the three (or four) - factor model, alternative responses to the poor performance of CAPM are to make modifications to the standard CAPM. Raei et al. (2011) makes a rough study of the development of asset pricing models, including the Downside CAPM of Hogan and Warren (1974), the Adjusted CAPM of Amihud and Mendelson (1989), the Intertemporal CAPM of Merton (1973), the Conditional CAPM of Hansen and Richard (1978), the Revised CAPM of Hawawini and Viallet (1999), the Consumption CAPM of Lucas (1978) and Breeden (1979), the Reward CAPM of Bornholt (2006) and Behavioural asset pricing which is still in the development stage although it is probably the most promising one. It is worth mentioning that among these developments, the intertemporal CAPM and the conditional CAPM are the most widely applied and various further extensions are proposed to better interpret the risk-return relation and portfolio structure.

The conditional versions of the CAPM try to preserve the single factor structure of the standard CAPM. The conditional CAPM assumes that all investors have the same conditional expectations for their asset returns. The advocates of conditional CAPM argue that the poor empirical performance of CAPM might be due to the failure to account for time-variation in conditional moments. Among the many implementations of the conditional CAPM, the ones which have proved most successful are proposed by Jagannathan and Wang (1996) and Lettau and Ludvigson (2001). The former one assumes that betas and the market risk premium vary over time and includes human capital when measuring the return on aggregate wealth. The latter one also assumes that risk premium is time-varying. In both cases, the evolution of the conditional distribution of returns is expressed as a linear function of the appropriate fundamental factors and the parameters of the functions are state dependent. In essence, the conditional linear factor model in turn implies conditional "beta" models. Adrian and Franzoni (2009) complement the conditional CAPM literature by modeling a new time-variation in conditional betas. By assuming that betas change over time following a mean-reverting process, the authors aim to explore the implications of long-run changes in factor loadings for the tests of conditional models.

The intertemporal capital asset pricing model (ICAPM), introduced by Merton (1973), is a momentous extension of the CAPM. Consistent with CAPM investors, ICAPM investors prefer a high expected return and low return variance. However, investors in the ICAPM are concerned not only with their end-of-period payoff, but also with the opportunities they will have to consume or invest the payoff. Thus, the ICAPM is designed as a linear factor model with wealth and status variables that forecast changes in the distribution of returns and future income. When market volatility is stochastic, the ICAPM predicts that asset risk premium is not only determined by the covariance of returns with the market return, but also covariance with the relevant state variables. Therefore, state variables that capture the evolution of the investors' opportunity set are necessary to explain observed asset prices. Campbell (1993) extends Merton's ICAPM model (1973) to a discrete-time version and shows that any variable that forecasts future returns or future volatility is a good candidate for a state variable. The common practice is to use the excess returns on the market portfolio, and innovations to macroeconomic variables as proxies for the other factors, as in Chen et al. (1986), Brennan et al. (2004) and Petkova (2006).

A large body of literature on option markets suggests a negative price of market volatility risk (Chernov and Ghysels, 2000; Burashi and Jackwerth, 2001; Pan, 2002; Benzoni, 2002; Jones, 2003; Bakshi and Kapadia, 2003). The argument is that purchasing options are hedges against significant market declines. Buyers of market volatility are willing to pay a premium for downside protection. Chen (2002) and Ang et al. (2006) examine whether volatility is a priced factor in the cross-section of equity returns. Chen (2002) develops the ICAPM in a framework in which the conditional means and variances of state variables are time varying and reflect changes in the investment opportunity set. Risk-averse investors tend to hedge against exposures to future market volatility. Ang et al (2006) directly study how exposure to market volatility is priced in the cross-section of stock returns. By sorting portfolios on idiosyncratic volatility, Ang et al (2006) find that stocks with high idiosyncratic volatility tend to have low average returns. The results are robust to controlling for value, size, liquidity, and momentum effects and also persist in bull and bear markets, volatile and stable periods, and recessions and booms.

Adrian and Rosenberg (2008) combine the insights of the asset pricing literature and the two-component structure of volatility. Within the framework of ICAPM, they decompose market volatility into persistent and transitory components to examine whether the two components of volatility are also priced as suggested in Ang et al. (2006). The idea of decomposing the stock return volatility into permanent and transitory components has been well developed and established in finance and econometric literature. Friedman and Laibson (1989) provide empirical evidence supporting a two-component representation of stock returns. Andersen and Bollerslev (1997) suggest that intro-day volatility may contain both short-run and long-run components due to the existence of heterogeneous information flows or heterogeneous market agents. Engle and Lee (1993) construct a component GARCH model where the conditional variance is decomposed into transitory and permanent components. Speight, McMillan and Gwilym (2000) utilise the component model and detect the existence of intra-day volatility components in the UK stock futures market. Adrian and Rosenberg (2008) present a model of market return volatility that parsimoniously captures short- and long-run volatility factors. This particular model with the two volatility components and the market return as pricing factors compares favorably to the Fama and French three-factor model.

In the UK stock market, the FF factor model seems to some extent to not be as successful as in US markets. One possible reason might be that the estimations of the SMB and HML differ across different researchers. In contrast to the literature of the US stock market in which the estimations of the size and book to market factors have become increasingly standardised, researchers in the UK use different ways to calculate SMB and HML. Michou et al. (2007) make an excellent survey of the various methods of estimating SMB and HML used on the UK data. They identify nine distinct methods that previous researchers have used to develop the factors. They then estimate them, following as closely as possible the descriptions given in the relevant papers, on data from July 1980 to April 2003. They use a variety of tests to examine whether the estimated factors capture risk effects and, combined with the market factor, explain returns for sets of portfolios. They conclude that different ways of estimating the factors can result in quite different characteristics for the factor time series. Furthermore, the evidence is unclear as to whether the various constructed SMB and HML factors capture risk and there is little evidence that the three factor model completely captures risk in the UK. As a consequence, the authors argue that the appropriate estimation of (ab)normal returns in the UK needs further research. One way of addressing this issue is proposed by Gregory et al. (2009) through the construction of alternative factors. The authors provide characteristic matched portfolio data available for the UK which is as free from survivorship bias as possible. The authors also conduct the three-factor test as well as the four-factor Carhart model. Their results are consistent with the findings of Michou et al. (2007). The authors are able to provide no comfort for those seeking to employ unconditional factor models to explain or analyse the cross-section of the UK stock returns. They suggest that conditional versions, or an alternative factor model, or an APT type model may offer a solution.

2.3 Methodology

This section introduces the outline of the ICAPM, theoretical motivations of pricing of volatility risk as well as its short- and long-run components.

2.3.1 The Intertemporal Capital Asset Pricing Model (ICAPM)

Cochrane (2000) presents the ICAPM model in a compact way. The ICAPM is a linear factor model with wealth and state variables that forecast changes in the distribution of future returns or income. The ICAPM generates linear discount factor models

$$m_{t+1} = a + b' f_{t+1}$$

in which the factors are "state variables" for the investor's consumption-portfolio decision.

Consumption is a function of the state variables z_t,$c_t = g(z_t)$. Use this fact to substitute out consumption, and write

$$m_{t+1} = \beta \frac{u'[g(z_{t+1})]}{u'[g(z_t)]}$$

It's a simple linearisation to deduce that the state variables z_{t+1} will be factors. The value function depends on the state variables

$$V(W_{t+1}, z_{t+1})$$

And hence

$$m_{t+1} = \beta \frac{V_W(W_{t+1}, z_{t+1})}{V_W(W_t, z_t)}$$

since the *envelope condition* requires $u'(c_t) = V_W(W_t, z_t)$.

To obtain a linear relation, the derivation takes a Taylor approximation, assumes normality and uses Stein's lemma, or, most conveniently, moves to continuous time. For simplicity of the formulas, any dividends are folded into the price process and the basic pricing equation in continuous time is given as

$$E\frac{dp}{p} - r^f dt = -E(\frac{d\lambda}{\lambda}\frac{dp}{p})$$

The discount factor, $\frac{d\lambda}{\lambda}$, is marginal utility, which is the same as the marginal value of wealth,

$$\frac{d\lambda}{\lambda} = \frac{du'(c_t)}{u'(c_t)} = \frac{dV_W(W_t, z_t)}{V_W(W_t, z_t)}$$

By applying Ito's lemma, the model is able to be expressed in terms of factors z rather than marginal utility or values

$$\frac{dV_W}{V_W} = \frac{WV_{WW}}{V_W}\frac{dW}{W} + \frac{V_{Wz}}{V_W}dz + \frac{1}{2}(\text{second derivative terms})$$

where the second derivative terms are negligible since the analysis is going to take $r^f dt = E_t(d\lambda/\lambda)$. The elasticity of marginal value with respect to wealth is often called the *coefficient of relative risk aversion,*

$$rra \equiv -\frac{WV_{WW}}{V_W}$$

Substituting, the ICAPM is obtained, which relates expected returns to the covariance of returns with wealth, and also with the other state variables,

$$E\frac{dp}{p} - r^f dt = rra \cdot E\left(\frac{dW}{W}\frac{dp}{p}\right) - \frac{V_{Wz}}{V_W}E(dz\frac{dp}{p})$$

From here, it is fairly straightforward to express the ICAPM in terms of betas rather than covariances, or as a linear discount factor model. Most empirical work occurs in discrete time; the continuous time result is often simplified approximately as

$$E(R) \approx rra\ cov(R, \Delta W) + \lambda_2 cov(R, \Delta z)$$

R denotes return in excess of the risk-free rate. The state variables z are the variables that determine how well the investor can do in his maximisation. Current wealth is obviously a state variable. Additional state variables describe the conditional distribution of income and asset returns the agent will face in the future or “shift in the investment opportunity set”.

If further assuming that change in wealth results from investment in stock market, and the following equation is obtained,

$$E(R) \approx rra\ cov(R, R^M) + \lambda_2 cov(R, \Delta z) \qquad (2.1)$$

This model represents the most parsimonious pricing framework in which to study the relationship between innovations of state variables and expected returns.

2.3.2 Theoretical Motivation of the Pricing of Volatility Risk

Ang et al. (2006), Petkova (2006) and Da and Schaumburg (2011) establish systematic theoretical motivations of pricing market volatility and are presented as follows. When investment opportunities vary over time, the multifactor models of Merton (1973) and Ross (1976) show that risk premia are associated with the conditional covariance between asset returns and innovations in state variables that describe the time-variation of the investment opportunities. Hence, covariance with these innovations will therefore be priced. In the Campbell's (1993, 1996) ICAPM framework, investors care about risks both from the current market returns and from changes in forecasts of future market returns. When the representative agent is more risk averse than log utility, assets that have a positive covariance with good news about future market expected returns enjoy higher average returns. These assets reduce a consumer’s ability to hedge against deterioration in investment opportunities and hence require risk compensation. The intuition from Campbell’s model is that risk-averse investors want to hedge against variations in aggregate volatility because volatility positively affects future expected market returns, as Merton (1973).

$$E(R) \approx rra\, cov(R, R^M) + \lambda_2 cov(R, \Delta v) \qquad (2.1)$$

However, as Ang et al. (2006) point out, in Campbell’s setup, there is no direct role for fluctuations in market volatility to affect the expected returns of assets because Campbell’s model is premised on homoscedastic consumption. Chen (2002) extends Campbell’s model to a heteroskedastic environment and allows for time-varying covariances and stochastic market volatility. Chen shows that risk-averse investors tend to directly hedge against changes in future market volatility. In Chen’s (2002) model, an asset’s expected return depends on risk from the market return, changes in forecasts of future market returns, and changes in forecasts of future market volatilities. For an investor more risk averse than log utility, Chen

(2002) demonstrates that an asset shall have a lower expected return if its return positively covaries with a variable that forecasts higher future market volatilities. This effect arises because risk-averse investors reduce current consumption to increase precautionary savings in the presence of increased uncertainty about market returns.

Motivated by these multifactor models, market volatility risk is expressed explicitly in equation (2.1),

$$E_t(R_{t+1}) \approx rra\ cov(R_{t+1}, R_{t+1}^M) + \lambda_2 cov(R_{t+1}, \Delta v_{t+1}) + \sum_{k=1}^{K} \lambda_k cov(R_{t+1,} f_{k,t+1}) \quad (2.2)$$

where f_k represents other factors other than aggregate volatility that induce changes in the investment opportunity set.

Recent empirical studies concentrate on how the volatility and other factors are priced in the cross-section of stock returns. For the convenience of empirical application, the above model can be written in terms of factor innovations. Suppose $R_{t+1}^m - \gamma_{m,t}$ represents innovation in the market return, $v_{t+1} - \gamma_{v,t}$ represents the innovation in the factor reflecting aggregate volatility risk, and innovations to the other factors are represented by $f_{k,t+1} - \gamma_{k,t}$. A true conditional multifactor representation of expected returns in the cross-section would take the following form:

$$R_{t+1}^i = a_t^i + \beta_{m,t}^i\left(R_{t+1}^M - \gamma_{m,t}\right) + \beta_{v,t}^i\left(v_{t+1} - \gamma_{v,t}\right) + \sum_{k=1}^{K} \beta_{k,t}^i\left(f_{k,t+1} - \gamma_{k,t}\right) \quad (2.3)$$

Where R_{t+1}^i is the excess return on stock *i*, $\beta_{m,t}^i$ is the loading on the excess market return, $\beta_{v,t}^i$ is the asset's sensitivity to market volatility risk, and the $\beta_{k,t}^i$ coefficients for *k=1, ..., K* represents loadings on other risk factors. In the full conditional setting in equation 2.3, factor loadings, conditional means of factors, and factor premia potentially vary over time. The conditional mean of the market and aggregate volatility are denoted by $\gamma_{m,t}$ and $\gamma_{v,t}$, respectively, while the conditional means of the other factors are denoted by $\gamma_{k,t}$. In equilibrium, the conditional mean of stock i is given by

$$a^i = E(R^i) = \beta_m^i \lambda_m + \beta_v^i \lambda_v + \sum_{k=1}^{K} \beta_k^i \lambda_k \quad (2.4)$$

where $\lambda_{m,t}$ is the price of risk of the market factor, $\lambda_{v,t}$ is the price of aggregate volatility risk, and the $\lambda_{k,t}$ are the prices of risks of the other factors. Note that only if a factor is traded is the conditional mean of a factor equal to its conditional price of risk, that is $\lambda_m = \gamma_{m,t}$, $\lambda_v = \gamma_{v,t}$ and $\lambda_k = \gamma_{k,t}$.

2.3.3 Econometric Methodology

2.3.3.1 Component GARCH Model

As an extension of GARCH model, Engle and Lee (1999) introduce a component GARCH model where the conditional variance is decomposed into transitory and permanent components. In this two-component model, transitory and permanent components are used to capture short- and long-term effects of shock respectively.

Following Engle and Lee (1999), let r_t denote the return on asset, the expected return being m_t, and the conditional variance of that return as $h_t \equiv E_{t-1}[(r_t - m_t)^2] = E_{t-1}[\varepsilon_t^2]$.
The simple GARCH (1,1) process is then defined by:

$$r_t = m_t + \varepsilon_t$$

$$h_t = \sigma^2 + \alpha(\varepsilon_{t-1}^2 - \sigma^2) + \beta(h_{t-1} - \sigma^2) \qquad (2.5)$$

Where σ^2 is the unconditional variance, and $\varepsilon_{t-1}^2 - \sigma^2$ serves as the shock to asset return volatility. (σ, α, β) are fixed parameters; ε_t serially is uncorrelated with the zero mean and conditional variance h_t; and the standardised error, $z_t = \varepsilon_t/\sqrt{h_t}$, is identically and independently distributed with a zero mean and unit variance. When $\alpha + \beta < 1$, called the mean-reverting rate or the persistent rate, the conditional variance will mean-revert to the unconditional variance at a geometric rate of $\alpha + \beta$. The smaller the mean-reverting rate, the less persistent the sensitivity of the volatility expectation to market shocks in the past.

However, whether the long-run volatility represented by σ^2 is truly constant over time is questioned. Engle and Lee suggest a more flexible specification, they replace σ^2 with the long-run volatility l_t, which is given a time series representation and allowed to evolve slowly in an autoregressive manner:

$$h_t - l_t = \alpha(\varepsilon_{t-1}^2 - l_{t-1}) + \beta(h_{t-1} - l_{t-1}) \quad (2.6)$$

$$l_t = \omega + \rho l_{t-1} + \varphi(\varepsilon_{t-1}^2 - h_{t-1}) \quad (2.7)$$

The component model above extends the expression in eq. (2.5) to allow the possibility that long-run volatility is not constant. The lagged forecasting error $\varepsilon_{t-1}^2 - h_{t-1}$ serves as the driving force for the time-dependent movement of that permanent component. The difference between the conditional variance and its trend, $h_t - l_t$, is called the short-run (transitory) volatility component, s_t. Rewriting these processes in an alternative form emphasises the symmetry in the representation:

$$h_t = l_t + s_t,$$

$$s_t = (\alpha + \beta)s_{t-1} + \alpha(\varepsilon_{t-1}^2 - h_{t-1}),$$

$$l_t = \omega + \rho l_{t-1} + \varphi(\varepsilon_{t-1}^2 - h_{t-1}).$$

Hence, the volatility innovation, $\varepsilon_{t-1}^2 - h_{t-1}$, drives both the permanent and the transitory volatility components. The conditional variance is covariance stationary in this model if the permanent and the transitory components are both covariance stationary, as satisfied by $\rho < 1$, and $\alpha + \beta < 1$, respectively. The values of ρ and $(\alpha + \beta)$also quantify the persistence of shocks to these component processes. The short-run volatility component mean-reverts to zero at a geometric rate of $(\alpha + \beta\ )$ if $0 < \alpha + \beta < 1$, while the long-run volatility component itself evolves over time following an AR process, which, if $0 < \rho < 1$, will converge to a constant level defined by $\omega/1 - \rho$. For $0 < \alpha + \beta < \rho < 1$, the transitory component decays more quickly than the permanent component such that the latter dominates forecasts of the conditional variance as the forecasting horizon is extended.

Note that the component model reduces to the GARCH (1,1) model if either $\alpha = \beta = 0$, or $\rho = \varphi = 0$. Thus, the GARCH model only is capable of describing, at most, one element of the more general variance component specification, and only represents the permanent component under the specific conditions, $\alpha = \beta = 0,$ and $\rho = 1$.

2.3.3.2 Exponential GARCH Model-EGARCH

Nelson, in 1991, argued that GARCH models, however, had at least three major drawbacks in asset pricing applications:

1. Researchers beginning with Black (1976) have found a negative correlation between current returns and future returns volatility - i.e., volatility tends to rise in response to "bad news" (excess returns lower than expected) and to fall in response to "good news" (excess returns higher than expected). GARCH models rule this out by assuming that only the magnitude and not the positivity or negativity of unanticipated excess returns determines volatility.
2. GARCH models impose parameter restrictions to ensure that volatility remains

nonnegative for all the time with probability one. The assumptions are often violated by estimated coefficients and that may unduly restrict the dynamics of the conditional variance process.

3. Interpreting whether shocks to conditional variance "persist" or not is difficult in GARCH models. In many studies of the time-series behaviour of asset volatility, the central question has been how long shocks to conditional variance persist. If volatility shocks persist indefinitely, they may move the whole term structure of risk premia, and are therefore likely to have a significant impact on investment in long-lived capital goods.

The answer to the third drawback can be the component GARCH model proposed by Engle and Lee (1999) which has been analysed at length in section 2.3.3.1. To address the leverage effect explained in the first drawback, many nonlinear extensions of GARCH have been proposed. The most widely used are the Exponential GARCH (EGARCH) model by Nelson (1991) and the so-called GJR-GARCH model by Glosten et al. (1993) which is similar to the threshold GARDH model. These models are termed as asymmetric GARCH models and they are all able to capture the leverage effect with asset prices where a positive shock has less effect on the conditional variance compared to a negative shock. However, the GJR-GARCH model has similar limitations to the GARCH model which has to impose parameter restrictions to ensure the non-negativity of the conditional variance. On the other hand, the EGARCH model meets these objects so that the non-negativity constraint does not need to be imposed and the asymmetries are also allowed for using this model.

As before, let $z_t = \varepsilon_t / \sqrt{h_t}$ where z_t is i.i.d. with zero mean and unit variance. Nelson (1991) proposes the following model for the evolution of the conditional variance of h_t:

$$\log{(h_t)} = \xi + \sum_{j=1}^{\infty} \pi_j \{ |z_{t-j}| - E|z_{t-j}| + \chi z_{t-j} \}$$

If $\pi_j > 0$, EGARCH model implies that a deviation of $|z_{t-j}|$ from its expected value causes the variance of ε_t to be larger than otherwise, an effect similar to the idea behind the GARCH specification.

The χ parameter allows this effect to be asymmetric. If $\chi = 0$, then a positive surprise ($z_{t-j} > 0$) has the same effect on volatility as a negative surprise of the same magnitude. If $-1 < \chi < 0$, a positive surprise increases volatility less than a negative surprise. If $\chi < -1$, a positive surprise actually reduces volatility while a negative surprise increases volatility. Since a lower stock price reduces the value of equity relative to corporate debt, a sharp decline in stock prices increases corporate leverage and could thus increase the risk of holding stocks. For this reason, the apparent finding that $\chi < 0$ is sometimes described as the *leverage effect*

.

2.3.3.3 EGARCH Component Model

Many studies find that the two-component volatility model is superior to the one-component specification in explaining equity market volatility and that the log-normal model of EGARCH performs better than square-root or affine volatility specifications. Due to the merits of the component GARCH and the EGARCH models, Adrian and Rosenberg (2008) incorporate the features of these two models and specify the dynamics of the market return in excess of risk-free rate R_t^M and the conditional volatility $\sqrt{h_t}$ as:

Market return: $R_{t+1}^M = \mu_t^M + \sqrt{h_t} z_{t+1} \qquad (1a)$

Market volatility: $ln\sqrt{h_t} = l_t + s_t$ $\quad (1b)$

Short-run component: $s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6 \left(|z_{t+1}| - \sqrt{2/\pi}\right)$ $\quad (1c)$

Long-run component: $l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10} \left(|z_{t+1}| - \sqrt{2/\pi}\right)$ $\quad (1d)$

In equation (1a), z_t is a normal i.i.d. error term with zero expectation and unit variance, and μ_t^M is the one-period expected excess return. The log-volatility in equation (1b) is the sum of two components l_t and s_t. Each component is an AR(1) process with its own rate of mean reversion. Without loss of generality, let l_t be the slowly mean-reverting, long-run component and s_t be the quickly mean-reverting, short-run component $(\theta_4 < \theta_8)$. The unconditional mean of s_t is normalized to zero.

The terms $|z_{t+1}| - \sqrt{2/\pi}$ in equations (1c) and (1d) are the shocks to the volatility components. Their expected values are equal to zero, given the normality of z_t. For these error terms, equal sized positive or negative innovations result in the same volatility change, although the magnitude can be different for the short- and long-run components (θ_6 and θ_{10}). The asymmetric effect of returns on volatility is allowed by including the market innovation in equations (1c) and (1d) with corresponding coefficients θ_5 and θ_9.

The market model defined by equations (1a) – (1d) converges to a continuous-time, two-factor stochastic volatility process. One advantage of this specification is that it can be estimated in discrete time via maximum likelihood. The daily log-likelihood function is:

$$f_t(\theta;\, s_t, l_t | R_t^M) = -\frac{1}{2} ln(2\pi) - (s_{t-1} + l_{t-1}) - \frac{(R_t^M - \theta_1 - \theta_2 s_{t-1} - \theta_3 l_{t-1})^2}{2h_{t-1}}$$

Where *t=1, ..., T* is the daily time index, *T* is the total number of daily observations, and R_t^M

is the daily market excess return.

3.3.3.4 Fama-MacBeth Regression for the Cross Section

Many asset pricing models, arbitrage pricing theory (APT), the capital asset pricing model (CAPM), and intertemporal CAPM (ICAPM), all have the following structure:

$$R = \beta\gamma$$

Where R is the excess return of an asset, β is the K-dimensional vector of factor loadings on a various factors, and γ is the vector of excess returns on those K factors. The Fama-MacBeth methodology provides a particularly robust way to test the theoretical model empirically. Fama and MacBeth (1973) pioneered an approach to asset pricing that is very widely used in cross-sectional regression. The two-stage Fama-MacBeth regression estimates the premium rewarded to particular risk factor exposure by the market.

The first stage provides estimates of betas for each asset from the N sets of time-series regressions. This stage is a set of regressions equal in number to the number of assets

$$R_t^i = \alpha^i + \beta_{F_1}^i F_{1,t} + \beta_{F_2}^i F_{2,t} + \cdots + \beta_{F_K}^i F_{K,t} + \varepsilon_t^i, \qquad i = 1 \ldots \ldots N$$

where F_1, $F_{2,} \ldots$ and F_K are the K factors that explain returns on the *N* assets at time *t*. $\beta_{F_K}^i$ is the factor loading of the K^{th} factor for asset *i*.

The second stage is a set of cross-sectional regressions to regress returns of each time period on estimated betas from stage one. This stage is a set of regressions equal in number to the number of time periods.

$$R_t^j = \omega_t + \gamma_t^1 \widehat{\beta_{F_1}^J} + \gamma_t^2 \widehat{\beta_{F_2}^J} + \cdots + \gamma_t^K \widehat{\beta_{F_K}^J} + \mu_t, t = 1 \ldots\ldots T$$

where the intercept is explicitly included to denote the zero-beta rate in excess of the risk-free rate and $\widehat{\beta_{F_K}^J}$ is the estimated factor loading of the K^{th} factor for asset *j*. γ_t^K is the estimated risk premium of asset *K* at time *t*. The second stage regression can be run using OLS, GLS (Shanken, 1985), or WLS using the diagonal elements (Litzenberger and Ramaswamy, 1979). Under the null, all three estimators converge to the same limit. The regression is run each period rather than once with sample average returns. The factor risk premium, if a factor and pricing error estimates are given as simple time-series averages of period by period estimates:

$$\hat{\gamma}^i = \frac{1}{T}\sum_{t=1}^{T} \hat{\gamma}_t{}^i, \qquad \hat{\mu} = \frac{1}{T}\sum_{t=1}^{T} \hat{\mu}_t$$

The advantage of the Fama-MacBeth procedure is that there is no need to compute the variance of estimates for each period but compute the variance of the average estimates using the time-series of these estimates. Hence, there is no need to worry about the cross-sectional correlation in pricing errors μ_{it}.

There are several advantages of the Fama-Macbeth approach summarised by Goyal (2012). Firstly, it can easily accommodate unbalanced panels. One uses returns on only those stocks which exist at time *t*, which could be different from those at another time period. Moreover, the distribution of the risk premium estimates does not depend on the number of stocks, which can vary over time. Secondly, even though constant betas are used, the procedure is flexible to allow for time-varying betas. Fama and Macbeth (1973) use rolling betas in their analysis although Fama and French (1992) report evidence that the use of rolling versus full-sample betas does not yield different inferences. Thirdly, it is possible that autocorrelation in returns (negligible at monthly frequencies) leads to autocorrelation in risk premium estimates. This is easily accounted for by Newey-West type corrections to variance formulas.

However, betas are estimated with error in the first-stage time-series regression consequently. An errors-in-variables (EIV) problem is introduced in the second-stage cross-sectional regression. Shanken (1992) finds that the Fama-MacBeth two-pass procedure for computing standard errors fails to reflect measurement errors in the betas and overstates the precision of the estimates of factor premium. However, Jagannathan and Wang (1998) argue that if the error terms are heteroskedastic, then the Fama-MacBeth procedure does not necessarily result in smaller standard errors of the risk premium estimated. Nevertheless, the correction procedure proposed by Jagannathan and Wang (1998) is adopted in this thesis to account for the errors-in-variables problem. Hence, the *p* values reported in this thesis are computed from the corresponding *t*-values which are adjusted to account for the first-step estimation error and potential heteroskedasticity and autocorrelation using the Newey-West (1987) correction with 12 lags.

2.4 Data Description

In this chapter, the EGARCH-component volatility model is estimated using daily excess returns. The daily data are used in order to improve the estimation precision and then aggregated to a monthly frequency for the cross-sectional analysis. The FTSE All Share Index with its dividend yield is used as the proxy for the market return, r^M, and one month return on Treasury Bills for the risk free rate, r^f. These daily data range from 01/09/1980 to 31/12/2012 and are collected from LSPD (London Stock Price Database) and Datastream.

The Fama and French 25 portfolios sorted on size and book-to-market (BE/ME) equity are applied for the cross-sectional price test of the ICAPM. The estimation of size and BE/ME factors and the formation of the 25 portfolios have become increasingly standardised in the USA. They are available from French's website and researchers can download them freely. In the UK, however, the situation is different and different researchers use different ways of calculating SMB and HML. Michou et al. (2007) survey the various methods of estimating SMB and HML used in the past on the UK data. They identify nine distinct methods that previous researchers have used to estimate the factors.

In the spirit of French's provision of the data to the international academic community, Gregory et al. (2009) construct the Fama and French size and BE/ME portfolio based on various breakpoints for portfolio formation each year and the SMB, HML and UMD (the momentum factor) of the UK stock market. They make all portfolios and factors downloadable from their website. Their data sources involve cross-matching company data from the following databases: The London Business School Share Price database (LSPD), which includes data on monthly returns, market capitalisation and also key dates of first listing and de-listing; Datastream; tailored Hemscott data obtained by subscription; and hand collected data on bankrupt firms. The Hemscott, Datastream and data on bankrupt firms are used to obtain estimates of book value used in portfolio formation. The LSPD data are used for the monthly share returns and the market capitalisation data. Combining these data sources means that Gregory et al. (2009) are able to fill in any missing data on any one firm in either of the Hemscott or Datastream. These data are as free from survivorship bias as possible.

Gregory et al. (2009) use the median firm in the largest 350 firms (excluding financials) by market capitalisation for the size breakpoint, and base the BE/ME breakpoints on the 30^{th} and 70^{th} percentiles of the largest 350 firms. Following the most popular sorting method applied by Fama and French (1993), stocks are allocated into two groups, i.e. small (S) or big (B), based on their market value (size). Stocks are also allocated in an independent sort to three BE/ME groups, low (L), medium (M) or high (H). March year *t* accounting data and end of September year *t* market capitalisation data are used and portfolios are formed at the beginning of October in year t and financial firms are excluded from the portfolios, as are negative BE/ME stocks and AIM stocks.

Six size-BE/ME portfolios (S/H, S/M, S/L, B/H, B/M, B/L) are created from the intersections of the two size and three BE/ME groupings and monthly returns for the portfolios are calculated. The size factor (SMB) return is defined as the difference each month between the average returns on the three small portfolios (S/L, S/M, and S/H) and the average returns on the three big portfolios (B/L, B/M, and B/H). The book-to-market factor, known as value factor, return is defined as the difference each month between the average returns on the two high BE/ME portfolios (S/H and B/H)and the average returns on the two low BE/ME portfolios (S/L and B/L). The calculations are given as:

$$SMB = (S/H + S/M + S/L)/3 - (B/H + B/M + B/L)/3$$

$$HML = (S/H + B/H)/2 - (S/L + B/L)/2$$

The momentum factor following Carhart (1997) is also constructed by Gregory et al. (2009). The monthly portfolios are the intersections of two portfolios formed on size and three portfolios formed on prior (2-12) returns. The momentum factor, denoted as UMD, is the difference each month between the average returns on the two high prior return portfolios minus the average return on the two low return portfolios. The calculation equation is given as:

$$UMD = (S/U + B/U)/2 - (S/D + B/D)/2$$

The 25 size-BE/ME portfolios are formed much like the six size-BE/ME portfolios. They use the whole sample of firms to form these portfolios. The five size portfolios are formed from quartiles of the largest 350 firms plus on portfolio formed from the rest of the sample. For the BE/ME portfolios they use quintiles of the largest 350 firms as break points for the BE/ME to create the 5 BE/ME groups. These portfolios are calculated on both an equally weighted and value-weighted basis. Gregory et al. (2009) emphasize that their choice of partitioning the size portfolios on the basis of the largest 350 stocks is designed to capture the investable universe for the UK institutional investors. To take account of the investment criteria, "large firms" are defined as being the upper quartile of the largest 350 firms (excluding financials) by market capitalisation. "Small firms" become the rest not in the top 350 firms. The 25 size and book to market portfolios employed in this chapter are based on the described criteria.

However, besides the portfolios described above, Gregory et al. (2009) also calculate portfolios using alternative criteria based on the firms on the main market and financial firms are excluded as well. These alternative criteria sorted portfolios (portfolio 2 to 5) are utilised as test assets to carry out the robustness checks.

1. 25 (5×5) intersecting size and book to market (BE/ME) portfolios (benchmark portfolios)
    - 5 size portfolios – 4 portfolios formed from the largest 350 firms and 1 portfolio formed from the rest.
    - 5 BE/ME portfolios – based on the largest 350 firms.
2. 25 (5×5) intersecting size and book to market (BE/ME) portfolios
    - 5 size portfolios – 3 portfolios formed from the largest 350 firms and 2 small portfolios formed from the rest.
    - 5 BE/ME portfolios formed from all firms.

3. 25 (5×5) intersecting size and momentum portfolios.
    - 5 size portfolios – 4 portfolios from the largest 350 firms and 1 portfolio from the rest.
    - 5 momentum portfolios – based o the largest 350 firms.
4. 5 size portfolios – 4 portfolios from the largest 350 firms and 1 from the rest.
5. 5 book-to-market (BE/ME) portfolios – formed from BE/ME of the largest 350 firms.

2.5 Empirical Results

2.5.1 Results of the Time Series Regression

The motivation of volatility as an asset pricing factor has been well established in the above section and Ang et al. (2006) have shown empirically that volatility is a significant cross-sectional asset pricing factor. If the short- and long-run volatility components are also asset pricing factors, in the spirit of the ICAPM, the equilibrium pricing kernel thus depends on both short- and long-run volatility components as well as the excess market returns. Denote returns on asset *i* in excess of the risk free rate by R_t^i. The equilibrium expected return for asset *i* is :

$$E_t\left(R_{t+1}^i\right) = \lambda_1\, cov\left(R_{t+1}^i, R_{t+1}^M\right) + \lambda_s cov\left(R_{t+1}^i, s_{t+1}\right) + \lambda_l cov\left(R_{t+1}^i, l_{t+1}\right) \quad (2.8)$$

where λ_1 is the coefficient of relative risk aversion, and λ_s and λ_l are proportional to changes in the marginal utility of wealth due to changes in the state variable s_t and l_t.

Equation (2.8) shows that expected returns depend on three risk premia. The first risk premium arises from the covariance of the asset return with the excess market return, multiplied by relative risk aversion λ_1. This is the risk-return tradeoff in a static CAPM. The second and third risk premia depend on the covariance of the asset return with the innovations in the short- and long-run factors. These are scaled by the impact of changes in the volatility factors on marginal utility of wealth, λ_s and λ_l.

In the case of the market portfolio, equation (2.8) implies that the conditional expected market return depends on its own conditional variance and the volatility components. To specify a market return model that captures the dependence of expected returns on the state variables of the economy, Adrian and Rosenberg (2008) propose a specification of μ_t^M which is:

$$\mu_t^M = \theta_1 + \theta_2 s_t + \theta_3 l_t \qquad (2.9)$$

This equation is interpreted as a first-order approximation to the functional relationship of the expected market return μ_t^M with the volatility components s_t and l_t. However, Adrian and Rosenberg (2008) point out that this specification does not allow the separate identification of the static risk-return tradeoff and the dynamic hedging component of volatility (short- and long-run components), but the cross-sectional approach does allow such identification.

The EGARCH component of Adrian and Rosenberg (2008) applied to UK stock market now becomes:

Market return: $R_{t+1}^M = \theta_1 + \theta_2 s_t + \theta_3 l_t + \sqrt{h_t} z_{t+1} \qquad (1a)$

Market volatility: $ln\sqrt{h_t} = l_t + s_t \qquad (1b)$

Short-run component: $s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6 \left(|z_{t+1}| - \sqrt{2/\pi}\right) \qquad (1c)$

Long-run component: $l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10} \left(|z_{t+1}| - \sqrt{2/\pi}\right) \qquad (1d)$

Examination of the risk-return relation is of fundamental importance to the asset pricing literature. One group of the existing research focuses on the time-series risk-return relation. Equation (2.2) may be transformed as:

$$E_t(R_{t+1}^M) = rra\ var(R_{t+1}^M) + \lambda_2 cov(R_{t+1}^M, \Delta v_{t+1})$$

Many authors either fail to detect a statistically significant intertemporal relation between risk and return of the market portfolio or find a negative relation.[3] More recently, estimating the relation between expected return and expected volatility or explicitly accounting for the hedging demands (the second term of the above equation), several papers have found a positive risk-return relation in the time series.[4]

Guo and Whitelaw (2006) model both the risk component and the hedging component, and the estimation coefficient of the relative risk aversion is positive, statistically significant and reasonable in magnitude. Under certain conditions, Merton (1980) argues that the hedge component is negligible and the conditional excess return is proportional to its conditional variance.

The estimation results of the volatility model are shown in Table 2.1. The expected return equation shows that short-run volatility has a significant positive coefficient θ_2, while θ_3, the coefficient of long-run volatility is significantly negative. The market excess return thus depends positively on short-run volatility but negatively on long-run volatility. In the US market, Adrian and Rosenberg (2008) identify a negative relationship between short-run volatility and market excess return but a positive relationship between long-run volatility and market excess return. Hence, short-run and long-run volatilities seem to have opposite effects on market excess return. This result might explain why previous research often has difficulty identifying a time-series relationship or mixed results of risk and return relation.

[3] Examples include, Baillie and Degennaro (1990), Whitelaw (1994), and Harvey (2001).
[4] For example, French et al. (1987), using squared daily returns, argue that there is a positive relation between the expected risk premium and *ex ante* volatility.

Table 2.1: Time series estimation of the volatility components daily 01/09/1980 to 31/12/2012

Market excess return: $R_{t+1}^{M} = \theta_1 + \theta_2 s_t + \theta_3 l_t + \sqrt{h_t} z_{t+1}$				
	θ_1	θ_2	θ_3	
Coef.	-0.007	0.267	-0.499	
Std.err.	0.010	0.106	0.031	
p-value	0.475	0.012	0.000	
Short-run component: $s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6 \left(\lvert z_{t+1}\rvert - \sqrt{2/\pi}\right)$				
	θ_4	θ_5	θ_6	
Coef.	0.807	-0.046	-0.009	
Std.err.	0.030	0.004	0.042	
p-value	0.000	0.000	0.829	
Long-run component: $l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10} \left(\lvert z_{t+1}\rvert - \sqrt{2/\pi}\right)$				
	θ_7	θ_8	θ_9	θ_{10}
Coef.	0.002	0.994	-0.032	0.028
Std.err.	0.000	0.001	0.001	0.002
p-value	0.000	0.000	0.000	0.000

The short- and long-run components are identified by their relative degrees of autocorrelation: the short-run volatility has an autoregressive coefficient of 0.807, and the long-run component has an autoregressive coefficient of 0.994. The long-run component is highly persistent. However, it is not permanent, the hypothesis that $\theta_8 = 1$ is rejected at the 1% significant level. The estimate of θ_4 is smaller than that of θ_8, which indicates that the short-run volatility is less persistent compared to the long-run component. However, the estimate of θ_4 is twice as large in magnitude as that estimated in the US stock market. This might suggest that the short-run volatility in the UK stock market is more persistent in comparison with that of the US stock market. Because the short- and long-run components determine log-volatility additively, it is impossible to identify the means of the two components separately, and only the mean of the long-run component is estimated.

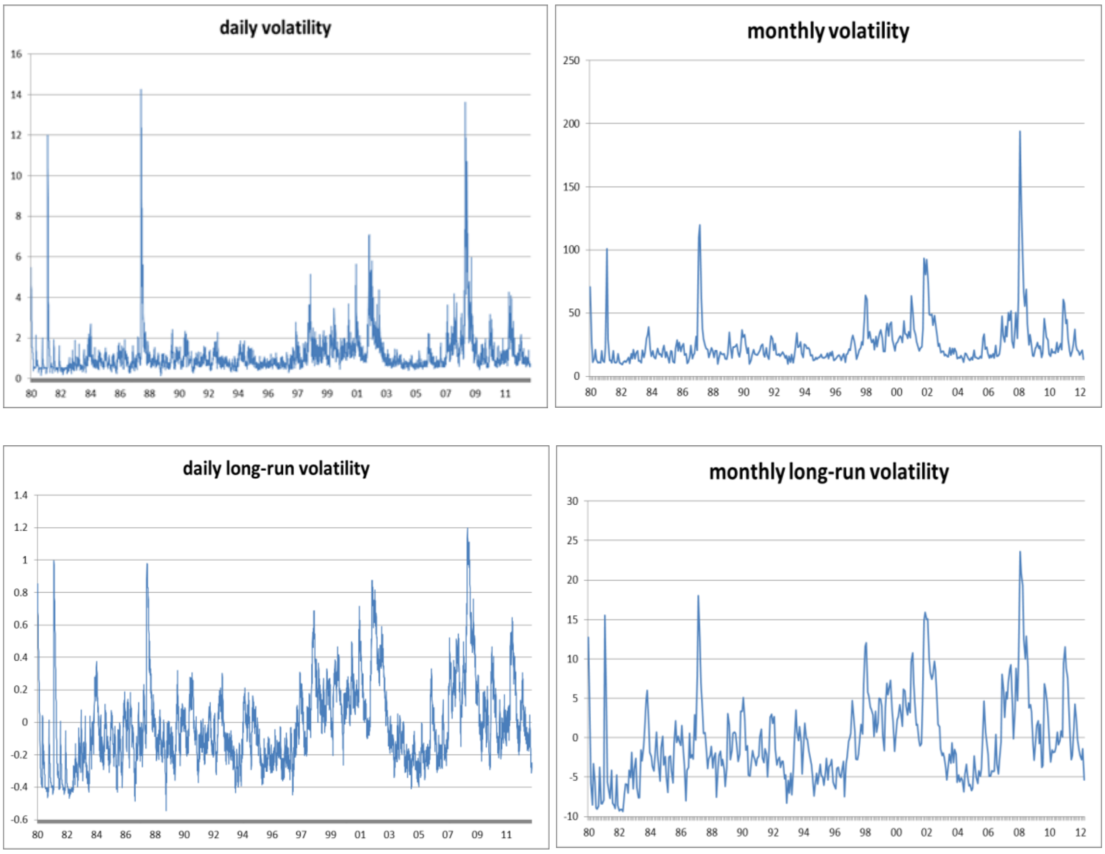
θ_5 and θ_9 detect the asymmetric effect on volatility. Both the estimates of θ_5 and θ_9 are significantly negative and larger than minus one. This suggests that a positive surprise (z_t) increases both the short- and long-run volatility less than a negative surprise.

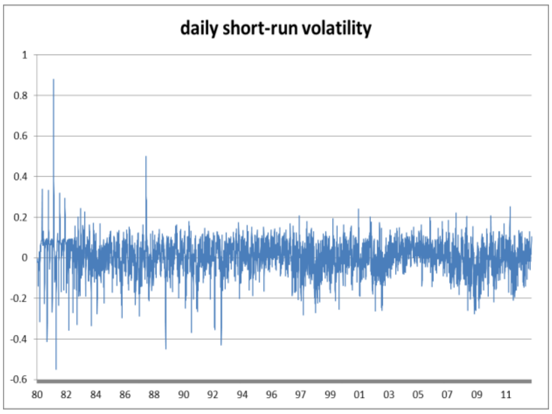
Table 2.2: Statistics of standardised residual: z_t

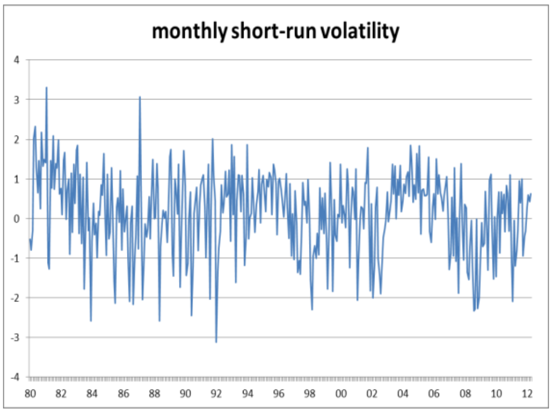
	Summary statistics of market excess return						
Mean	Median	Std. Dev.	Skewness	Kurtosis			
0.025	-0.013	1.104	-0.514	20.084			
		10 lags	20 lags			1 lag	2 lags
Ljung-Box		12.64	26.226	ARCH-LM		0.008	0.111
Q-statistics of z_t	*P*-value	0.268	0.158	*Chi^2* Test	*P*-value	0.929	0.946

The Ljung-box Q statistic suggests that there is no remaining serial correlation in the mean equation of the market excess return, while the ARCH-LM test reveals that there is no additional ARCH effect exhibiting in the standardised residuals.

Figure 2.1: Daily and monthly volatility and its short- and long-run components







2.5.2 Results of the Cross-sectional Tests

Monthly data are employed to carry out the cross-sectional tests. The daily short- and long-run volatility components are obtained from the time-series regression. The 21-step out-of-sample forecasts of the short- and long-run components are made respectively. Daily innovations of the volatility components are calculated by subtracting the short- and long-run components from the forecasted values. The daily innovations in each month are then aggregated to a monthly frequency to obtain the monthly innovations of the short- and long-run components.

$$sres_m = \sum_{t=1}^{N} (s_t - E_{t-21}[s_t]) \qquad (2.10)$$

$$lres_m = \sum_{t=1}^{N} (l_t - E_{t-21}[l_t]) \qquad (2.11)$$

where *sres* and *lres* denote the innovations of the short- and long-run volatility respectively. N is the trading days in month m. The market variance v is aggregated to a monthly frequency, and the time series follows an AR(2) process. Hence, variance innovations (*vres*) are estimated as residuals of a monthly autoregressive process with two lags. The statistics of the innovations and the other pricing factors are summarised in table 2.3.

Table 2.3: Summary statistics of the monthly pricing factors

Pricing factors	Mean	Std. Dev.	Skewness	Kurtosis
Short-run volatility*(sres)*	.000	1.064	-0.309	3.192
Long-run volatility*(lres)*	.000	2.989	1.697	11.083
Market variance *(vres)*	.000	14.520	4.429	47.87
Value factor (*HML*)	0.004	0.037	0.270	11.092
Size factor (*SMB*)	0.001	0.034	0.712	7.200
Momentum factor (*UMD*)	0.008	0.042	-1.258	10.844

Under the ICAPM described in section 2.3.1 and 2.3.2, the pricing kernel is a linear function of the excess return on the market portfolio and the innovations in the state variables, so that the unconditional risk premium on asset i may be written as:

$$a^i = E(R^i) = \beta_m^i \lambda_m + \beta_s^i \lambda_s + \beta_l^i \lambda_l \qquad (2.12)$$

where $\lambda_{m,t}$ is the price of risk of the market factor, $\lambda_{s,t}$ is the price of the short-run volatility risk, and the $\lambda_{l,t}$ is the price of risk of the long-run volatility. This equation states that a portfolio's expected return is equal to the sum of the multiplication of its factor loadings and the prices of the risk factors.

The implication of the ICAPM for stock returns can be tested directly by implementing the two-stage cross-sectional procedure. In order to determine whether the ICAPM with market excess return, short- and long-run volatility innovations can account for the cross-section of returns on the 25 Fama-French size and BE/ME-sorted portfolio of the UK stock market, the two-stage Fama-MacBeth regression procedure is applied. The monthly excess returns on the 25 Fama and French size and BE/ME sorted portfolios for the period from Oct. 1980 to Dec. 2012 provided by Gregory et al. (2009) are used. In the first stage, the 25 portfolio returns are regressed on the market excess return, and the monthly innovations of the short- and long-run volatility components are calculated from equation (2.10) and (2.11).

The time-series regressions of equation (2.13) are performed. The factor loadings for each portfolio are shown in table 2.4.

$$R_t^i = c + \beta_m^i R_t^M + \beta_s^i sres_t + \beta_l^i lres_t + \varepsilon_t, \quad i = 1,2,\dots 25 \qquad (2.13)$$

where R_t^i is the excess return of each portfolios; R_t^M, $sres_t$ and $lres_t$ are monthly market excess returns and monthly innovations of short- and long-run volatilities; β_m^i, β_s^i and β_l^i represent the factor loadings of market excess returns, short- and long-run volatilities for portfolio i, respectively. This stage involves 25 (the total number of portfolios) regressions and each regression has 387 (the total sample) observations.

In the second stage, the portfolio returns are regressed on the estimated betas from the first stage to obtain the prices of market risk, short-run volatility risk and long-run volatility risk.

$$R_t^i = c + \widehat{\beta_m^\iota}\lambda_{m,t} + \widehat{\beta_s^\iota}\lambda_{s,t} + \widehat{\beta_l^\iota}\lambda_{l,t} + \varepsilon_t^i, \quad t = 1,2,\dots T \qquad (2.14)$$

where $\widehat{\beta_m^\iota}$, $\widehat{\beta_s^\iota}$ and $\widehat{\beta_l^\iota}$ are the factor loadings for portfolio i estimated from the first stage; and $\lambda_{m,t}$, $\lambda_{s,t}$, and $\lambda_{l,t}$ are regression coefficients. The second stage involves 387 (the total sample) regressions and each regression has 25 (the total portfolios) observations.

The full specification of the cross-sectional regression takes the following form corresponding to equation (2.12):

$$\overline{R^\iota} = \widehat{\beta_m^\iota}\lambda_m + \widehat{\beta_s^\iota}\lambda_s + \widehat{\beta_l^\iota}\lambda_l + \varepsilon_t, \qquad R^i \quad i = 1,2 \dots 25$$

where $\overline{R^\iota}$ is portfolio i's sample mean; betas are the values estimated in the first stage; and λ_m, λ_s, and λ_l are the average value of $\lambda_{m,t}$, $\lambda_{s,t}$, and $\lambda_{l,t}$ obtained from the second stage.

The model pricing error of portfolio i, α^i, is then defined by:

$$\alpha^i = \overline{R^i} - (\widehat{\beta_m^i}\widehat{\lambda_m} + \widehat{\beta_s^i}\widehat{\lambda_s} + \widehat{\beta_l^i}\widehat{\lambda_l})$$

The sum of squared portfolio pricing errors and the root-mean-squared pricing errors are defined as $\sum_{i=1}^{25}(\alpha^i)^2$ and $\sqrt{\sum_{i=1}^{25}(\alpha^i)^2/25}$ respectively. Table 2.5 reports the two-stage cross-sectional regression results under the Fama and French three-factor model, and the ICAPM model with different state variables. The risk premia for each portfolio are then calculated as the multiplication of the factor loading and the prices of risk and the results are shown in table 2.4.

Table 2.4: Factor loadings for the 25 size and BE/ME sorted portfolios

This table reports the beta estimates under the ICAPM, in the first stage of the two-stage cross-sectional regression for the 25 size and BE/ME sorted portfolios, where the portfolio excess returns are regressed on the market excess return, innovations of short-run volatility and long-run volatility. The monthly data is from October 1980 to December 2012.

Multivariate loadings on the market factor					
	Small	Size 2	Size 3	Size 4	Big
Growth	0.866***	0.929***	0.991***	0.978***	0.943***
BE/ME 2	0.732***	0.839***	0.933***	0.919***	0.961***
BE/ME 3	0.674***	0.811***	0.888***	0.873***	1.059***
BE/ME 4	0.722***	0.787***	0.892***	1.060***	0.952***
Value	0.690***	0.833***	0.890***	1.020***	0.948***
Multivariate loadings on short-run volatility innovations (*sres*)					
	Small	Size 2	Size 3	Size 4	Big
Growth	0.638*	0.306	0.372	0.215	0.207
BE/ME 2	0.741**	0.552*	0.176	-0.127	0.112
BE/ME 3	0.416	0.556**	0.328	-0.236	0.241
BE/ME 4	0.455**	-0.134	-0.032	0.251	-0.162
Value	0.376	0.152	-0.065	0.339	0.000
Multivariate factor loadings on the long-run volatility innovations *(lres)*					
	Small	Size 2	Size 3	Size 4	Big
Growth	−0.424***	−0.252***	−0.353***	−0.296***	0.042
BE/ME 2	−0.467***	−0.404***	−0.338***	−0.219***	-0.038
BE/ME 3	−0.403***	−0.340***	−0.393***	−0.268***	-0.054
BE/ME 4	−0.395***	−0.339***	−0.269***	−0.256***	−0.129***
Value	−0.429***	−0.405***	−0.339***	−0.341***	0.094

***, **, and * denote significance level at 1%, 5% and 10% level, respectively.

Table 2.4 reports the first-stage factor loadings on market factor, innovations of short-run volatility and long-run volatility across the size dimension. There is wide dispersion across the portfolios in their exposures to innovations in the state variables. Small firms have lower values of β_m and β_l, but higher values of β_s than big firms. The average value of β_l for small firm portfolios is below that of the big firm portfolio by 0.41 while the average value of β_s exceeds that of the big firm portfolio by 0.45. However, unfortunately, factor loadings on short- and long-run volatility don't exhibit significant variability across the BE/ME dimension.

In table 2.5, the pricing of volatility risk in the cross-section of the 25 size and BE/ME-sorted portfolios is reported. The regressions of the CAPM (column i), the Fama and French three factor model (column ii), Carhart's momentum model (column iii), and a model analogous to Ang et al. (2006) with innovations to market variance as risk factor (column iv) are also presented in table 2.5.

Consistent with the results of Ang et al. (2006), the regressions also identify a significant negative price for market variance risk using innovations in estimated market variance from the EGARCH component model. Following the implication of the ICAPM that the state variables of market volatility should be priced, the research goes on to investigate the pricing of each component. Column (v) reports that the short- and long-run volatility components are significant pricing factors at the 5% level. The prices of short- and long-run components are -0.334 and -0.842 respectively. This implies that an asset with a short-run volatility beta of unity requires a 0.334% lower returns than an asset with zero exposure to the short-run component. These results are consistent with the hypothesis that the cross-section of stock returns reflects exposure to volatility risk. Column (vi) and (vii) present the prices of risk when the short- and long-run volatility enters as separate factors. Each of the components has a negative price of risk at the 10% significant level. The negative price of short- and long-run volatility is consistent with the findings of Adrian and Rosenberg (2008). Campbell (1993, 1996) and Chen (2002) show that investors intend to hedge against market volatility and they are willing to pay a premium for market downside risk. The hedge motive is indicative of a negative price of market volatility. The negative prices of the decomposed components of market volatility would suggest that risk-averse investors attempt to hedge the overall exposures to market risk, no matter whether the exposures are transitory or persistent.

Table 2.5: Pricing the cross section of the 25 size and BE/ME-sorted portfolios

This table reports the two-stage cross-sectional regression results for the 25 size and BE/ME-sorted portfolios under various model specifications, including the ICAPM, the FF three-factor model, and the CAPM. The *t*-ratios are calculated using the Jagannathan and Wang (1998) and the Newey and West (1987) procedures to account for the estimation errors in first-stage estimation and correct for possible heteroskedasticity and autocorrelation. The corresponding *p*-values are reported according to the adjusted *t*-ratios. The adjusted R^2 and the root-mean-squared pricing errors (RMSPE) are reported.

		(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
Excess market return	Coef.	0.596	0.454	0.492	0.439	0.453	0.608	0.465	0.443	0.477
	p-value	*0.033*	*0.073*	*0.051*	*0.083*	*0.073*	*0.026*	*0.066*	*0.080*	*0.049*
Short-run volatility *(sres)*	Coef.					-0.33	-0.27		-0.23	-0.32
	p-value					*0.047*	*0.097*		*0.091*	*0.042*
Long-run volatility *(lres)*	Coef.					-0.84		-0.60	-0.62	-0.75
	p-value					*0.034*		*0.071*	*0.074*	*0.049*
Market variance *(vres)*	Coef.				-3.25					
	p-value				0.049					
Value factor *(HML)*	Coef.		0.518	0.431					0.518	0.423
	p-value		*0.025*	*0.029*					*0.024*	*0.028*
Size factor *(SMB)*	Coef.		0.165	0.247					0.156	0.263
	p-value		*0.386*	*0.000*					*0.212*	*0.000*
Momentum factor *(UMD)*	Coef.			0.583						0.654
	p-value			*0.013*						*0.013*
Adjusted R^2		0.441	0.613	0.632	0.405	0.548	0.476	0.485	0.625	0.654
RMSPE		0.210	0.120	0.108	0.245	0.188	0.210	0.197	0.113	0.101

Column (ii) shows that HML and SMB have positive prices of risk. When the short- and long-run components are augmented to HML and SMB factors, the estimates of the short- and long-run components become significant at the 10% level, while the estimates of the HML and SMB coefficients are essentially unchanged. The estimations of coefficients of Carhart's four-factor model coefficient are similar. When adding the SMB, HML and UMD factors to short- and long-run volatility, the two volatility components become significant at the 5% level. Furthermore, the short- and long-run volatility factor is inferior to the FF three-factor model and Carhart's four-factor model, in terms of pricing performance. The adjusted R^2 and root-mean-squared pricing errors (RMSPE) are reported to evaluate the pricing performance of the different models[5]. The models with the Fama and French factors and the momentum factor (column iii and ix) achieve the lowest adjusted R^2 and pricing errors. Both the FF three-factor model and the momentum model outperform the short- and long-run volatility component model.

However, it's worth noting that the two volatility component factor model compares favorably to the standard CAPM model and the model with market variance as a pricing factor. Furthermore, adding the two volatility components to the FF three-factor model and momentum model reduces the pricing errors. This suggests that the volatility components and the Fama and French factors (or momentum factors) capture some orthogonal source of the priced risk.

The tightness of financial constraints and business cycles risk are two drivers of market volatility. Hong and Stein (2003) find that the skewness of asset price distributions increase with information asymmetry and borrowing constraints. Yuan (2005) also suggests that return skewness arises endogenously with financial constraints. Adrian and Rosenberg (2008) interpret market skewness as a proxy for the tightness of financial constraints. Schwert (1989a and 1989b) demonstrates that market volatility move with the business cycle. Since

[5] Lewellen et al (2010) argue that when returns follow factor structures, the OLS R^2 from cross-sectional regression may not be a good model performance measure. Therefore, the sum of squared pricing errors and the root-mean-squared pricing error (RMSPE) are reported to evaluate the pricing performance of the different models in addition to the adjusted R^2.

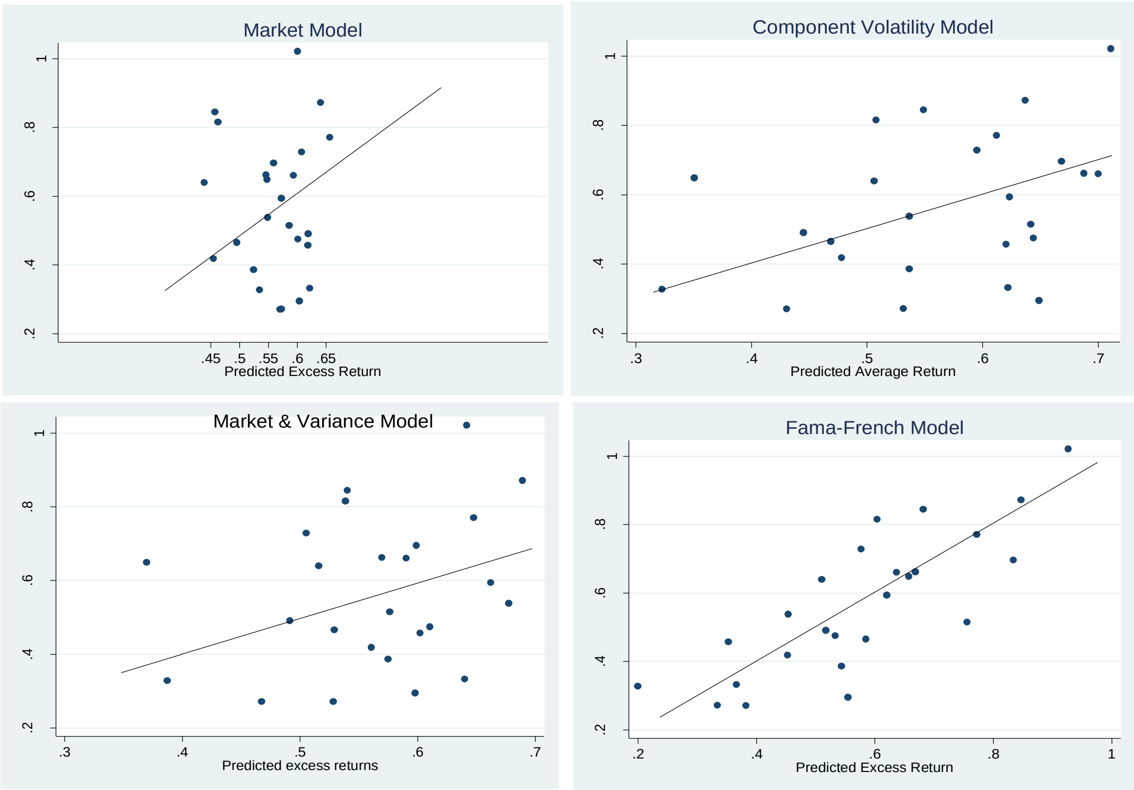
gross domestic product is only released at a quarterly frequency, Adrian and Rosenberg (2008) use industrial production growth as the proxy for the state of the business cycle.

Adrian and Rosenberg (2008) demonstrate that market skewness and industrial growth innovations are significantly priced in the cross-section. However, the inclusion of short- and long-run volatility innovations eliminates the significance of the two economic factors. Therefore, the short-run volatility component captures shocks to market skewness and the long-run volatility captures shocks to industrial production growth. Hence, short-run and long-run volatilities are related to the tightness of financial constraint and the business cycle in economic terms.

The scatter graphs of average excess returns for the 25 size and book to market portfolios against predicted returns from four different models are provided in Figure 2.2. The models included are: the traditional CAPM, the volatility decomposition model, the Fama-French model, the Ang et al. (2006) volatility model. Note that for the purpose of better visuals, the scales of the horizontal and vertical axes are different. Consequently, any point on the straight lines in each panel, although not 45-degree lines, represents the situation when the predicted excess return is equivalent to the actual excess return. The figure graphically depicts that the Fama-French model (lower-right panel) fits the cross-sectional variation better in the excess returns across the 25 portfolios and therefore outperforms the other three specifications. The volatility component model only improves upon the CAPM model (upper-left panel).

Figure 2.2: Actual excess returns versus predicted excess returns for the 25 size and book-to-market sorted portfolios

This figure shows the average excess returns for the 25 size and BE/ME-sorted portfolios against the fitted excess returns from different model specifications. The upper-left panel is CAPM. The upper-right panel is the permanent and transitory component volatility model. The lower-left panel is the variance model that is analogous to that of Ang et al (2006). The lower-right panel is the FF three-factor model. The scales of the horizontal and vertical axes are different. Any point on the straight lines in each panel, although not 45-degree lines, represents the situation when the predicted excess return is equivalent to the actual excess return.



As pointed out in table 2.4, the factor loadings have significant variations across the size dimension, however but less significant varations across the BE/ME dimension. Small firms have lower values of β_m and β_l than big firms. The dispersions have large effects on estimated risk premia as shown in table 2.4. The average value of β_m for the small firm portfolio is lower than that of the big firm portfolio by 0.24. Using the price of risk of market factor reported in table 2.6, this translates into an annualised exceed risk premium for big firms over small firms due to market risk of 1.3% per year. The average value of β_s for the small firms exceeds that of the large firms by 0.44, which translates into an annualised risk premium difference of -1.76% per year. The difference between the average values of β_l for the small firm and large firm portfolio is -0.41, which translates into an annualised risk premium difference of 4.14% per year. Only the risk premium of the long-run volatility is positive, but with a much bigger magnitude. Hence, combining the three risk-premium differences yields an average excess risk premium for small firms relative to large firms of 1.08%. The analysis suggests that the size effect of small cap firms earning higher risk adjusted returns may be attributed to the long-run volatility component.

Table 2.6: Factor risk premia of the 25 size and BE/ME-sorted portfolios

This table reports the risk premia of portfolio returns on the market excess return, short-run volatility innovations and long-run volatility innovations. The risk premia are computed by multiplying the factor loadings of Table 2.4 and the prices of risk of Table 2.5, column 5.

	Market risk premium					
	Small	Size 2	Size 3	Size 4	Big	Average
Growth	0.392	0.421	0.4489	0.443	0.427	0.427
BE/ME 2	0.332	0.380	0.423	0.417	0.435	0.398
BE/ME 3	0.305	0.368	0.403	0.396	0.480	0.390
BE/ME 4	0.327	0.357	0.404	0.480	0.431	0.400
Value	0.313	0.378	0.403	0.462	0.429	0.397
Average	0.334	0.381	0.416	0.439	0.441	0.402
	Short-run volatility risk premium					
	Small	Size 2	Size 3	Size 4	Big	Average
Growth	-0.213	-0.102	-0.124	-0.072	-0.069	-0.106
BE/ME 2	-0.247	-0.184	-0.059	0.042	-0.037	-0.092
BE/ME 3	-0.139	-0.186	-0.109	0.079	-0.080	-0.056
BE/ME 4	-0.152	0.045	0.011	-0.084	0.054	-0.039
Value	-0.125	-0.050	0.022	-0.113	0.000	-0.065
Average	-0.175	-0.096	-0.052	-0.029	-0.027	-0.076
	Long-run volatility risk premium					
	Small	Size 2	Size 3	Size 4	Big	Average
Growth	0.357	0.212	0.104	0.249	-0.035	0.177
BE/ME 2	0.393	0.341	0.074	0.184	0.032	0.205
BE/ME 3	0.339	0.286	0.105	0.225	0.045	0.200
BE/ME 4	0.332	0.286	0.069	0.215	0.109	0.202
Value	0.361	0.341	0.116	0.287	-0.079	0.205
Average	0.357	0.293	0.094	0.232	0.014	0.198

The value spreads for the BE/ME dimension are much smaller compared to the size dimension and the pattern is less distinct. High BE/ME firms have lower values of β_l and β_s. The difference of annualised risk premiums between the high BE/ME firms and low BE/ME firms due to the risk of short-run volatility components is 0.50% per year, while the difference due to the long-run component is 0.33% per year. Hence, the short- and long-run volatility components have the same effect on the BE/ME firm portfolio. Combining the value spread due to market risk, the total effect that the high BE/ME firm portfolio earns is a 1.32% higher risk premium per year relative to a low BE/ME firm portfolio. The analysis suggests that the BE/ME effect that high BE/ME firms earn higher returns may be explained by both the short- and long-run volatility components.

2.5.3 Sub-periods of the Cross-sectional Tests

Table 2.7: Pricing the cross-section of other sample periods

This table reports the empirical results of the two-stage Fama-MacBeth (1973) regressions using different sample periods and different sets of portfolios. The *t*-ratios are calculated using the Jagannathan and Wang (1998) and Newey and West (1987) procedures to account for the estimation errors in first-stage estimation and correct for the possible heteroskedasticity and autocorrelation. The corresponding *p*-values are reported according to the adjusted *t*-ratios. The adjusted R^2 and the root-mean-squared pricing errors (RMSPE) are reported.

		(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Excess market return	Coef.	0.453	0.430	0.474	0.553	0.347	0.659	0.456
	p-value	*0.073*	*0.096*	*0.068*	*0.032*	*0.093*	*0.024*	*0.023*
Short-run volatility *(sres)*	Coef.	-0.334	-0.43	-0.331	-0.317	-0.356	-0.637	-0.659
	p-value	*0.047*	*0.044*	*0.049*	*0.071*	*0.037*	*0.006*	*0.007*
Long-run volatility *(lres)*	Coef.	-0.842	-0.85	-0.825	-0.989	-1.133	-1.359	-1.677
	p-value	*0.034*	*0.032*	*0.035*	*0.028*	*0.012*	*0.009*	*0.00*
Adjusted R^2		0.548	0.511	0.598	0.525	0.532	0.560	0.541
RMSPE		0.188	0.191	0.184	0.189	0.186	0.181	0.185

Column (i): benchmark portfolio - 25 size and book to market portfolio (4 portfolios formed from the largest 350 firms and 1 portfolio formed from the rest) from 09/1980 to 12/2012.
Column (ii): 25 size and book to market portfolio from 09/1980 to 12/2005.
Column (iii): 25 size and book to market portfolio from 09/1980 to 06/2007.
Column (iv): 25 size and book to market portfolio (3 portfolios formed from the largest 350 firms and 2 small portfolios formed from the rest) from 09/1980 to 12/2012.
Column (v): 25 size and momentum sorted market portfolio from 09/1980 to 12/2012.
Column (vi): 5 book to market sorted market portfolio 09/1980 to 12/2012.
Column (vi): 5 size sorted market portfolio 09/1980 to 12/2012.

Pricing results for alternative portfolios and sample periods are presented in table 2.7. This analysis ensures that the significance of the short- and long-run volatility components is not specific to the particular sorted portfolios and sample period used in the pricing tests. In a misspecified pricing model, the prices of risk of the volatility components are most probable to change substantially across different sets of test assets or sample periods. In the six alternative tests, both short- and long-run volatility are highly significant pricing factors with negative prices of risk. The magnitudes of the prices of risk for the volatility components are fairly similar across different sets of assets and sample periods.

2.5.4 Robustness Analysis of the Volatility Model

As a robustness examination of the cross-sectional pricing results, this section examines the pricing of volatility factors using some alternative volatility model specifications. In panel A of table 2.8, the estimation results of two alternative specifications are reported together with the benchmark specifications. The two alternative specifications are the generalised autoregressive conditional heteroskedasticity component (component GARCH) model by Engle and Lee (1999) and the exponential generalised autoregressive conditional heteroskedasticity (EGARCH) model by Nelson (1991). The ARCH in mean specification is used in the previous analysis and hence in each alternative model, the market variance is also included in the expected return equation. The Bayesian information criterion is used to compare the models, since all the three models are non-nested.

The Adrian and Rosenberg's EGARCH component model achieves the lowest information criterion, indicating that it is preferable to the other two specifications. Panel B collects the cross-sectional estimation of the price of risk, and shows that all the models have negative prices of volatility risk significant at the 10% level. The benchmark model again achieves the lowest adjusted R^2 and the root-mean-squared pricing error.

Table 2.8: Comparison to alternative market volatility model

Panel A: The estimation of alternative volatility model specifications using the same data. The Bayesian Information Criterion of Schwarz (1978), BIC, allows comparison of goodness of fit across the models.
Panel B: The corresponding prices of risk from two-stage cross-sectional regressions are provided. The significant levels result from t-ratios that are calculated using the Jagannathan and Wang (1998) and Newey and West (1987) procedures to account for the estimation errors in the first-stage estimation and correct for possible heteroskedasticity and autocorrelation. The adjusted R^2 and the root-mean-squared pricing errors (RMSPE) are reported.

Panel A: Time series estimation

(i) Benchmark specification

$R_{t+1}^M = -0.007 + 0.267^{***} s_t - 0.499^{***} l_t + \sqrt{h_t} z_{t+1}$

$s_{t+1} = 0.807^{***} s_t - 0.046^{***} z_{t+1} - 0.009^{***} \left(|z_{t+1}| - \sqrt{2/\pi} \right)$ Log likelihood:-18346.03

$l_{t+1} = 0.002^{***} + 0.994^{***} l_t - 0.032^{***} z_{t+1} + 0.028^{***} \left(|z_{t+1}| - \sqrt{2/\pi} \right)$ BIC:4.648

(ii) GARCH-component model, Engle and Lee (1999)

$R_{t+1}^M = 0.032^{*} + 0.016 h_t + \sqrt{h_t} z_{t+1}$

$h_{t+1} = l_t + 0.548^{***} (h_t - l_t) + 0.065^{***} \left[(\sqrt{h_t} z_{t+1})^2 - l_t \right]$ Log likelihood:-18349.30

$l_{t+1} = 1.051^{***} + 0.989^{***} l_t - 0.021^{***} \left[(\sqrt{h_t} z_{t+1})^2 - h_t \right]$ BIC:4.650

(iii) EGARCH model, Nelson (1991)

$R_{t+1}^M = 0.113^{***} - 0.040^{**} h_t + \sqrt{h_t} z_{t+1}$ Log likelihood:-184484

$\ln(h_{t+1}) = -0.032^{***} + 0.973^{***} \ln(h_t) - 0.095^{***} z_{t+1} + 0.039^{***} |z_{t+1}|$ BIC:4.662

Panel B: Cross sectional pricing

	(i) Benchmark	(ii) GARCH-component	(iii) EGARCH
Excess market return	0.453^{*}	0.438^{*}	0.471^{*}
Short-run volatility	-0.334^{**}	-0.302^{*}	
Long-run volatility	-0.842^{**}	-2.112^{*}	
Market variance			-1.993^{*}
Adjusted R^2	0.548	0.535	0.501
RMSPE	0.188	0.189	0.199

***, **, and * denote significance level at 1%, 5% and 10% level, respectively.

The research further examines the robustness of the mean equation and the specification of the expected market return. Recall that the equilibrium pricing kernel of asset i is:

$$E_t\left(R_{t+1}^i\right) = \lambda_1 \, cov\left(R_{t+1}^i, R_{t+1}^M\right) + \lambda_s cov\left(R_{t+1}^i, s_{t+1}\right) + \lambda_l cov\left(R_{t+1}^i, l_{t+1}\right) \quad (2.8)$$

In the benchmark specification, the mean market excess return is defined as:

$$\mu_t^M = \theta_1 + \theta_2 s_t + \theta_3 l_t \qquad (2.9)$$

The time-series and cross-sectional results of the volatility components model using six alternative specifications of the market return instead of equation (2.9), are presented in panel A and B of table 2.9.

Table 2.9: Specification analysis of the expected market returns

Panel A: The time-series estimation of the daily volatility component. The models incorporate different expected market return specifications; the baseline model is in column (i). The Bayesian Information Criterion of Schwarz (1978), BIC, allows the comparison of goodness of fit across models. The estimated time-series models are:

$R_{t+1}^M = \theta_1 + \theta_2 s_t + \theta_3 l_t + \theta_h h_t + \theta_R R_t^M + \theta_z \sqrt{h_{t-1}} z_t + \sqrt{h_t} z_{t+1}$,

$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6 \left(|z_{t+1}| - \sqrt{2/\pi}\right)$, $l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10} \left(|z_{t+1}| - \sqrt{2/\pi}\right)$.

Panel B: The corresponding prices of risk from the two-stage cross-sectional regressions are provided. The significant levels result from t-ratios that are calculated using the Jagannathan and Wang (1998) and Newey and West (1987) procedures to account for the estimation errors in first-stage estimation and correct for the possible heteroskedasticity and autocorrelation. The adjusted R^2 and the root-mean-squared pricing errors (RMSPE) are reported.

Panel A: Time series regression

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
θ_1	−0.007	−0.115***	−0.111***	-0.111***	−0.106***	−0.107***	0.230***
θ_2	0.267***		−1.798***	−1.798***	−1.798***	−0.077***	0.201***
θ_3	−0.499***			−0.499***	−0.411***	−0.414***	−0.061***
θ_h		−0.081***	−0.095***	−0.095***	−0.010***	−0.054***	−0.214***
θ_R					-0.003		-0.007
θ_z						−0.031***	0.010
θ_4	0.807***	0.709***	0.770***	0.770***	0.869***	0.737***	0.819***
θ_5	−0.046***	−0.053***	−0.030***	−0.030***	−0.015***	−0.026***	0.024***
θ_6	−0.009***	−0.041***	−0.019***	−0.018***	−0.018***	−0.026***	−0.151***
θ_7	0.002***	0.012***	0.009***	0.010***	0.009***	0.006***	0.008***
θ_8	0.994***	0.971***	0.976***	0.976***	0.979***	0.978***	0.984***
θ_9	−0.032***	−0.037***	−0.041***	−0.041***	−0.041***	−0.036***	−0.104***
θ_{10}	0.028***	0.039***	0.012***	0.011***	0.012***	0.016***	0.114***
LLL	-18346.03	-18543.72	-18485.63	-18565.27	-185598	-18518.75	-18388.93
BIC	4.648	4.696	4.683	4.704	4.702	4.694	4.662

Note: LLL: Log-Likelihood

Panel B: Cross sectional estimation

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Excess market return	0.453*	0.508**	0.509**	0.508**	0.505**	0.501**	0.530**
Short-run volatility (sres)	−0.334*	−0.354*	−0.332*	−0.341*	−0.340*	−0.316*	−0.312*
Long-run volatility (lres)	−0.842**	−0.889**	−0.663*	−0.573*	−0.645*	0.689*	−0.978***
Adjusted R^2	0.548	0.513	0.507	0.498	0.497	0.497	0.488
RMSPE	0.188	0.194	0.197	0.203	0.203	0.202	0.208

***, **, and * denote significance level at 1%, 5% and 10% level, respectively.

The benchmark specification is reported in column (i). In column (ii)-(iv), the volatility components are adjusted in the mean return equation. In column (v)-(vii), autoregressive and moving average terms are augmented to the market return equation. Although some of the alternative models contain more explanatory variables than the benchmark model, the benchmark model still achieves a higher value of likelihood. Furthermore, the benchmark model is also preferred by the Bayesian information criteria.

In terms of cross-sectional pricing, panel B of table 2.9 shows that the benchmark specification is superior to the alternatives with a lowest adjusted R^2 and root-mean-squared error. It is interesting to see that using the volatility component or market variance separately results in only a small change in pricing accuracy (column i to iii). In contrast, using market variance and its two components together in the mean equation results in a noticeable deterioration in the pricing errors (column iv-vii versus i-iii)

2.6. Conclusions

Intertemporal capital asset pricing models predict that financial asset risk premia are not only due to the covariation of returns with the market excess return, but are also associated with innovations in the state variables that describe the investment opportunities. Multifactor models of risk already predict that aggregate volatility should be a cross-sectional risk factor. Adrian and Rosenberg (2008) further decompose the aggregate volatility into a transitory and a permanent component. They conclude that the short- and long-run volatility components have negative, highly significant prices of risk and the conclusion is robust across sets of portfolios, sub-periods, and volatility model specifications, using American stock market data.

Applying Adrian and Rosenberg's decomposition of market risk to the UK stock market, the analysis reveals that the short- and long-run volatility components also have significantly negative prices of risk. The negative prices of the volatility components suggest that risk-averse investors tend to hedge all the exposures to market risk, no matter whether the volatility is transitory or persistent. Investors are willing to pay a premium for downside protection. The results are robust across sets of portfolios, sample periods and model specifications.

The short- and long-run volatility might provide an explanation of the size and value anomaly of the financial market. Specifically, the size effect of small cap firms earning higher risk adjusted returns may be attributed to the long-run volatility component, whereas the value effect that high BE/ME firms earn higher returns may be explained by both the short- and long-run volatility components. However, the performance of the decomposition model is inferior to the Fama-French three factor model, and Carhart's four factor model. This might suggest further investigation and improvement on Adrian and Rosenberg's volatility decomposition model.

Chapter 3: The Effects of Sentiment on Market Return and Volatility and The Cross-Sectional Risk Premium of Sentiment-affected Volatility

3.1 Introduction

A long-running debate in financial economics concerns the role and possible effect of investor sentiment on asset prices. There are various ways to define investor sentiment. It is the feeling or tone of a market, or its crowd psychology, as revealed through the activity and price movement of the securities traded in that market. Market sentiment is also called "investor sentiment" and is not always based on fundamentals. Baker and Wurgler (2006) explain it as the propensity to speculate or the overall optimism or pessimism about an asset. Baker and Wurgler (2007) further define investor sentiment broadly, as a belief, usually influenced by emotion, about future cash flows and investment risks that is not justified by the facts at hand.

Traditional asset pricing theory suggests that rational arbitrage necessarily forces prices closer to fundamentals and leaves no role for investor sentiment. The capital asset pricing model (CAPM) theoretically argues that systematic risk is measured by the exposure to the market portfolio. Prior literature has shown, however, that the standard CAPM cannot explain the returns on stocks with certain firm characteristics or price histories such as the size effect, value effect and momentum effect which have been termed as asset-pricing anomalies in the literature. In an attempt to capture the dimensions of risk other than exposure to the market risk, Fama and French (1992, 1993) further include size and value factors and Pastor and Stambaugh (2003) consider a liquidity factor.

The existing literature documents that investor sentiment exhibits a certain degree of predictability of the time-series stock returns. Fisher and Statman (2003) reveal the level of investor sentiment in one month is negatively related to the stock returns over the next month and the next 6 or 12 months. Meanwhile, there is a positive relationship between the monthly changes in investor sentiment and contemporaneous market excess returns. Brown and Cliff (2004, 2005) suggest that their measures of sentiment co-move with the market in the long run. They find that returns over future multi-year horizons are negatively associated with investor sentiment. Lee et al. (2002) demonstrate that excess returns are contemporaneously positively related to shifts in sentiment.

Baker and Wurgler (2006, 2007) illustrate the sentiment effects on the cross-section of stock returns. They give us an excellent illustration of the theoretical effects of sentiment on the cross-section and conclude that stocks that are hard to value and arbitrage are most vulnerable to waves of investor sentiment.

The behavioural finance literature shows that sentiment has an impact on asset price and trading decisions[6]. The influence of investors' future expectations can lead to the over- or under-pricing of stocks, and thus affect pricing models. Various studies provide supportive evidence that investor sentiment plays a critical role in determining stock price behaviour. Hence, the question now is no longer whether investor sentiment affects stock prices, but how to measure investor sentiment and quantify its effects.

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[6] Early research into behavioural finance is grounded on psychological evidence about how people actually behave. For instance, Barberis et al. (1998) and Daniel et al. (1998a, 1998b) propose models based on psychological evidence such as the representativeness heuristic, conservatism, overconfidence and self-attribution, to model investor sentiment and demonstrate that sentiment has an impact on asset pricing. Baker and Wurgler (2006) and Fisher and Statman (2000) have shown that there are profitable trading strategies that take advantage of stock price movement induced by investor sentiment.

DeLong et al. (DSSW hereafter; 1990) presents a model of asset pricing based on the idea that the unpredictability of opinions of irrational investors (noise traders) impounds resale price risks on their trading assets. They illustrate four effects of noise trading: the hold more effect, the create space effect, the Friedman effect and the price pressure effect. The DSSW model suggests that the four effects of noise trading influence stock expected returns and lead to a variation of assets' price risks. The noise traders act in concert and induce systematic risk that should be priced in asset pricing. The implication of the DSSW model is that investor sentiment has effects on stock market returns and volatility.

There is a large body of literature exploring the effect of noise trader sentiment on market volatility. Shiller (1981), Leroy and Porter (1981) and Roll (1988) show that volatility cannot be explained solely by changes in fundamentals. Anything that changes the amount or character of noise trading will change the volatility of price (Fischer Black, 1986, p.533). Much of the literature suggests that the sentiment of noise traders is a determinant of returns volatility. Bauer (1993) estimates that around 7% of the variation in fund discounts/premiums can be explained by noise trading. Brown (1999) reveals that noise trading may influence higher moments of return such as volatility. He finds that unusual levels of individual investor sentiment are associated with greater volatility in closed-end fund returns. DSSW models the influences of noise trading on equilibrium prices. In this model, investor sentiment induces unpredictable deviations of asset prices from their intrinsic values. Noise traders' poor market timing and misperceptions about asset's risk increases price uncertainty. R. Verma and P. Verma (2007) investigate the relative effects of fundamental and noise trading on the formation of conditional volatility. They show that there are significant effects of investor sentiment on stock returns (volatilities) for both individual and institutional investors. They find evidence that investor error is a significant determinant of stock volatilities. Foucault et al. (2011) show that retail activity has a positive effect on the volatility of stock returns.

Adrain and Rosenberg (2008) point out that the short-run volatility might be related to market skewness. Yeh and Yang (2011) show that overconfidence increases market volatility, price distortion and trading volume. The phenomena of the fat-tail of return distribution and volatility clustering are more significant when traders are overconfident. Shleifei (2000) considers noise trader risks as the main factors affecting the transitory component of stock return volatility. He shows that noise trader risk is extremely important for relatively horizon investors engaged in arbitrage against noise traders. He asserts that noise traders' collective shifts of opinion increase the riskiness of returns to assets. Frankel and Rose (1997) suggest that the microstructure of the foreign exchange markets may explain the endogenous speculative bubbles. They recognise that some short-run dynamics may arise from the trading process itself, such as noise trading that generates volatility which swamps macro fundamentals on a short-term basis. Da et al. (2013) construct a Financial and Economic Attitudes Revealed by Search (FEARS) index as a new measure of investor sentiment and find their sentiment measures predict short-term return reversals and a temporary variation of market volatility. There is also an interesting trend in the literature which examines sentiment following non-economic events such as weather conditions (Hirahleifer and Shumway (2003)), seasonal affective disorder (SAD, Kamstra et al. (2003)), sports (Edmans et al. (2007)) and aviation disasters (Kaplanski and Levy (2010)) and shows that these sentimental changing events induce variations in asset prices, at least in the short run.

While there is a growing consensus that noise traders can induce large price movements and excess volatility in the short-run, the survival of noise traders and the effects of noise trading in the long-run remains open for debate. Friedman (1953) argues that irrational traders will consistently lose money to rational investors, will not survive, and therefore, cannot influence long-run asset prices. In response, Figlewski (1979) points out that it might take irrational investors a very long time to lose their entire wealth, but he agrees that in the long run those who choose portfolios irrationally are doomed. DeLong et al. (1991) present a model and show that in the long run noise traders can come to dominate the market despite their taking of excessive risk and higher consumption. Kogan et al. (2006) demonstrate that survival and price impact are two independent concepts. The price impact of irrational traders does not rely on their long-run survival, and they can have a significant long-run impact on asset prices even when their wealth becomes negligible. Jouini and Napp (2010) obtain waves of pessimism and optimism that lead to a countercyclical market price of risk and procyclical risk-free rates. The long-run risk-return relation is modified where the long run market price of risk might be higher than both the instantaneous and the rational ones. Kräussl and Mirgorodskaya (2014) investigate the impact of news media sentiment on financial market returns and volatilities in the long-term. They indicate that pessimistic news media sentiment is positively related to global market volatility and negatively related to global market returns. They show that their media sentiment indicator accurately reflects the financial market crises and pricing bubbles over the past 20 years.

The motivation for this chapter stems from the numerous bodies of research on the impact of market sentiment on stock return, volatility, short-run volatility and long-run volatility. Inspired by the empirical framework of Lee et al. (2002), investor sentiment is augmented to Adrian and Rosenberg's EGARCH component model by adding the sentiment to mean and variance equations. However, the model in this chapter differs from their model in the following aspects: Firstly, the main framework of the model is the EGARCH component model proposed by Adrian and Rosenberg (2008), while Lee et al. (2002) utilise the GARCH-in-mean framework. Furthermore, Adrian and Rosenberg (2008) do not consider investor sentiment in their model. Secondly, the dummy variables of sentiment enter their model as an intercept dummy which suggests that sentiment affects the conditional volatility directly. However, the investigation suggests that the direct effects of sentiment on short- and long-run volatilities are statistically insignificant. Therefore, this chapter adapts the approach by adding the dummy variables as slope dummies rather than intercept dummies. The empirical results suggest that sentiment has influences on short- and long-run volatilities through their impacts on previous short- and long-run volatilities. Third, both the level and change of sentiment are investigated in each model framework.

The analysis and results of this chapter contribute to the existing literature by investigating the extent to which the impact of investor sentiment has on stock market volatility and returns. Furthermore, the cross-sectional prices of risks of sentiment-affected volatilities are investigated. First, the results complement earlier work which shows that sentiment helps to explain the time-series of returns. Previous research has focused on the influence of investor sentiment on the mean of stock returns. The study investigates the impact of investor sentiment on both the market excess returns and the volatility of returns. Second, most research utilises the .S data and to my best knowledge, there is very little empirical research on market sentiment concentrating on the UK market. The existing studies related to UK market mainly discuss the international sentiment and the UK market is just one part of the European or global market. Third, the market volatility is decomposed into transitory and permanent components. By applying investor sentiment to this model, this chapter investigates the influences of sentiment on decomposed market volatility and examines the effects on short- and long-run volatilities separately. Finally, the short- and long-run sentiment-affected volatilities are added to the framework of the ICAPM to further examine whether the sentiment-affected variables are priced factors in the cross-section.

In this chapter, the study focuses on three aspects. Firstly, limited by the availability of data, five sentiment measures are obtained, consumer confidence, market turnover by volume, market turnover by value, the number of IPOs in each month, and the initial day return of IPOs within each month. The first principal component analysis (PCA) is employed to construct a composite sentiment index. Secondly, the study examines whether investor sentiment affects time-series market excess returns. Also, it examines whether market excess returns are indirectly affected by investor sentiment through the risk caused by sentiment in the form of volatility. Thirdly, the cross-sectional examination attempts to demonstrate whether the short- and long-run sentiment-affected volatilities obtained from the time-series regression are priced factors in the 25 Fama-French size and BE/ME-sorted portfolios.

The chapter is organised as follows. The next section displays a brief literature review on investor sentiment and a survey of proxies for sentiment proposed in the literature. Section 3.3 provides the methodology of the construction of investor sentiment and the empirical model of this chapter. Section 3.4 describes the summary statistics of sentiment measures and the construction of the composite index. Section 3.5 presents the empirical analysis of the time-series and cross-sectional estimations. Section 3.6 provides robustness checks for both the model specification and the measure of investor sentiment and the last section concludes.

3.2 literature Review

3.2.1 Measures of Investor Sentiment

3.2.1.1 Economic Variables as Sentiment Measures

The existing literature has established several different measures of investor sentiment. One approach is directly through economic variables. A number of studies use observable economic variables to measure levels of sentiment. Baker and Wurgler (2007) summarise some potential economic proxies for sentiment, including retail investor trades; mutual fund flows; trading volume; premium on dividend-paying stocks; closed-end fund discounts; option implied volatility; first day returns on initial public offerings (IPOs); volume of initial public offerings; new equity issues; and insider trading.

Retail Investor Trades. Barber et al. (2007) and Kumar and Lee (2006) find in micro-level trading data that trading of retail investors is highly correlated and persistent, which is consistent with systematic sentiment. Consequently, Kumar and Lee (2006) suggest constructing sentiment measures for retail investors based on their trading comovements.

Mutual Fund Flows. Brown et al. (2002) find evidence that daily mutual fund flows may be instruments for investor sentiment about the stock market and provide evidence that this sentiment factor is priced. Frazzini and Lamont (2006) find some affirmative evidence by using fund flows to proxy for sentiment for individual stocks. They find that strong inflows of stock within a mutual fund predict a relative low future return.

Trading Volume. Trading volume, or more generally liquidity, can be viewed as an investor sentiment index. Baker and Stein (2004) note that in the presence of short-sales constraints, which is actually the case in practice, irrational investors are more likely to trade, and thus add liquidity, when they are optimistic and betting on rising stocks rather than when they are pessimistic and betting on falling stocks. Higher turnover predicts lower subsequent returns in both firm-level and aggregate data. Similarly, Scheinkman and Xiong (2003) claim that trading volume reveals an underlying difference of opinions, which is accompanied by bubbles in asset price when short selling is difficult.

Dividend Premium. Baker and Wurgler (2004a, b) define the dividend premium as the difference between the average market-to-book-value ratios of dividend payers and nonpayers. When dividends are at a premium, firms are more likely to pay them, and are less so when they are discounted. In other words, on the margin, when the prevailing demand for the stock market dividend premium is high, the propensity to pay dividend increases, whereas with a low demand, the propensity to pay dividends decreases.

Closed-End Fund Discount. The closed-end fund discount (or occasionally premium) is the difference between the net asset value of a fund's actual security holding and the fund's market price. Many authors, including Lee et al. (1991) and Neal and Wheatley (1998) consider the closed-end fund discounts to measure individual investor sentiment. They have argued that if closed-end funds are disproportionately held by retail investors, the average discount on closed-end equity funds may be a sentiment index, with the discount increasing when retail investors are bearish. Both these two papers suggest that closed-end fund discounts predict the size premium.

Option Implied Volatility. The Market Volatility Index (VIX), which measures the implied volatility of options on the Standard and Poor's 100 stock index, is often referred to as an "investor fear gauge" by practitioners. Whaley et al. (2008) define VIX as a measure of an investor's certainty (or uncertainty) regarding volatility. It is about the fear of the unknown such as the higher the VIX is, the greater the fear.

IPO First-Day Returns and IPO Volume. The IPO market is often viewed as being sensitive to sentiment. Specifically, a high first day return on IPOs is considered to be a measure of investor enthusiasm, and the low idiosyncratic return on IPOs is often interpreted as a symptom of market timing. The underlying demand for IPOs is also said to be extremely sensitive to investor sentiment. Furthermore, average first-day returns display peaks and troughs which are highly correlated with the IPO volume.

Equity Issues over Total New Issues. Baker and Wurgler (2000) find that high values of the equity share predict low stock market returns, and suggest that this pattern reflects firms shifting successfully between equity and debt to reduce the overall cost of capital. The authors argue that this pattern need not imply that individual firms or their managers can predict prices on the market as a whole. Rather, correlated mispricings across firms may lead to correlated managerial actions, which may then forecast correlated corrections of mispricings, that is, forecast market returns.

Insider Trading. Seyhun (1998) presents evidence on the ability of insider trading activity to predict stock return and reap significant profits. Corporate executives, board members and large shareholders have better information about the true value of their firms than outside investors. Thus, legalities aside, their personal portfolio decisions may also reveal their views about the mispricing of their firms. If sentiment leads to correlated mispricings across firms, insider trading patterns may contain a systematic sentiment component.

There are a few other economic variables that have been employed as proxies for sentiment in the recent literature. Brown and Cliff (2004) and Wang et al.(2006) outline and examine a number of sentiment indicators, such as the ARMS index, put-call trading volume and open interest ratios, the percentage change in margin borrowing, the percentage change in short interest, and the ratio of odd-lot sales to purchases.

ARMS Index. The ARMS index on day *t* is equal to the number of advancing issues scaled by the trading volume (shares) of advancing issues divided by the number of declining issues scaled by the trading volume (shares) of declining issues. ARMS can be interpreted as the ratio of volume per declining issue to the volume in each advancing issue. If the index is greater than one, more trading is taking place in declining issues, whilst if it is less than one, more volume in advancing stocks outpaces the volume in each declining stock. Its creator, Richard Arms (1989), argues that if the average volume in declining stocks far outweighs the average volume in rising stocks then the market is oversold and that this should be treated as a bullish sign. Likewise, he argues that if the average volume in rising stocks far outweighs the average volume in falling stocks then the market is overbought and this should be treated as a bearish sign.

Put-Call Trading Volume. The put-call trading volume ratio is a measure of market participants' sentiment derived from options and equals the trading volume of put options divided by the trading volume of call options. The ratio of CBOE equity put to call trading volume is widely viewed as a bearish indicator in the US market. When market participants are bearish, they buy put options either to hedge their spot positions or to speculate bearishly.

Therefore, when the trading volume of put options becomes large relative to the trading volume of call options, the sentiment goes up, and vice versa.

Put-Call Open Interest ratios. Wang et al. (2006) further introduce the approach of using the open interest of options instead of trading volume to calculate the put-call ratio. The ratio can be calculated on a daily basis using the day or on a weekly basis using the open interest of options at the end of the week. Wang et al. (2006) claim that this might be a preferred measure of sentiment as it may be argued that the open interest of options is the final picture of sentiment at the end of the day or the week and is therefore likely to have better predictive power for volatility in subsequent periods.

Percentage Changes in Margin Borrowing. Simply put, margin borrowing is to use borrowed money to purchase stocks. This measure is frequently cited as a bullish indicator since it represents investors using borrowed money to invest. Brown and Cliff (2004) use this indicator as one of the indirect sentiment measures.

Percentage Changes in Short Interest. Short interest is the total number of shares of a particular stock that have been sold short by investors but have not yet been covered or closed out. Percentage changes in short interest are the number of shorted shares divided by the number of shares outstanding. The argument is made that the specialists are well-informed and relatively savvy investors, so when their short-selling becomes relatively large, the market is likely to decline. Hence, the percentage change in short interest is usually viewed as a bearish indicator. Brown and Cliff (2004) also use this indicator as a sentiment proxy.

The Ratio of Odd-Lot Sales to Purchases. An indicator of small-investor sentiment, equal to the amount of odd lot buying divided by the amount of odd lot selling over a given period. Fosback (1993) suggests this ratio to be a sentiment measure. A number greater than one indicates a positive sentiment, a number less than one indicates a negative sentiment.

3.2.1.2 Survey Data as Sentiment Measures

Another strand of recent research expands the direct measures of investor sentiment to consider aggregate market views regarding sentiment across investor types, including both institutional and individual investors. Brown and Cliff (2004) assume that the survey data conducted by the American Association of Individual Investors (AAII) and Investors Intelligence (II) are reasonable proxies for the true sentiment. They demonstrate that surveys measuring investor sentiment are related to other popular measures of investor sentiment and recent stock market returns. Brown and Cliff (2005) use survey data from Investors Intelligence (II) as a contrarian indicator. Lemmon and Portniaguina (2006) explore the time-series relationship between investor sentiment and the small-stock premium using consumer confidence conducted in the US as a measure of investor optimism. One of the survey data is collected by the Conference Board [the Index of Consumer Confidence (CBIND)] and the other is independently conducted by the University of Michigan Survey Research Centre [the Index of Consumer Sentiment (ICS)]. Schmeling (2009) examines whether consumer confidence - as a proxy for individual investor sentiment – affects expected stock returns internationally in 18 industrialised countries.

3.2.1.3 Composite Sentiment Index

The last measure is to construct a composite proxy index from the available economic variables. Prior research presents a number of proxies for sentiment to use as time-series conditioning variables. However, there are no definitive or uncontroversial measures. Brown and Cliff (2004) indicate that the survey data alone are most likely incomplete measures of sentiment. Conceptually, it is appealing to extract the common component (s) of the available economic series which might represent a cleaner measure of investor sentiment. In order to exploit as much information as possible, they combine the various sentiment measures, indirect and direct ones, and use two well-established methods to extract common features of the data: the Kalman filter and the principal component analysis (PCA). Likewise, Baker and Wurgler (2006, 2007) argue that data availability narrows the list of sentiment measures considerably. They suggest a composite index of sentiment which is based on the common variation in the available underlying proxies for sentiment. They propose the principal component methodology, like Brown and Cliff (2004), to define a sentiment index, which captures the common component in the underlying economic variables.

3.2.2 Empirical Studies of Investor Sentiment

Behavioural finance argues that the arbitrage will be limited in some senses, and investors might be affected by psychology biases, noise, or sentiment. As Baker and Wurgler (2007) summarise, researchers in behavioural finance have therefore been working to modify the standard model with an alternative model built on two basic assumptions.

The first assumption, put forward by DeLong et al. (1990), is that investors are subject to sentiment. Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that are not justified by facts or economic theory. The remarkable work of DeLong et al. (1990) models the influence of noise trading on equilibrium prices, in which noise traders act in concert on non-fundamental signals. The simultaneous actions introduce a systematic risk that is priced. In their model, the deviations in price from fundamental values induced by changes in investor sentiment are unpredictable. Arbitrageurs betting against mispricing run the risk that investor sentiment becomes more extreme and prices vary even further away from fundamental values, at least in the short run. The possibility of loss and the arbitrageurs' risk aversion reduce the size of positions they are willing to take. Consequently, arbitrage fails to completely eliminate mispricing and investor sentiment affects asset prices in equilibrium. The DSSW model predicts that the direction and magnitude of changes in noise trader sentiment are relevant in asset pricing.

The second assumption, emphasised by Shleifer and Vishny (1997), is that betting against sentimental investors is costly and risky and hence there are limits to arbitrage. Rational arbitrageurs are not as aggressive in bringing prices to fundamentals as the standard model would suggest.

A pioneering and well-known set of studies of sentiment and aggregate stock returns appeared in the mid-1980s. In this research, the role of sentiment was left implicit and the statistical evidence was not very strong. Nowadays, the systematic role of investor sentiment has been suggested by many empirical and theoretical studies. One set of studies focuses on demonstrating how sentiment predicts future returns in stock markets.

Neal and Wheatley (1998) utilise three popular measures of investor sentiment: closed-end fund discount, net mutual fund redemptions and the ratio of odd-lot sales to purchases as sentiment measures. They exploit the forecast power of these three measures and show that the first two measures forecast the size premium, but little evidence that the odd-lot ratio predicts returns. Fisher and Statman (2000) report a negative relationship between investor sentiment and future stock returns. Baker and Wurgler (2000) use the share of equity issues in total new issues, that is equity and debt issues to proxy for investor sentiment. They demonstrate that this measure significantly predicts negative market returns which cannot be explained by efficient market hypotheses. Brown and Cliff (2005) use a direct survey measure of investor sentiment to forecast market returns over the following 1-3 years. The estimation of coefficient on investor sentiment is significantly positive which suggests the market is overvalued during periods of optimism. They further show that sentiment is positively related to changes in market valuations, in the error correction version of the cointegrating regression. Corredor et al. (2013) analyse the forecast performance of investor sentiment in four European stock markets: France, Germany, Spain and the UK. They claim that sentiment has a significant effect on returns, though there is a dispersion in intensity across different countries.

The second set of studies exploits the possibility of a causal relationship between market returns and investor sentiment or changes in investor sentiment. The Granger causality tests of Brown and Cliff (2004) failed to reject the null hypothesis of no predictability in returns to sentiment for small and large stocks. On the other hand, changes in investor sentiment appear to significantly negatively impact on subsequent market returns of small but not of large stocks. By estimating bivariate VAR models, Wang et al. (2006) also take a look at the causality between sentiment and market returns in both directions. They confirm the results of Brown and Cliff (2004) that sentiment is not a causal variable of market returns. On the contrary, sentiment is Granger caused by market returns. Schmeling (2009) reports that there is a two-way causality between sentiment measures and stock returns.

Recent research sheds more light on the cross-sectional effects of investor sentiment. Brown and Cliff (2005) use the 25 Fama and French portfolios, together with 5 portfolios sorted from univariate size sorts, 5 portfolios from book-to-market sorts and the overall market portfolio. They show that for large firms or low book-to-market firms, sentiment is a significant predictor of future returns at the 1-, 2-, and 3-year horizon. Baker and Wurgler (2006) examine how investor sentiment impacts the cross-section of stock returns. They form equal-weighted decile portfolios based on several firm characteristics, and look for patterns in the average returns across decile conditioning on the beginning-of-period level of sentiment. They demonstrate that the subsequent returns are relatively low for small stocks, young stocks, high volatility stocks, distressed stocks, unprofitable stocks, stocks with no dividend payment, and stocks experiencing extreme growth, when sentiment measures are high, and vice versa. Berger and Turtle (2012) report that investor sentiment sensitivities increase directly with the opacity of firms in the cross-section. They display an inverse relation between *ex ante* investor sentiment and the marginal performance of opaque stocks. The performance of translucent stocks, on the contrary, exhibits relatively little variability across levels of sentiment.

3.3 Methodology

3.3.1 Principal Component Analysis (PCA)

Principal component analysis (PCA) is a statistical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly correlated variables called principal components. The transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components. PCA is sensitive to the relative scaling of the original variables.

PCA is a common technique for finding patterns in data of high dimensions, and using the dependencies between the variables to represent it in a more tractable, lower-dimensional form, without losing too much information. It is one of the oldest techniques, and has been rediscovered many times in many fields, such as the Karhunen-Loève transformation (KLT) in signal processing, the Hotelling transformation in multivariate quality control, proper orthogonal decomposition (POD) in mechanical engineering and many other fields.

Mathematically, PCA is defined as an orthogonal linear transformation that transforms the data to a new coordinate system so that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. Consider a data matrix, X, with zero empirical mean (the sample mean of the distribution has been subtracted from the data set), where each of the *n* rows represents a different repetition of the experiment, and each of the ρ columns gives a particular kind of datum (say, the results from a particular probe).

Mathematically, the transformation is defined by a set of ρ-dimensional vectors of weights or loadings $\mathrm{W}_{(\mathrm{k})} = (\omega_1, \dots, \omega_\mathrm{p})_{(\mathrm{k})}$ that maps each row vector $\mathrm{X}_{(\mathrm{i})}$ of X to a new vector of principal component scores $\mathrm{t}_{(\mathrm{i})} = (\mathrm{t}_1, \dots, \mathrm{t}_\mathrm{p})_{(\mathrm{i})}$, given by

$$\mathrm{t}_{\mathrm{k}(\mathrm{i})} = \mathrm{X}_{(\mathrm{i})} * \mathrm{W}_{(\mathrm{k})}$$

in such a way that the individual variables of t considered over the data set successively inherits the maximum possible variance from x, with each loading vector w constrained to be a unit vector.

3.3.2 Empirical Models

The DSSW model presents a notable paper that suggests that in a simple overlapping generations model of an asset market, irrational noise traders with erroneous stochastic beliefs affect prices and actually enjoy higher expected returns. In this model, there are two types of investors: rational investors and noise traders. In each period, rational investors and noise traders trade assets based on their respective beliefs of expected return. There are two crucial assumptions of this model. First, the authors assume that the investment horizons of rational investors are short, so that they care about the interim resale prices of the assets they hold, not just the present values of future dividends. Second, this model assumes that noise traders' sentiment is stochastic and cannot be perfectly predicted by rational investors.

The optimism or pessimism of noise traders creates a risk in the price of the asset that causes transitory divergences between price and intrinsic value, even in the absence of fundamental risk. Rational investors run the risk that sentiment will become more extreme and prices deviate further away from fundamentals. The risk aversion and pressure in the fund of rational investors limit their willingness of taking extremely volatile positions to bring the prices back to intrinsic values. Therefore, noise trading limits the effectiveness of arbitrage and rational arbitrage fails to eliminate mispricing. Furthermore, sentiment induces trading that occurs contemporaneously across many assets in the markets. This introduces additional variability in returns which is a non-diversifiable systematic risk that is priced in equilibrium.

In the DSSW model, the impact of noise trading on the returns of risk assets is the result of an interaction of four effects. The DSSW model summarises that holding more effect and creating space effect tends to increase noise traders' relative expected returns. The Friedman effect and price pressure effect tend to lower noise traders' relative expected returns. In particular, the hold more and price pressure effect affect mean returns directly, since they are related to the *direction* of shifts in noise trader sentiment. Meanwhile, the Friedman effect and the create space effect are related to the *magnitude* of the shifts in noise trader sentiment. Hence, the influence is indirectly on mean returns through changes in noise traders' misperceptions of the asset's risk.

In accordance with the research by DeLong et al. (1990), Lee et al. (2002) propose a sentiment-augmented GARCH-in-mean model to capture the four effects of noise trading. Contemporaneous shifts in investor sentiment are included in the mean equation and lagged shifts in the magnitude of investor sentiment are embodied in the conditional volatility equation. Their model takes the following form:

$$R_t - R_{ft} = \alpha_0 + \alpha_1 h_t + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 \Delta S_t + \varepsilon_t$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2 I_{t-1} + \beta_3 h_{t-1} + \beta_4 R_{ft} + \beta_5 (\Delta S_{t-1})^2 D_{t-1} + \beta_6 (\Delta S_{t-1})^2 (1 - D_{t-1})$$

where R_t is the weekly return on a market index, R_{ft} is the risk free rate, and ΔS_t is a measure of noise trader risk. Lee et al. (2002) apply two alternative measures of the noise trader risk. One is the changes in Investor's Intelligence (II) sentiment index and the other one is the percentage changes in II sentiment index. Furthermore, $\varepsilon_t \sim N(0, h_t)$ and I_{t-1}

andD_{t-1} are dummy variables where (i) $I_{t-1} = 0$ if $\varepsilon_{t-1} \leq 0$ and $I_{t-1} = 1$ if $\varepsilon_{t-1} > 0$; and (ii) $D_{t-1} = 0$ if $\Delta S_{t-1} \leq 0$ and $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$.

Arik (2012) also examines the impact of sentiment on stock returns in the framework of the GARCH process. The author augments his sentiment measures to the mean equation of the GARCH specification. Inspired by the model specifications of Lee et al. (2002) and Arik (2002), the research intends to include investor sentiment in Adrian and Rosenberg's EGARCH component model. Levels of Investor sentiment or changes in investor sentiment are introduced into the mean and variance equations. Besides the base model used in the last chapter, three alternative sets of empirical models are tested.

Model 1: Benchmark model - EGARCH component model of Adrian and Rosenberg (2008)

Market return: $R^M_{t+1} = \theta_1 + \theta_2 s_t + \theta_3 l_t + \sqrt{h_t} z_{t+1} \qquad (1a)$

Market volatility: $ln\sqrt{h_t} = l_t + s_t \qquad (1b)$

Short-run component: $s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6 \left(|z_{t+1}| - \sqrt{2/\pi}\right) \qquad (1c)$

Long-run component:$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10} \left(|z_{t+1}| - \sqrt{2/\pi}\right) \qquad (1d)$

This model has been analysed in detail in the last chapter. In this chapter however the monthly data are utilised instead of the daily data in the last chapter.

Model 2: Investor sentiment in the mean and variance equation in accordance with the GARCH-in-mean model of Lee et al. (2002)

$$R^M_{t+1} = \theta_1 + \theta_2 s_t + \theta_3 l_t + \theta_{11} SENT_{t+1} + \sqrt{h_t} z_{t+1}$$

$$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6 \left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{12} SENT_t^2 D_t + \theta_{13} SENT_t^2 (1 - D_t)$$

$$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10}\left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{14} SENT_t^2 D_t + \theta_{15} SENT_t^2 (1 - D_t)$$

Where $D_t = 0$ if $SENT_t \leq 0$ and $D_t = 1$ if $SENT_t > 0$. Since the mean of the sentiment index ($SENT_t$) is close to zero, which will be shown later in this chapter, the variance of the sentiment index can be approximated by $SENT_t^2$. Furthermore, both the levels and changes in investor sentiment are examined. Hence, in a parallel regression, all the levels of sentiment are replaced by changes in sentiment ($\Delta SENT_t$). $D_t = 0$ if $\Delta SENT_t \leq 0$ and $D_t = 1$ if $\Delta SENT_t > 0$. Similarly, the levels together with changes in investor sentiment are applied respectively to Models 3 and 4. Coefficients of θ_{12}, θ_{13}, θ_{14} and θ_{15} describe the asymmetric effects of sentiment on short- and long-run volatilities.

It is worth pointing out that Lee et al. (2002) introduce the dummy variable I_{t-1} in their model. The intuition of the inclusion of I_{t-1} is to encompass the well-known volatility asymmetry or leverage effect in the financial market. The argument is that investors form their expectations of conditional volatility which may perceive positive and negative shocks differently. If β_2 is negative as expected, a negative shock is more likely to induce a larger upward revision of volatility than a positive shock of the same magnitude. However, this dummy is not included in the EGARCH component model since the parameters of θ_5 and θ_9 of the model already allow for the leverage effect.

Model 3: Investment sentiment only in mean equation which is consistent with Arik (2012)

$$R_{t+1}^M = \theta_1 + \theta_2 s_t + \theta_3 l_t + \theta_{11} SENT_{t+1} + \sqrt{h_t} z_{t+1}$$

$$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6\left(|z_{t+1}| - \sqrt{2/\pi}\right)$$

$$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10}\left(|z_{t+1}| - \sqrt{2/\pi}\right)$$

This model assumes that market sentiment affects the contemporaneous stock returns and has no direct effect on volatility components.

Model 4: Investor sentiment in mean equation and variance equation which is different from the model of Lee et al. (2002)

$$R_{t+1}^{M} = \theta_1 + \theta_2 s_t + \theta_3 l_t + \theta_{11} SENT_{t+1} + \sqrt{h_t} z_{t+1}$$

$$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6 \left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{16} s_t D_t + \theta_{17} s_t (1 - D_t) + \theta_{18} Z_{t+1} D_{t+1} + \theta_{19} Z_{t+1} (1 - D_{t+1})$$

$$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10} \left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{20} l_t D_t + \theta_{21} l_t (1 - D_t) + \theta_{22} Z_{t+1} D_{t+1} + \theta_{23} Z_{t+1} (1 - D_{t+1})$$

Model 2 is in accordance with the framework of Lee et al. (2002) where sentiment enters the models as the intercept dummy and the sentiment directly affects the level of short- and long-run volatilities. In Model 4, sentiment dummies act as the slope dummies, and sentiment influences the short- and long-run volatilities through their impacts on market shocks (Z_{t+1}) and lagged short- and long-run volatilities (s_t and l_t). Through the dummy variables $D_t$and $(1 - D_t)$, both the direction and magnitude of investor sentiment can have an asymmetric impact on conditional variance and market returns.

The short- and long-run sentiment-affected volatility components are obtained from the time series regressions. After that, the Fama-Macbeth two-stage regressions are employed to investigate the cross-sectional pricing abilities of the short- and long-run volatility.

3.4 Data

3.4.1 Data Summation and Description of Sentiment Proxies

Data availability narrows down the sentiment measures considerably. The existing literature suggests a variety of approaches of proxies for sentiment. However, there are no definitive or uncontroversial measures. Hence, the composite index of sentiment which is based on the common variation in the available underline proxies for sentiment is constructed, in accordance with Baker and Wurgler (2004, 2005) and Brown and Cliff (2004). Baker et al. (2012) study the UK stock market as part of their global market; the volatility premium, number and first-day returns of IPOs and turnover by value are employed to construct the UK sentiment index. Corredor et al. (2013) use consumer confidence, turnover and volatility premium to measure the UK sentiment as a part of the European stock market. In this chapter, the individual proxies include share turnover by value on the LSE, share turnover by volume on the LSE, the number and average first-day returns on the IPOS, and consumer confidence. The first four variables are the same as those used in the Baker and Wurgler index, and the aim of the last variable is to compensate for the lack of closed-end fund discounts. The sentiment proxies are measured monthly from October 1986 to December 2012. However, the beginning five data are omitted due to the data process procedure and hence the sample period starts from March 1987.

Market share turnover can be defined both by trading volume and trading values. Market turnover by value is the total sterling value over the month divided by the total capitalisation of the London Stock Exchange (LSE). Market turnover by volume is the number of total share traded on the LSE over the month divided by the number of shares listed on the exchange. The daily trading volume, trading values, total capitalisation of the LSE and total share traded on the LSE are aggregated within each month to get the monthly data respectively. The data are extracted from Datastream Global Equity Indices, which are calculated on a representative list of stocks for each market. The number of stocks for each market is determined by the size of the market and the sample covers a minimum of 75% - 80% of the total market capitalisation.

The numbers of IPOs within each month, denoted by *NO_IPO*, are taken from two sources. One is the New Issue and IPO Summary spreadsheet from the London Stock Market website which has contained the IPO summary since June 1995. The other source is the London Share Price Database (LSPD). The population of the IPOs are identified using the LSPD "birth maker" and investment trust offerings are excluded since they are classified as financial institution offerings.

The first-day return of IPOs is defined as the difference between the initial trading price and the offer price divided by the offer price of the IPO stock. The offer prices are obtained from the Thomson One Bank, the LSE new issue and the IPO Summary, together with the LSPD. The initial trading prices are collected from Datastream as the first day open price. The equal-weighted average first-day returns are then computed and denoted by *RE_IPO*.

Consumer confidence, denoted by *CC*, is a form of business survey data reported by the European Commission for Economic and Financial Affairs. UK respondents express their economic or financial expectations over the next 12 months in the following areas: the general economic situation, the unemployment rate, the personal household financial position and personal savings.

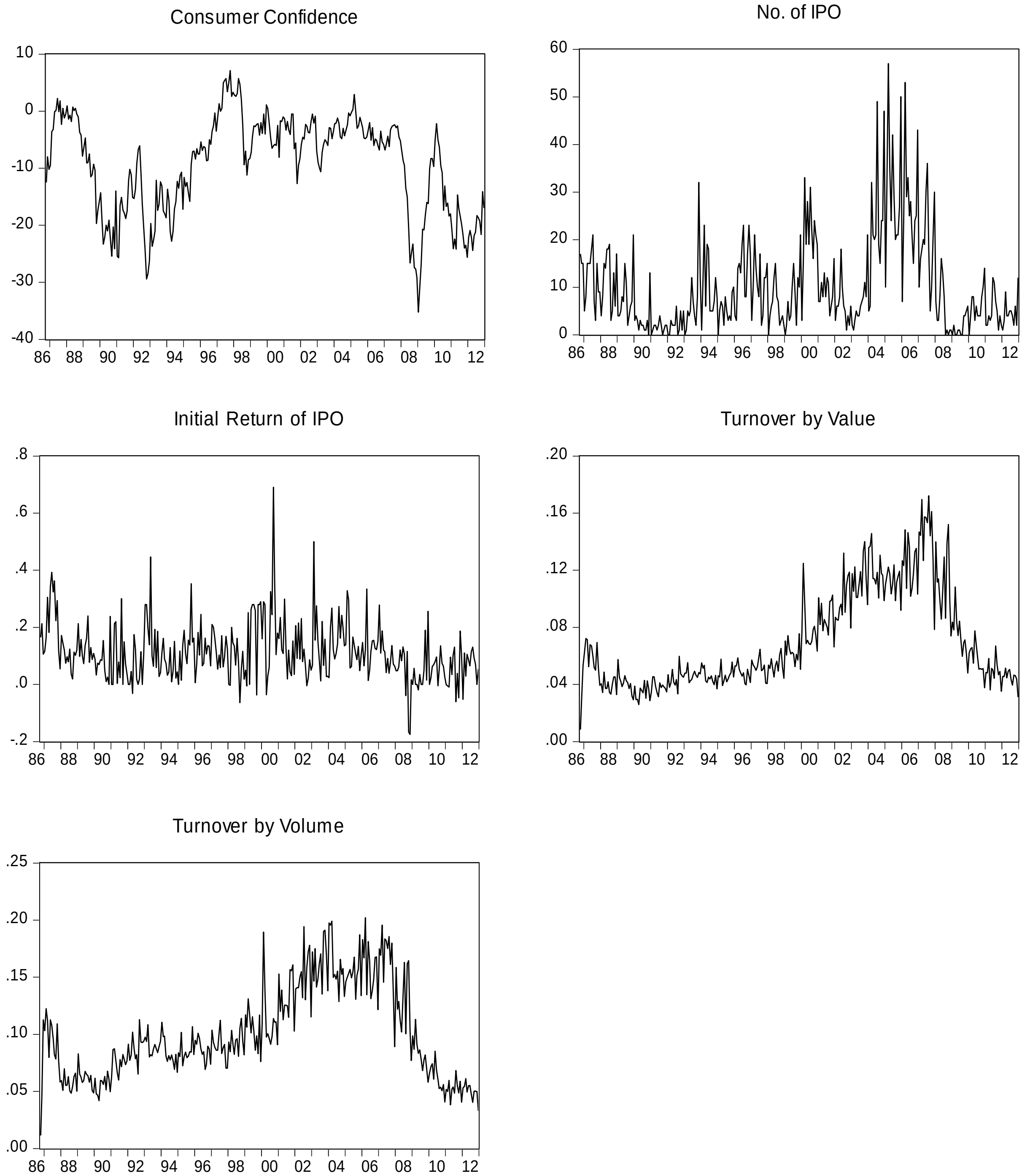


Figure 3.1: Figures of the five raw sentiment measures

3.4.2 Construction of the Level Sentiment Index

Table 3.1: Summary statistics of monthly investor sentiment measures

	Mean	Std. Dev.	Skewness	Kurtosis	Unit root test	*1st lag autocorrelation*
CC	-9.314	8.575	-0.562	2.412	$I(0)^{*}$	0.941^{***}
NO_IPO	10.263	10.025	1.734	6.689	$I(0)^{**}$	0.636^{***}
RE_IPO	0.114	0.102	1.157	6.555	$I(0)^{***}$	0.322^{***}
Turnover_value	0.070	0.034	0.976	2.877	$I(1)$	0.895^{***}
Turnover_volume	0.101	0.041	0.648	2.428	$I(1)$	0.854^{***}

Note: CC represents consumer confidence; NO_IPO represents the number of IPOs within each month; RE_IPO represents the first day return of IPOs; Turnover_value represents the market turnover by value; and Turnover_volume represents the market turnover by volume.

The statistics of the five sentiment measures are presented in table 3.1. All these measures display a skewed and leptokurtic pattern and are rejected by the null hypothesis of normality. The unit root tests detect that there is a time trend in both turnover by value and by volume, so the log of turnovers is used and detrended with an up-to-five-month moving average. The detrended turnovers by value and by volume are defined by *TURN1* and *TURN2*, respectively. After detrending, these two time series become I(0) process. The autocorrelation tests show that the five time series suffers from high autocorrelations, including *TURN1* (with the first lag correlation of 0.103) and *TURN2* (with the first lag correlation of 0.089). The log transformation is applied to the Number and first-day returns of IPOs and the transformed variables are denoted as *NIPO* and *RIPO*.

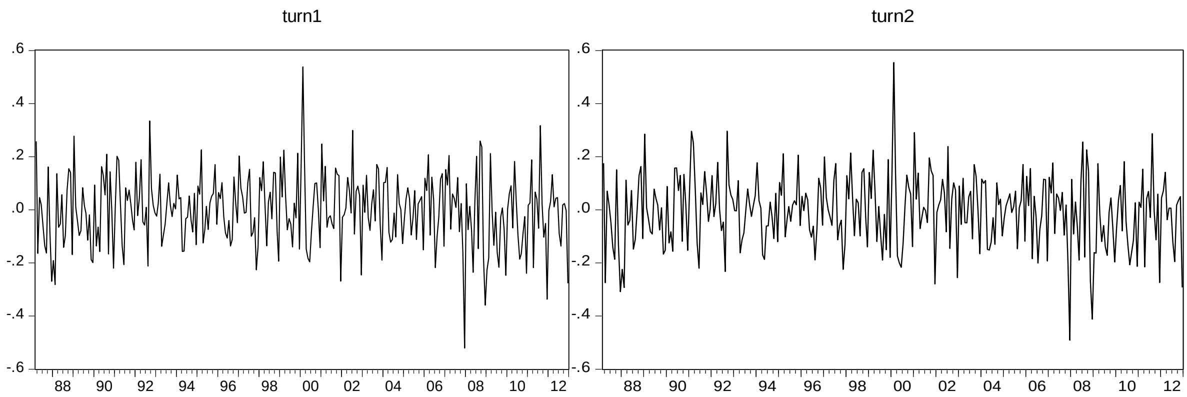


Figure 3.2: Detrended market turnover by value (TURN1) and turnover by volume (TURN2)

Furthermore, sentiment measures reflect economic fundamentals to some extent and hence are likely to contain a sentiment component as well as idiosyncratic components that are not related to sentiment. To control and remove the information about rational factors that the sentiment measures may contain, each proxy are orthogonalised to six available macro series, following Brown and Cliff (2005) and Baker and Wurgler (2006, 2007, 2012).[7] According to the data availability, the following variables are chosen as macro control variables: 1-month Treasury bill return which is the short-term return, the difference in monthly return on 3- and 1-month T-bills, the term spread as measured by the spread in yields on the 10-year Gilt and the 3-month T-bills, inflation rate, industrial production growth, and consumption growth as the control variables.

Table 3.2 shows the correlations of each of the raw proxies and its own variable orthogonalised by the above mentioned macro variables. It turns out that the macro series explains comparatively little of the variation in the sentiment measures, except for consumer confidence. The correlation between the raw and orthogonalised proxies is 88.67% on average across the five measures. The macro control variables that contain contemporaneous and forward-looking information about economic fundamentals are largely unrelated to the investor sentiment proxies. However, Baker and Wurgler (2012) emphasize that it is impossible to rule out that there might be an as-yet undiscovered risk factor driving all of the various relationships between the expected returns and the sentiment measures.

[7] The macro variables suggested by Brown and Cliff (2005) include the 1-month Treasury bill return, the difference in monthly returns on 3-month and 1-month T-bills, the term spread, default spread, dividend yield and rate of inflation. The control variables chosen by Baker and Wurgler (2006, 2007, 2012) are consumption growth, industrial production growth, employment growth, the short-term rate, and the term premium.

Table 3.2: Correlations of the raw proxies and their orthogonalised results

	Raw and orthogonalised *CC*	Raw and orthogonalised *TURN1*	Raw and orthogonalised *TURN2*	Raw and orthogonalised *NIPO*	Raw and orthogonalised *RIPO*
Correlation	0.6628	0.9807	0.9772	0.8645	0.9483

Note: CC represents consumer confidence; Turn1 represents the detrended market turnover by value; and Turn2 represents the detrended market turnover by volume; NIPO represents the log of the number of IPOs with each month; and RIPO represents the log of the first day return of IPOs.

Furthermore, Baker and Wurgler (2006) point out that the sentiment measures might exhibit lead-lag relationships. Some economic variables may reflect a given shift in sentiment earlier than others, and hence the relative timing of the variables should be determined to form a composite index. Baker and Wurgler (2006) assert that proxies that are based directly on investor demand or investor behaviour can be expected to be one period ahead of proxies that involve firm supply responses. Consequently, the turnover and return of IPOs might be one period before the IPO volume. Perhaps sentiment is partly behind the high initial-day returns, and high sentiment attracts more IPO volume with a lag. Similarly, high sentiment triggers more trading volume, and leads to a higher turnover, both in volume and value.

To encompass the issue of the relative timing of the variables, the six proxies together with their lags are included in the principal component analysis (PCA), which will give us a first-stage index with ten loadings, one for each of the current and lagged measures. The correlation between the first-stage index and the current and lagged variables are computed, and each respective proxy's lead and lag, whichever gives a higher correlation with the first-stage index, will be kept for the PCA construction of the final sentiment index. It is worth pointing out that the principal component analysis (PCA) is sensitive to the scaling of the variables. Hence, each orthogonalised variable should be normalised to have a zero mean and unit variance before applying the PCA procedure.

The procedure gives a parsimonious index:

$$SENT_t = 0.202 * CC_{t-1} + 0.670 * TURN1_{t-1} + 0.669 * TURN2_{t-1} + 0.210 * NIPO_t + 0.135 * RIPO_{t-1} \qquad (3.1)$$

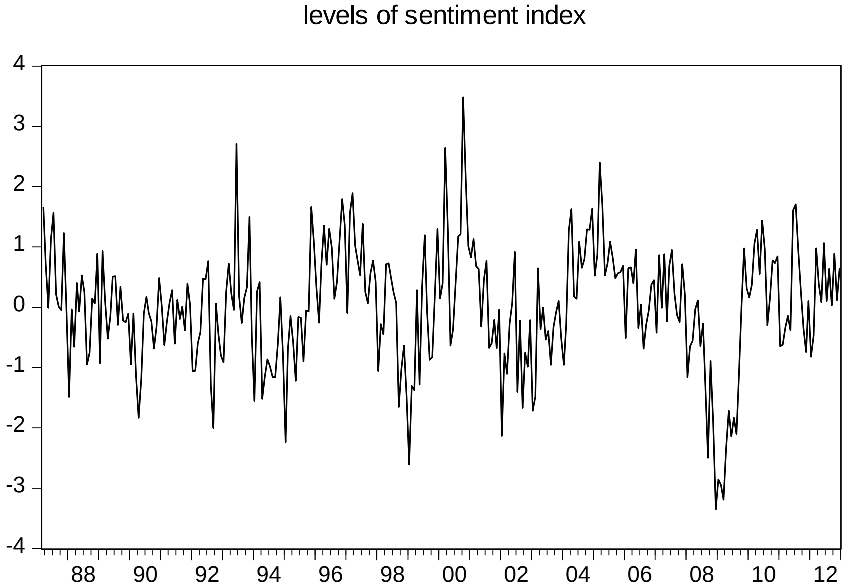
where each of the proxy has been orthogonalised by the mentioned macro variables and then normalised. Note that CC represents consumer confidence; TURN1 represents the detrended market turnover by value; and TURN2 represents the detrended market turnover by volume; NIPO represents the log of the number of IPOs with each month; and RIPO represents the log of the first day return of the IPOs. All the five variables have been orthogonalised to available macro variables. The fraction of variance explained by the first principal component is 52.13%, which suggests that this composite factor captures much of the common variation. Meanwhile, the correlation between the sentiment in equation (3.1) and the 10-term first-stage index is 95.87%. Hence, it may conclude that there is little information loss in dropping the five terms with other time subscripts. The composite sentiment index already has a zero mean and is then standardised to have unit variance.

The SENTIMENT index has two appealing properties: First, as expected, all the five sentiment measures are positively associated with sentiment levels. Second, each individual proxy enters with the expected timing, so that price and investor behaviour variables (consumer confidence, market turnover, returns of IPOs) lead firm supply variables (IPOs volume).

The changes in the index of sentiment levels are obtained by taking the first-order difference.

Figure 3.3: Levels and changes in sentiment index

Panel A: Index of sentiment levels



Panel B: Index of sentiment changes

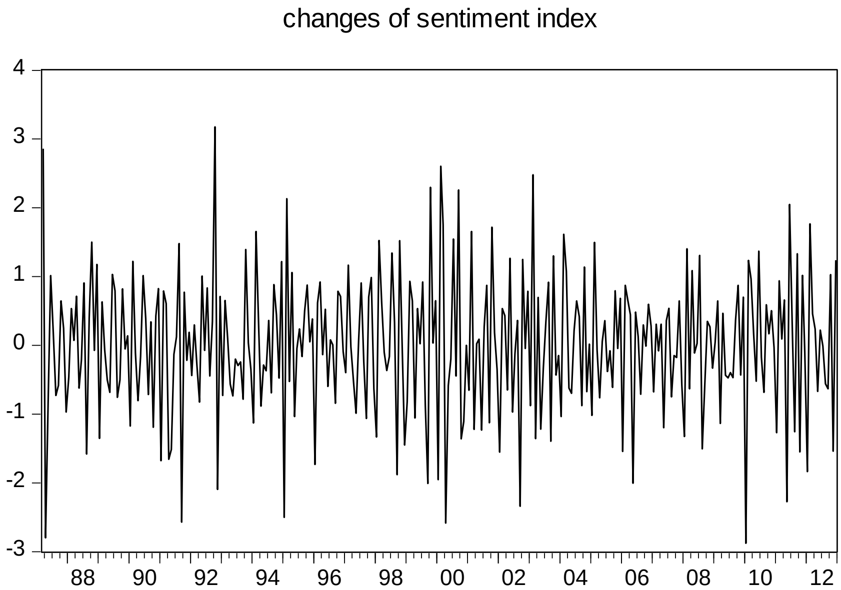


Figure 3.3 depicts the sentiment levels and changes from March 1987 to the end of 2012. There are two obvious patterns that coincide with the history of the UK stock markets. First, sentiment peaks in 2000 which may result from end of the internet bubble in early 2000. Second, sentiment crashes in 2008 and recovers thereafter which may depict the financial crisis from 2007 to 2010.

3.4.4 Granger Causality Test of Market Returns and Sentiment Indices

Recognising that sentiment itself is affected by recent market behaviour, this study seeks to determine the direction of any causal relationships between market return and sentiment. Results from simple bivariate (stock returns and investor sentiment) Granger-Causality tests are shown in table 3.3. As can be inferred, the hypothesis of market return and sentiment are not causal variables to each other and cannot be significantly rejected for lags of one and two. This suggests the time-series independencies between the sentiment measures and market excess returns in the short run. In contrast, for lags of six or twelve, market return is more likely to Granger cause level sentiment, and changed sentiment are more likely to Granger cause excess returns.

Table 3.3: Granger Causality tests of market excess return and investor sentiment (levels and changes) for 1-, 2-, 6 and 6-month lags

Null hypothesis		Lag 1	Lag 2	Lag 6	Lag 12
Market excess return does not Granger cause levels of sentiment	F-stat.	0.480	0.837	3.492	2.293
	p-value	*0.489*	*0.434*	*0.002*	*0.009*
Levels of sentiment does not Granger cause market excess return	F-stat.	1.092	1.264	1.552	2.182
	p-value	*0.297*	*0.284*	*0.161*	*0.013*
Market excess return does not Granger cause changes in sentiment	F-stat.	0.424	0.481	1.674	1.229
	p-value	*0.515*	*0.619*	*0.127*	*0.262*
Changes in sentiment does not Granger cause market excess return	F-stat.	0.012	0.009	3.397	1.189
	p-value	*0.915*	*0.991*	*0.003*	*0.036*

3.5 Empirical Results

3.5.1 Time-series Estimations

The estimation results of the four models are reported in table 3.4. For each of the models including investor sentiment, both the levels and changes of sentiment are estimated respectively. It is worth noting that daily data are applied to the EGARCH component model in the last chapter. However, since the sentiment data are at monthly frequencies, Models 2, 3 and 4 have to be estimated using monthly data. To make the results comparative, the bench mark model, Model 1 is re-estimated using monthly data. Consistent with the daily data, the short-run volatility is positively related to future market returns and the long-run volatility is negatively related to future market returns. The major findings are summarised below.

Table 3.4: Estimation results of the four models in section 3.3.2

	Levels of Sentiment					Changes in Sentiment			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 2	Model 3	Model 4	Model 5
θ_1	3.234**	3.090***	3.535***	1.142***	0.423***	1.179***	2.280***	-0.371	1.171***
θ_2	0.508**	0.139**	0.883***	0.919***	0.664***	0.401***	0.666***	0.780***	1.889***
θ_3	−2.225**	−2.323***	−2.683***	−0.743***	−0.498***	−0.633***	−2.152***	−0.417**	−1.016***
θ_4	0.815***	0.834***	0.898***	0.646***	0.706***	0.705***	0.893***	0.830***	0.717***
θ_5	−0.149***	−0.105***	−0.133***	0.178***	−0.218***	−0.158**	−0.134***	−0.125***	−0.018***
θ_6	0.144**	0.191***	0.096***	−0.173***	0.128***	0.276***	0.225***	0.182***	0.037***
θ_7	0.033***	0.024***	0.036***	0.024***	0.001***	−0.007***	0.056***	0.030**	0.019***
θ_8	0.975***	0.987***	0.975***	0.980***	0.989***	0.947***	0.962***	0.979***	0.988***
θ_9	0.065*	0.057***	0.092***	−0.087***	0.034***	0.043	0.127***	−0.003***	0.037***
θ_{10}	−0.065**	0.016	0.057***	0.314***	−0.037***	−0.178***	−0.003	−0.099***	0.015***
θ_{11}		0.173**	0.426***	0.373***	1.046***				
$\Delta\theta_{11}$						1.576***	1.629***	1.182**	1.656***
θ_{12}		-0.004				0.082***			
θ_{13}		-0.006				−0.602			
θ_{14}		0.008				−0.006			
θ_{15}		0.008				−0.180***			
θ_{16}				0.011**	0.003***			0.120***	0.087***
θ_{17}				−0.001***	−0.001***			−0.034***	−0.123***
θ_{18}				-0.133				-0.034	
θ_{19}				-0.148				0.036	
θ_{20}				−0.337***	−0.345***			−0.065***	−0.659***
θ_{21}				0.362***	0.140***			0.220***	0.627***
θ_{22}				0.188*				0.075	
θ_{23}				0.159				-0.006	
L.H.	-1158.9	-1175.73	-1171.42	-1167.99	-1164.23	-1175.73	-1167.50	-1172.72	-1154.42
AIC	7.542	7.683	7.629	7.648	7.608	7.682	7.628	7.688	7.545
SC	7.662	7.862	7.809	7.877	7.789	7.816	7.761	7.917	7.617

This table shows the time-series regression results of EARCH component and sentiment-augmented EGARCH component model, where sentiment are augmented in various ways, with levels and changes of sentiment respectively.

Model 1: the benchmark model.

$$R_{t+1}^{M} = \theta_1 + \theta_2 s_t + \theta_3 l_t + \sqrt{h_t} z_{t+1} \qquad (1a)$$

$$ln\sqrt{h_t} = l_t + s_t \qquad (1b)$$

$$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6 \left(|z_{t+1}| - \sqrt{2/\pi}\right) \qquad (1c)$$

$$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10} \left(|z_{t+1}| - \sqrt{2/\pi}\right) \qquad (1d)$$

Model 2:

$$R_{t+1}^{M} = \theta_1 + \theta_2 s_t + \theta_3 l_t + \theta_{11} SENT_{t+1} + \sqrt{h_t} z_{t+1}$$

$$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6\left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{12} SENT_t^2 D_t + \theta_{13} SENT_t^2 (1 - D_t)$$
$$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10}\left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{14} SENT_t^2 D_t + \theta_{15} SENT_t^2 (1 - D_t)$$

Model3:

$$R_{t+1}^M = \theta_1 + \theta_2 s_t + \theta_3 l_t + \theta_{11} SENT_{t+1} + \sqrt{h_t} z_{t+1}$$
$$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6\left(|z_{t+1}| - \sqrt{2/\pi}\right)$$
$$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10}\left(|z_{t+1}| - \sqrt{2/\pi}\right)$$

Model 4:

$$R_{t+1}^M = \theta_1 + \theta_2 s_t + \theta_3 l_t + \theta_{11} SENT_{t+1} + \sqrt{h_t} z_{t+1}$$
$$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6\left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{16} s_t D_t + \theta_{17} s_t (1 - D_t) + \theta_{18} Z_{t+1} D_{t+1} + \theta_{19} Z_{t+1}(1 - D_{t+1})$$
$$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10}\left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{20} l_t D_t + \theta_{21} l_t (1 - D_t) + \theta_{22} Z_{t+1} D_{t+1} + \theta_{23} Z_{t+1}(1 - D_{t+1})$$

Model 5:

$$R_{t+1}^M = \theta_1 + \theta_2 s_t + \theta_3 l_t + \theta_{11} SENT_{t+1} + \sqrt{h_t} z_{t+1}$$
$$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6\left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{16} s_t D_t + \theta_{17} s_t (1 - D_t)$$
$$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10}\left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{20} l_t D_t + \theta_{21} l_t (1 - D_t)$$

*Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

The estimation results of the four models are reported in table 3.4. For each of the models including investor sentiment, both the levels and changes of sentiment are estimated respectively. It is worth noting that daily data are applied to the EGARCH component model in last chapter. However, since the sentiment data are at monthly frequencies, Models 2, 3 and 4 have to be estimated using monthly data. To make the results comparative, the bench mark model, Model 1 is re-estimated using monthly data. Consistent with the daily data, the short-run volatility is positively related to future market returns and the long-run volatility is negatively related to future market returns. The major findings are summarised below.

First, across the three models with investor sentiment, almost all of the estimated coefficients in the base models $(\theta_1, \theta_2, \dots, \theta_9)$ are significant, for both levels and changes of sentiment indices. The only one estimate that is not significant is θ_1, which is trivial in the model. The estimates of the short- and long-run volatilities are opposite for all the cases, which supports the fact that existing studies have difficulty detecting a time-series relationship between aggregate risk and expected returns.

Second, the levels and changes of sentiment are significantly positively related to market returns. This suggests that sentiment is an important factor in explaining equity excess returns. On the contrary, in Model 2 where sentiment enters directly into the conditional volatility, the regressions reveal that estimates of both levels and changes of sentiment ($\theta_{12}, \theta_{13}, \dots, \theta_{15}$) are insignificant and the magnitudes are very small. In Model 4, sentiment dummies influence transitory and permanent volatilities through their impacts on market shocks and lagged short- and long-components of volatilities ($\theta_{16}, \theta_{17}, \dots, \theta_{23}$). However, the estimates of sentiment dummy affecting market shocks ($\theta_{18}, \theta_{19}, \theta_{22},\ \theta_{23}$)are insignificant throughout the levels and changes of sentiment. The hypothesis that sentiment or changes of sentiment have no effect on market shocks in the EGARCH component model cannot be rejected statistically. On the contrary, sentiment has significant effects on the short- and long-run volatility ($\theta_{16}, \theta_{17}, \theta_{20}, \theta_{21}$).

The empirical results of Model 2 and 4 suggest further refinement of the specifications of empirical models. In model 3, after dropping the sentiment elements in the volatility equations, all the estimates are significant and the log likelihood and information criteria are improved. Therefore, Model 3 can be treated as a remedy with respect to Model 2. Model 5 which drops the effects of sentiment dummy on return shocks is proposed to rectify Model 4.

$$R_{t+1}^{M} = \theta_1 + \theta_2 s_t + \theta_3 l_t + \theta_{11} SENT_{t+1} + \sqrt{h_t} z_{t+1}$$

$$s_{t+1} = \theta_4 s_t + \theta_5 z_{t+1} + \theta_6 \left(|z_{t+1}| - \sqrt{2/\pi} \right) + \theta_{16} s_t D_t + \theta_{17} s_t (1 - D_t)$$

$$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 z_{t+1} + \theta_{10}\left(|z_{t+1}| - \sqrt{2/\pi}\right) + \theta_{20} l_t D_t + \theta_{21} l_t (1 - D_t)$$

After the refinement, the estimates are all significant. Again, the shift in sentiment has a significant positive impact on market excess returns. The increase in log-likelihood value and the decrease of information criteria attest to an improvement in the goodness of fit for either the level or the changes of sentiment index. The estimation results are shown in Table 3.4.

As pointed out by the DSSW model, when investor sentiment is bullish, the trading of noise traders creates a price pressure that leads to a purchase price higher than the fundamental value and thereby lowers expected returns. On the other hand, when noise traders are bullish, they increase their demand for the risky assets which amplifies the level of market risk, which is known as hold-more effect. Hence, they thereby expect to enjoy a higher return. The overall effect of sentiment on stock returns depends on which effect dominates. Therefore, the significant positive estimates of sentiment ($\theta_{11}, \Delta\theta_{11}$) imply that the hold-more effect dominates the price-pressure effect. The hold-more effect tends to dominate the price-pressure effect and leads to an increase in market excess return when investors are more bullish.

Third, the estimations of Model 5 illustrate that both the levels and changes of sentiment have significant and asymmetric effects on short- or long-run volatility that in turn influence the future short- or long-run volatility respectively. When noise traders are bullish, sentiment has a significantly positive, though little, impact on short-run volatility (θ_{16}) which further increases future short-run volatility, whereas sentiment is negatively related to long-run volatility (θ_{20}) and decreases future long-run volatility. Combined with the signs of coefficients on short- (θ_2) and long-run volatility (θ_3) in the mean equation, the overall outcome of direct sentiment, variations of short- and long-run volatilities triggered by sentiment is an increase in market excess return, when investors are optimistic. On the contrary, when sentiment is bearish, sentiment has a negative impact on short-run volatility and a positive impact on long-run volatility. The overall effect of sentiment, variations of short- and long-run volatilities triggered by sentiment is a decrease in market excess return.

Specifically, given a positive sentiment, a 1% increase in sentiment results in a 0.3% increase in future short-run volatility and -34.5% decrease in future long-run volatility. The overall effect of a 1% increase in sentiment leads to a 1.220% increase in market excess return. When sentiment is bearish, the overall effects of a 1% decrease in sentiment leads to a 1.116% lower excess return. The patterns of the effects of changes in sentiment on excess return are similar to levels of sentiment. A 1% upward shift after a positive change in sentiment results in a 2.49% increase in market excess return. A 1% percent downward shift after a negative change in sentiment results in a 2.53% decrease in market excess return.

Finally, Model 3 is preferred to Model 2, and Model 5 is preferred to Model 4. However, Models 3 and 5 are not more favourable compared to the benchmark model in the time-series analysis, since the log-likelihood value and information criteria are not improved.

3.5.2 Cross-sectional Regressions

In section 5.1, the sentiment affected transitory and permanent volatilities are obtained from the time- series estimation of the sentiment-augmented Adrian and Rosenberg's EGARCH component model.

In this section, the short- and long-run sentiment-augmented volatilities are treated as state variables. The Fama-Macbeth two-stage regression is employed to determine whether these two volatilities are at different horizons after the introduction of investor sentiment remains significantly priced across assets. Meanwhile, the adjusted R-square and the root-mean-squared pricing errors are reported to examine whether the sentiment-augmented EGARCH component model outperforms the benchmark model which does not take investor sentiment into account.

For the cross-sectional pricing tests, the innovations of short- and long-run volatilities are acquired by subtracting the short- and long-run components from the value expected one month earlier. This is different from the way that innovations are constructed in the last chapter, since the monthly frequency data are employed directly in this chapter.

$$sres_m = s_m - E_{m-1}\ [s_m] \tag{3.2}$$

$$lres_m = l_m - E_{m-1}\ [l_m] \tag{3.3}$$

This section analyses the refined models where investor sentiment affects the mean equation only (Model 3) and impacts both the mean and conditional volatility (Model 5). The estimated prices of risks, including the transitory volatility, the permanent volatility and the aggregate volatility, are presented in table 3.5. Panel A reports the results of Model 3 and Panel B reports the results of Model 5. Both panels are displayed with the statistics of the benchmark model, Model 1. To compare the overall performance of the model specifications, the adjusted cross-sectional R-square and root-mean-squared pricing errors are provided to describe how well the model fits the data.

Table 3.5: Summary statistics of the cross-sectional Fama-MacBeth regression for the 25 size and book-to-market-sorted portfolios

This table reports the two-stage cross-sectional regression results for the 25 size and BE/ME-sorted portfolios under ICAPM model with different state variables. Specifically, column (i) uses market excess return and innovations of short- and long-run volatilities from Model 1 of Table 3.4 as state variables. Column (ii) uses market excess return and aggregate volatility innovation from Model 1 of Table 3.4 as state variables. Columns (iii) to (vi) of Model 3 use market excess return and innovations of short- and long-run volatilities from Model 3 of Table 3.4. Columns (iii) to (vi) of Model 5 use market excess return and innovations of short- and long-run volatilities from Model 5 of Table 3.4. The *t*-ratios are calculated using Jagannathan and Wang (1998) and Newey and West (1987) procedures to account for the estimation errors in the first-stage estimation and correct for possible heteroskedasticity and autocorrelation. The adjusted R^2 and root-mean-squared pricing errors (RMSPE) are reported.

Panel A: The cross-sectional regression of Model 3, using levels and changes of sentiment respectively

		Model 1		Model 3			
		No sentiment		Level of sentiment		Change in Sentiment	
		(i) (s,l)	(ii) (variance)	(iii) (s,l)	(iv) (variance)	(v) (s,l)	(vi) (variance)
Market excess return	Coef.	-0.432^{***}	-0.853^{***}	-0.456^{***}	-0.848^{***}	-0.392^{***}	-0.577^{***}
	t-stat.	*-3.266*	*-4.302*	*-3.552*	*-3.981*	*-2.871*	*-3.142*
Short-run volatility	Coef.	-0.289^{**}		-0.278^{***}		-0.237^{*}	
	t-stat.	*-3.567*		*-5.355*		*-1.723*	
Long-run volatility	Coef.	-0.303^{***}		-0.300^{**}		-0.285^{***}	
	t-stat.	*-3.812*		*-2.732*		*-3.299*	
Market variance	Coef.		-1.789^{*}		-3.862^{**}		-3.964^{***}
	t-stat.		*-1.847*		*-2.161*		*-4.151*
Adjusted R-square		0.392	0.326	0.552	0.488	0.545	0.455
RMSPE		0.181	0.233	0.102	0.129	0.107	0.184

Panel B: The cross-sectional regression of Model 5, using levels and changes of sentiment respectively

		Model 1		Model 5			
		No sentiment		Level of Sentiment		Change in Sentiment	
		(i) (s,l)	(ii) (variance)	(iii) (s,l)	(iv) (variance)	(v) (s,l)	(vi) (variance)
Market excess return	Coef.	-0.432^{***}	-0.853^{***}	-0.262^{*}	-0.298^{**}	-0.927^{***}	-1.267^{***}
	t-stat.	-3.266	-4.302	-2.045	-2.353	-3.171	-3.455
Short-run volatility	Coef.	-0.289^{***}		-0.579^{***}		-0.337^{**}	
	t-stat.	-3.567		-4.698		-2.264	
Long-run volatility	Coef.	-0.303^{***}		-0.457^{***}		-0.390^{***}	
	t-stat.	-3.812		-5.238		-4.040	
Market variance	Coef.		-1.789^{*}		-4.718^{**}		-3.883^{**}
	t-stat.		-1.847		-2.161		-2.536
Adjusted R-square		0.392	0.382	0.555	0.522	0.537	0.520
RMSPE		0.181	0.240	0.101	0.112	0.114	0.116

*Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

Column (i) of Panel A shows that by applying monthly data, the short- and long-run components of volatility have significant negative prices. The price of aggregate volatility is also significantly negative as shown in column (ii). The short- and long-run sentiment (or sentiment changes)-affected volatility of Model 3 are significantly negative pricing factors in the cross-section as shown in column (iii) and (column (v)). Their respective aggregate volatilities are also significantly negatively priced across portfolios. The conclusions hold true for Model 5 as reported in Panel B.

In terms of pricing performance, there are three main inferences. First, the EGARH component volatility decomposition model compares favourably with the aggregate volatility model proposed by Ang et al. (2006). Second, after the introduction of investor sentiment, the goodness of fit of Model 3 and Model 5 is greatly enhanced. Finally, level sentiment-affected specifications outperform the specifications with changed sentiment-affected volatilities, for both Model 3 and Model 5.

3.6 Robustness Analysis

3.6.1 Robustness Analysis with Alternative Sample Period

In this section, the cross-sectional pricing results over different sample periods are examined and depicted in Table 3.6. The regressions show that the prices of risk for the two volatility components are significantly negative across sample periods, regardless of the model specification, for both levels and changes in investor sentiment. The magnitudes of the prices of risk for the two volatility components are fairly similar across sample periods, suggesting that the results are robust to model specification and sample selections.

Table 3.6: Prices of risks over different sub-samples

This table reports the two-stage cross-sectional regression results for the 25 size and BE/ME-sorted portfolios using different sample periods. The state variables used are market excess return and innovations of short- and long-run volatilities from Model 3 and Model 5 of Table 4, respectively. The *t*-ratios are calculated using the Jagannathan and Wang (1998) and Newey and West (1987) procedures to account for the estimation errors in first-stage estimation and correct for possible heteroskedasticity and autocorrelation. The adjusted R^2 and root-mean-squared pricing errors (RMSPE) are reported.

Panel A: summary statistics of Fama-MacBeth regressions of Model 3 using different sample periods, for levels and changes of sentiment respectively

		Level of Sentiment			Change in Sentiment		
		(i)	(ii)	(iii)	(i)	(ii)	(iii)
Excess market return	Coef.	−0.456*	−1.005*	−1.118**	-0.392**	-1.817***	−1.25**
	t-stat.	*-2.011*	*-2.636*	*-3.322*	*-2.667*	*-3.523*	*-2.611*
Short-run volatility	Coef.	−0.417***	−0.378*	−0.391**	−0.237*	−0.347***	−0.358**
	t-stat.	*-5.355*	*-2.868*	*-2.116*	*-1.723*	*-3.577*	*-2.533*
Long-run volatility	Coef.	-0.450**	−0.463*	−0.415*	−0.285***	−0.404**	−0.305*
	t-stat.	*-2.732*	*-1.918*	*-1.944*	*-3.299*	*-2.481*	*-1.771*
Adjusted R-square		0.552	0.637	0.488	0.545	0.516	0.455
RMSPE		0.102	0.081	0.097	0.107	0.116	0.185

Panel B: summary statistics of Fama-MacBeth regressions of Model 5 using different sample periods, for levels and changes of sentiment respectively

		Level of Sentiment			Change in Sentiment		
		(i)	(ii)	(iii)	(i)	(ii)	(iii)
Excess market return	Coef.	−0.262***	−1.625***	−1.697*	-0.927***	−1.930***	−1.386*
	t-stat.	*-2.878*	*-2.978*	*-1.756*	*-2.853*	*-3.918*	*-1.965*
Short-run volatility	Coef.	−0.579***	−0.473***	−0.346**	-0.337**	−0.297*	−0.491*
	t-stat.	*-4.698*	*-3.126*	*-2.140*	*-2.264*	*-1.867*	*1.773*
Long-run volatility	Coef.	−0.457***	−0.470**	−0.461*	−0.390***	−0.325*	−0.396***
	t-stat.	*-5.238*	*-2.266*	*-1.188*	*-4.040*	*-1.930*	*-4.988*
Adjusted R-square		0.555	0.567	0.491	0.537	0.548	0.446
RMSPE		0.101	0.099	0.112	0.114	0.100	0.179

Column (i): sample period from 1987m03 to 2012m12, which is the full sample period;
Column (ii): sample period from 1987m03 to 2007m06, which is before crisis period;
Column (iii):sample period from 1987m03 to 2012m12, excluding period of 2007m07 to2010m06, which is clarified as crisis period.
*Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

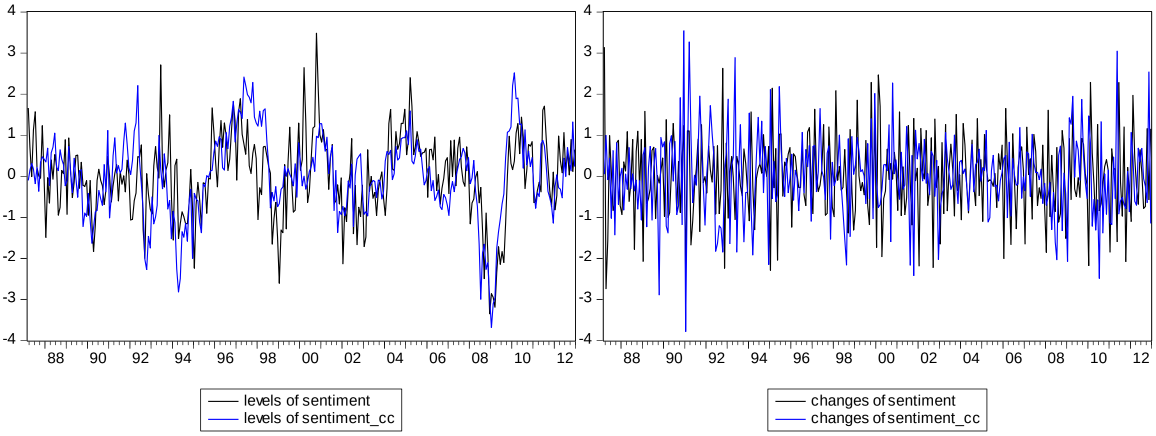
The estimations of the sample period before the crisis shown in column (ii) achieve the highest adjusted cross-sectional R^2 and lowest pricing errors. It can be inferred that the sentiment-augmented EGARCH component model fits the sample period better before the crisis period, whereas the estimations of the sample excluding the crisis period acquire the lowest goodness of fit.

3.6.2 Robustness Analyses of Different Measures of Investor Sentiment

This section demonstrates a robustness test on the construction of the sentiment index. A host of robustness checks is undertaken to examine if the results are driven by some admittedly arbitrary choice. An alternative proxy for investor sentiment, the consumer confidence, as a direct investor sentiment measure is considered. Furthermore, in the framework of principal component analysis, the put-call trading volume and open interest ratios of the derivative market are included to construct a new composite sentiment index, in comparison with the sentiment analysed in the previous sections.

3.6.2.1 Consumer Confidence as an Alternative to Proxy for Investor Sentiment

Figure 3.4: Graphs of sentiment from different measures (March 1987 to December 2012)



The consumer confidence is orthogonalised to the control variables and the residuals are taken as the level sentiment measures ($SENT^{CC}$). The residuals from the changed consumer confidence are treated as measures of changed sentiment ($\Delta SENT^{CC}$). There is no Granger causality relationship between market excess return and consumer confidence in the short duration, for example, within 2 months. The correlation between the $SENT$ and $SENT^{CC}$ is 0.578, while the correlation between the changed sentiment between $\Delta SENT$ and $\Delta SENT^{CC}$ is 0.231 which is surprisingly not very high. The graphs of these sentiment measures are depicted in Figure 3.4.

Table 3.7 presents the cross-sectional estimation results using short- and long-run volatilities from the sentiment-augmented EGARCH component model where the consumer confidence is used directly as the measure of investor sentiment. The prices of the short- and long-run components are significantly negative. The magnitudes of the estimates are smaller compared to those reported in Table 3.5.

Table 3.7: The Fama-MacBeth regressions of prices of short- and long-run sentiment-affected volatilities.

This table reports the two-stage cross-sectional regression results for the 25 size and BE/ME-sorted using innovations of short- and long-run volatilities estimated from Model 3 and Model 5 employing consumer confidence as investor sentiment. The *t*-ratios are calculated using the Jagannathan and Wang (1998) and Newey and West (1987) procedures to account for the estimation errors in first-stage estimation and correct for possible heteroskedasticity and autocorrelation. The adjusted R^2 and root-mean-squared pricing errors (RMSPE) are reported.

		Level of Sentiment		Change in Sentiment	
		Model 3	Model 5	Model 3	Model 5
Market excess return	Coef.	-0.639^{**}	-0.815^{**}	-0.782^{**}	-0.262^{*}
	t-stat.	*-2.455*	*-2.572*	*-2.263*	*-1.956*
Short-run volatility	Coef.	-0.151^{***}	-0.222^{***}	-0.167^{**}	-0.269^{**}
	t-stat.	*-3.302*	*-3.321*	*-2.374*	*-2.068*
Long-run volatility	Coef.	-0.270^{***}	-0.204^{*}	-0.331^{**}	-0.211^{*}
	t_stat.	*-3.219*	*-1.993*	*-2.105*	*-2.051*
Adjusted R-square		0.447	0.516	0.491	0.555
RMSPE		0.171	0.106	0.134	0.105

Note: Consumer confidence works as a direct proxy for investor sentiment
*Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

3.6.2.2. The first principal analysis of sentiment index with the inclusion of data of FTSE 100 options

The put-call trading volume ratio, denoted as PCT, is widely recognised as a bearish indicator. It is a measure of the market participants' sentiment derived from options which is equal to the trading volume of put options over the trading volume of call options. Investors tend to buy put options either to hedge their spot positions or to speculate when they are bearish. When the trading volume of the put options becomes large with respect to the trading volume of the call option, the ratio goes up, and vice versa.

An alternative approach to calculate the put-call volume ratio is to use the open interest of options instead of the trading volume. It may be argued that the open interest ratio is the final picture of sentiment at the end of the day or on a monthly basis and therefore, it might be a preferred measure of sentiment index. The put-call open interest ratio is labelled as PCO.

The trading volume and open interests of FTSE 100 option (UKX) are used to calculate the put-call trading volume and open interest ratios. The data of the trading volume and open interest are taken from Bloomberg. Unfortunately, the trading volume data start from 31/10/1994 while the complete data of open interests only originate from 31/12/1998. For convenient consideration, the new composite sentiment index is formed from December 1998 to December 2012. The procedure of forming this new sentiment and its changed values are the same as described in Section 3.4.2. The parsimonious new sentiment is presented in Equations (3.4).

$$SENT_t^{new} = 0.341 * CC_{t-1} + 0.542 * TURN1_{t-1} + 0.547 * TURN1_{t-1} + 0.3506 * NIPO_t \\ + 0.231792 * RIPO_{t-1} + 0.192 * PCO_{t-1} + 0.279 * PCT_t \tag{3.4}$$

The first principal component of level proxy explains 51.79% of the total variance. There is no Granger causality relationship between the new sentiment index and market excess returns for one- and two-month lags.

Table 3.8: Correlations of the three sentiment measures and changes in sentiment measures

	$SENT$	$SENT^{CC}$	$SENT_t^{new}$		$\Delta SENT$	$\Delta SENT^{CC}$	$\Delta SENT_t^{new}$
$SENT$	1.000			$\Delta SENT$	1.000		
$SENT^{CC}$	0.674	1.000		$\Delta SENT^{CC}$	0.293	1.000	
$SENT_t^{new}$	0.906	0.674	0.622	$\Delta SENT_t^{new}$	0.935	0.210	1.000

The correlation of the levels of sentiment and changes in sentiment measured from three alternative approaches are reported in Table 3.8. Sentiment with and without the inclusion of option data are highly correlated with each other, for both levels and changes of sentiment. The graphs of levels and changes of sentiment measured from three different ways are exhibited in Figure 3.5.

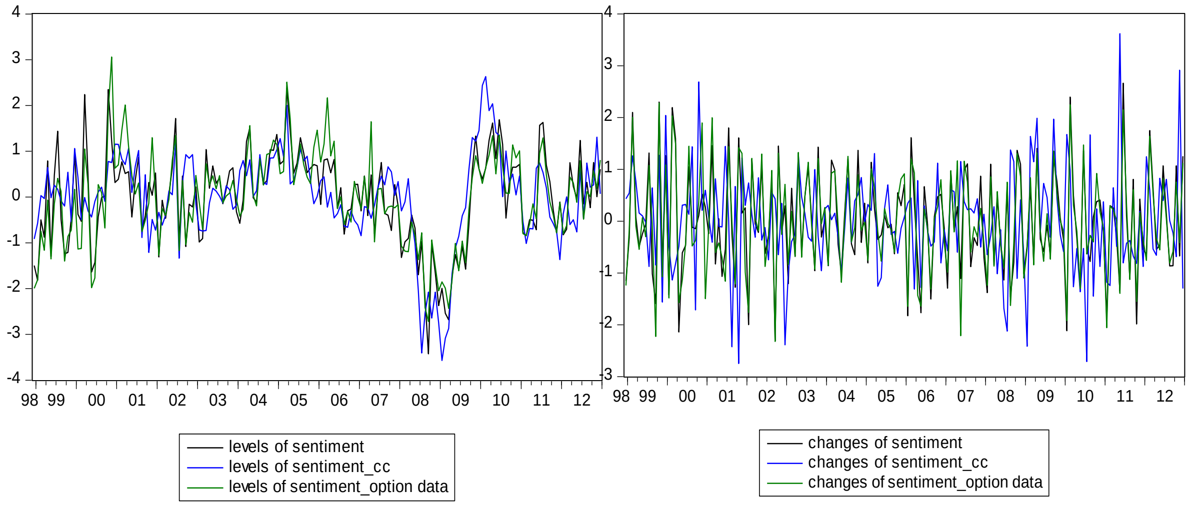


Figure 3.5: Graphs of sentiment from different measures (December 1998 to December 2012)

Table 3.9 shows the cross-sectional estimation results using short- and long-run volatilities from the sentiment-augmented EGARCH component model where the put-call trading volume, as well as the open interest ratios of the FTSE 100 options, are taken into account for the first principal analysis. The prices of the short- and long-run components are significantly negative. As displayed in table 3.7, the magnitudes of the estimates are higher compared to those shown in Table 3.5. However, the adjusted R-square is reduced and the root-mean-squared price errors are increased in most cases.

Table 3.9: The Fama-MacBeth regressions of prices of short- and long-run sentiment-affected volatilities

This table reports the two-stage cross-sectional regression results for the 25 size and BE/ME-sorted using innovations of short- and long-run volatilities estimated from Model 3 and Model 5 employing the new composite sentiment index with option data. The *t*-ratios are calculated using the Jagannathan and Wang (1998) and Newey and West (1987) procedures to account for the estimation errors in the first-stage estimation and correct for possible heteroskedasticity and autocorrelation. The adjusted R^2 and root-mean-squared pricing errors (RMSPE) are reported.

		Level of Sentiment		Change in Sentiment	
		Model 3	Model 5	Model 3	Model 5
Market excess return	Coef.	-1.081^{**}	-0.488^{*}	-1.214^{***}	-0.483^{**}
	t-stat.	*-2.195*	*-2.038*	*-2.793*	*-2.288*
Short-run volatility	Coef.	-0.462^{*}	-0.880^{***}	-0.489^{***}	-0.343^{***}
	t-stat.	*-2.037*	*-2.973*	*-2.346*	*-5.636*
Long-run volatility	Coef.	-0.576^{*}	-0.926^{***}	-0.611^{**}	-0.599^{***}
	t-stat.	*-1.835*	*-2.601*	*-2.011*	*-3.490*
Adjusted R-square		0.434	0.437	0.437	0.520
RMSPE		0.155	0.157	0.189	0.118

Note: Levels of Investor sentiment are measured in Equations (3.5) with the inclusion of put-call trading data in addition to the previous five variables.
*Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

In conclusion, the volatility components remain highly significant for different sample periods and the significance is robust to the choice of the measures of investor sentiment.

3.7 Conclusion

lassical finance theory leaves no role for investor sentiment in cross-section of stock prices, realised returns, or expected returns. This view has been challenged by researchers in behavioural finance. Empirical results suggest that investor sentiment has significant cross-sectional effects.

The DSSW model predicts that the direction and magnitude of noise trading risk are relevant in asset pricing. Noise traders' belief, recognised as investor sentiment, affects asset returns and systematic risks in this model. Lee et al. (2002) propose a GARCH-in-mean specification to explicitly test the impact of noise trader risk on both the formation of expected return and conditional volatility. Inspired by the studies of DSSW (1990), Lee et al. (2002) and Adrian and Rosenberg (2008), a sentiment-augmented EGARCH component model is used to exploit the time-series relationship between sentiment and market return and market volatilities. This study further tests the cross-sectional prices of the short- and long-run components of market volatility which are affected by investor sentiment.

By augmenting sentiment to the mean of Adrian and Rosenberg's EGARCH component model, or to both the mean and variance equations, market excess returns are significantly positively related to investor sentiment and the changes in investor sentiment in the time-series estimations. This suggests that investor sentiment helps to explain market excess return and risk-averse investors require sentiment risk compensation for holding market portfolio. The significance of sentiment on conditional short- and long-run volatility implies that Adrian and Rosenberg's EGARCH component model and other conventional measures of temporal variation in risk neglect an important factor. Market sentiment and noise trading should affect the volatility of market return. The permanent effect of noise trading on expected returns is also through its impact on the market's formation of risk. These results are in line with the market reaction to noise trading as suggested by the DSSW model. Hold-more and price-pressure effects impact stock return directly while Friedman and create-space effects increase price variation risk and further alter stock return.

In the cross-sectional estimations, significantly negative prices of the short- and long-run components of volatility are detected. The results are consistent with those in the previous chapter and risk-averse investors are willing to pay a premium to hedge against future uncertainty. The models which take market sentiment into consideration outperform the pure EGARCH component model since they achieve higher explanatory power indicated by a larger adjusted R-square and lower pricing errors. Therefore, the incorporation of sentiment enhances the pricing ability of the short- and long-run volatilities of the EGARCH component model. Investor sentiment has important effects on stock returns and volatility. The conclusion is robust to the choice of sample periods and alternative constructions of investor sentiment.

Chapter 4 Cross-Sectional Effects of Investor Sentiment on Stock Returns in UK Stock Market

4.1 Introduction

Behavioural finance theory advocates that investor sentiment has an impact on trading decisions. The influence of sentiment on investors' future expectations leads to the over- or under-pricing of stocks and hence affects the pricing of assets. There are two basic assumptions of behavioural finance. First, investors are subject to sentiment; investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by facts or economic theory. Second, betting against sentimental investors is costly and risky. Noise traders are subject to the influence of sentiment. They act in concert on non-fundamental signals and drive price away from asset's intrinsic value (Black, 1986; Kumar and Lee, 2006). Rational arbitrageurs are risk averse and have limits on arbitrage positions and investment horizons. Their limitation of arbitrage leads to a failure of completely eliminating mispricing. Therefore, investor sentiment introduces a systematic risk that is priced and affects asset prices in equilibrium (DeLong et al., 1990).

The previous chapter concentrates on the effect of sentiment and market return and aggregate volatility and demonstrates that investor sentiment influences market return directly and also through their effects on the previous short- and long-run volatility. This chapter shifts the research interest to examine the impact of sentiment on individual firms. A large body of research provides theoretical and empirical evidences that sentiment exhibits cross-sectional effects and predictive power and on individual stock returns.

First, theoretical studies base their research on premises derived from evidence in psychological studies to explain the effect of sentiment on individual stocks. Barberis et al. (1998) propose a parsimonious model of investor sentiment motivated by two psychological phenomena known as the representativeness heuristic and conservatism. Their model suggests that particular categories of stocks will be more affected by sentiment than others; there are differences in the response of stock prices to the bullishness or bearishness of the market leading to relative mispricing; and stocks of firms with specific characteristics are more exposed to noise trader sentiment. Daniel et al. (1998a, 1998b) also construct a model of investor sentiment using concepts from psychology such as overconfidence and self-attribution. They suggest that the effects of overconfidence should be more severe in less liquid securities and assets and hence large liquid stocks tend to be more rationally priced. On the other hand, less liquid or small stocks are more exposed to sentiment.

Second, recently, more empirical studies attempt to explore the predictive ability of investor sentiment on the cross-section of stock returns (Solt and Statman, 1988; Brown and Cliff, 2005). More specifically, most of the research attempts to examine the impact of the aggregate wave of sentiment on individual stocks with different firm characteristics. Using various measures of investor sentiment and methodologies, research focuses on the exploration of return spreads of firms with distinct characteristics, such as firms with different market capitalisation and BE/ME (Brown and Cliff (2005); Baker and Wurgler (2006); Lemmon and Portniaguina (2006); Berger and Turtle (2012) and Ho and Hung (2013)). Baker and Wurgler (2006) suggest that stocks that are hard to arbitrage and difficult to value are more vulnerable to investor sentiment.

Despite the fact that numerous publications focus on the cross-sectional effect of investor sentiment, most of the research concentrates on the US stock market. Studies related to the UK stock market are mostly as a constituent of international financial markets and examine the impact of investor sentiment on the aggregate stock market (Baker and Wurgler, 2012; Bathia and Bredin, 2013; Corredor et al., 2013).

This chapter studies the role of investor sentiment on the cross-section of stock returns of the UK market. Two measures of sentiment index are employed as in the previous chapter. The principal component analysis (PCA) is employed to construct a composite sentiment index following Baker and Wurgler (2006) and survey data; consumer confidence, is used as a direct measure of sentiment for the purpose of robustness.

In the first part of the study, stocks are sorted into 10 portfolios according to their different levels of sensitivities to investor sentiment and examined characteristics of stocks that display different levels of sentiment sensitivity. The study starts with the estimation of the sensitivity of the excess returns on individual stocks to the changes of investor sentiment index (Lee et al.,1991; Berger and Turtle, 2012). The sentiment beta is estimated for each non-financial stock listed on the London Stock Exchange from March 1987 to December 2012 on a monthly rolling basis and stocks are then ranked by their absolute values of sentiment beta. The research finds that the sensitivities of investor sentiment vary monotonically with certain firm characteristics in the cross-section corroborating the conjecture of Baker and Wurgler (2006).

In the next part of the study, stocks are sorted into ten portfolios based on their firm characteristics to examine their returns conditional on investor sentiment. Two models are used to investigate the predictive power of the long-short portfolios. The first model follows Baker and Wurgler (2006) and the second model is in line with Lemmon and Portniaguina (2006). Both methodologies suggest that the measures of investor sentiment forecast the returns of portfolios that consist of buying stocks with high values of a characteristic, and selling stocks with low values. In particular, Lemmon and Portniaguina (2006) decompose investor sentiment into rational and irrational components. In the framework of conditional ICAPM, their model compromises the rational and irrational components of sentiment and both components exhibit the predictive power on returns of long-short portfolios. Further evidence is provided that the cross-sectional effects of investor sentiment are not likely to be compensation for systematic risk.

The empirical results suggest that investor sentiment is an important factor in the return generating process of common stocks. Given the predictive power of investor sentiment, the profitability of the strategy that is long on stocks most exposed to sentiment and short on stocks least exposed to sentiment is explored. This strategy generates a significant profit which cannot be fully explained by the traditional risk factors, such as market excess return, size risk factor (SMB), value risk factor (HML), momentum risk factor (UMD) or liquidity risk premium (LIQ).

To test whether investor sentiment exerts explanatory power in the cross-section of stock returns, a sentiment risk factor is constructed. The sentiment risk premium is defined as the difference of the average returns of firms most sensitive to sentiment and the average returns of firms least sensitive to sentiment. Although sentiment index is directly calculated using various methods in the existing literature, such an index describes the aggregate market investment and does not shed light on the sensitiveness at the level of individual stocks. The analysis has demonstrated that firms that are most exposed to sentiment also tend to be the smallest firms and firms with extreme BE/ME ratios. To avoid confounding the size and value effects with the sentiment effect, the independent triple-sort procedure is proposed. Stocks are sorted into groups independently by size, BE/ME ratio and stock sentiment beta. Eighteen portfolios are constructed from the intersections of the two size groups, three BE/ME groups and three sentiment-prone groups. The return spread of the six portfolios most exposed to sentiment and the six portfolios least exposed to sentiment is the sentiment risk premium factor, denoted as SRP in the rest of this chapter.

After the construction of the sentiment risk premium factor, the research attempts to investigate whether this factor contributes to explaining the abnormal returns of portfolios with high sentiment sensitivities and the increments of the explanatory power of these portfolios. Furthermore, the effects of sentiment risk factor on size and BE/ME portfolios are explored.

The motivations and contributions of this study to the literature are summarised as follows. Firstly, to my best acknowledge, the existing research relating to the UK market mainly examines the UK stocks as part of the international stock market. There is little in-depth research to explore the sentiment effect on stock returns concentrating on the UK stock market. Secondly, the research related to the UK stock market only investigates the impacts of sentiment on the aggregate stock market. None of them look into the cross-sectional effects of investor sentiment on individual stocks despite the fact that the cross-sectional effects of sentiment have been well examined in the US market. This thesis focuses on the UK stock market and involves a large set of data, including financial and accounting data, to examine sentiment effects on stocks with different firm characteristics. Thirdly, this chapter constructs sentiment-prone portfolios according to sentiment sensitivity of each stock. A triple-sort procedure is established to construct the sentiment risk factor. The independent sorting procedure enables us to isolate the size and value effects. The factor model augmented by the sentiment risk factor in addition to the traditional risk factors outperforms the traditional factor model.

The rest of this chapter is organised as follows. The next section provides a brief literature review and section 4.3 describes the data used in this chapter. The first part of section 4.4 constructs portfolios based on sentiment sensitivities and investigates portfolio attributes in terms of various firm characteristics. The second part constructs portfolios based on various firm characteristics and investigates portfolio returns conditional on investor sentiment. The first two parts of section 4.5 examine the predictive power of sentiment on long-short portfolios and the last part provides evidence to rule out the systematic risk explanation of the predictive power. Section 4.6 demonstrates that the strategy of investing portfolios with high sentiment sensitivities leads to significant profit that cannot be explained by traditional risk factors. Section 4.7 firstly illustrates the procedure of forming the sentiment risk factor, and then explores the effects of the sentiment risk factor on sentiment-prone portfolios, size portfolios and BE/ME portfolios in section 4.2 and 4.3 respectively. Finally, section 7.4 presents the Fama-MacBeth results of the six-factor model (market excess return, SMB, HML, UMD, LIQ, and SRP). The conclusion is given in section 4.8.

4.2 Literature Review

Over the past decades, investor sentiment has been widely studied in the finance literature, theoretically and empirically. As a matter of fact, the relationship between sentiment and asset valuation has led to considerable debate. A growing body of research suggests that investor sentiment affects stock price behaviour. The attention now is no longer on whether investor sentiment affects stock prices, but rather on how to measure investor sentiment and quantify its effects.

Rational-based asset pricing models assume market efficiency, with investor rationality, uncorrelated errors and unlimited arbitrage. The behavioural hypothesis explores the impacts of investor sentiment on stock markets resting on the re-examination of the three assumptions. According to the EMH, investors are rational and prices are always equal to their fundamental values. Black (1986) suggests that individuals also often trade on noise that has no fundamental component. DeLong et al. (1990) clarify traders into noise traders and rational arbitrageurs. Proponents of the EMH argue that investors' trading behaviours are random. The uncorrelated errors will be cancelled out and hence the impact of noise traders is insignificant. Kumar and Lee (2006) show that retail investors are systematically related. Hence, individuals tend to buy or sell in concert. Noise traders may drive prices to deviate from fundamentals. Rational arbitrageurs bring prices back to fundamentals and keep markets efficient by taking opposite positions against noise traders. However, arbitrageurs face two types of risk: fundamental risk and noise trader risk. Rational arbitrageurs are assumed to be risk averse in the EMH, and hence their willingness of betting against noise traders and the size of opposite positions against noise traders would be deterred. As a result, stock prices deviate from their fundamental values. In practice, the length of the arbitrageurs' investment horizon and the ownership of the money that is used to engage in arbitrage further limit arbitrage and hence noise-trader sentiment can persist in financial markets and affect asset prices.

The cross-sectional variation in the equity returns has constituted an important subject of research in the recent financial literature. The underlying reasons for this variation are still under debate. On the one hand, rational economists believe that stock excess returns are compensation for the risk involved. On the other hand, proponents of behaviour finance attribute the excess returns to investor sentiment. A great strand of empirical research investigates how sentiment influences investors' decisions, and consequently influences returns of stocks with different firm characteristics.

A mispricing is the result of an uninformed demand shock and a limit on arbitrage. Baker and Wurgler (2006) suggest that investor sentiment might impact the cross-section of stock prices through two distinct channels: In the first channel, sentimental demand shocks vary across stocks, while arbitrage forces are assumed to be constant. Investor sentiment here is defined as the propensity of speculation by Baker and Wurgler. Under this definition, sentiment drives the relative demand for speculative investment, resulting in cross-sectional effects even if arbitrage limits are the same across equities. If the available information of the stocks is difficult to interpret, unsophisticated investors may have difficulty in determining the values of these stocks. The stocks, whose valuations are more subjective, are more vulnerable to broad shifts in the propensity of speculation. For instance, the valuation of a more transparent firm, which has a long earning history, more tangible assets and stable dividend payments, is less subjective compared to a firm with no earnings and dividend-paying history and less fixed assets.In the second channel, the arbitrage limits are different in cross-section, but sentiment is uniform. Investor sentiment is interpreted as optimism or pessimism about the stock markets in general. The effect of changes in sentiment is uniform, whereas the difficulty of arbitrage differs among stocks. The literature has reported that young, small, unprofitable, extreme growth stocks or distressed stocks are more costly and risky to arbitrage. The two channels appear to have overlapping effects and affect the same type of stocks. The same stocks that are the most difficult to arbitrage also tend to be the hardest to value, and they are expected to be most affected by sentiment. However, the empirical results of cross-sectional returns and investor sentiment are not always consistent. Some research reveals significant cross-sectional effects of sentiment, while some studies suggest there is weak or little evidence of the influence of investor sentiment on firms with different characteristics.

Baker and Wurgler (2006) look for the relation between stock returns and firm characteristics in both a nonparametric way and a quantitative method. They demonstrate that the cross-section of future stock returns is conditional on beginning-of-period proxies for sentiment. When sentiment is estimated to be high, young stocks, small stocks, unprofitable stocks, non-dividend paying stocks, high volatility stocks, extreme growth stocks, and distressed stocks, tend to realise relatively low subsequent returns. These stocks attract optimists and speculators but are unattractive to arbitrageurs.

Lee et al. (1991) provide evidence that the closed-end fund discount is a measure of the sentiment of individual investors and the same sentiment impacts returns of small stocks. When the discounts of closed-end funds narrow, smaller stocks gain more excess returns. Elton et al. (1998) follow the study of Lee et al. and use the change in the discount on closed-end equity fund as proxy for investor sentiment. They employ the same two-factor model of Lee et al. to examine return sensitivity to investor sentiment across size categories and obtain the same pattern. However, this pattern disappears when they expand the two-factor model to a more general multi-factor model. Their empirical test suggests the relation between size and sentiment might be eliminated after the inclusion of additional risk factors.

Brown and Cliff (2005) utilise Investor's Intelligence as a direct measure of investor sentiment to explore the predictability of sentiment for the long horizons. They confirm that asset values are strongly affected by investor sentiment. Over- optimism drives prices above fundamental values and these pricing errors incline to revert over a multi-year horizon. However, when examining the cross-sectional relationship between investor sentiment and size and book-to-market portfolio, it is contrary to conventional wisdom that small and growth firms would be most affected by sentiment. Their regressions show that for larger firms or low book/market firms, sentiment significantly predicts future returns at the 1-, 2-, and 3 year horizons.

Lemmon and Portniaguina (2006) employ consumer confidence as a measure of investor optimism, exploring the relationship between investor sentiment and the small-stock premium. They find that their investor sentiment measure has forecast the return of small stocks for the past 25 years. They further indicate that their sentiment component of consumer confidence forecasts returns on stocks predominantly held by individuals. Their results are consistent with the predictions of models in which arbitrage limitation and correlated errors of noise trading can drive prices of assets primarily held by noise traders away from economic fundamentals. However, there is no clear evidence that sentiment forecasts time-series variation in the value and momentum premia.

Berger and Turtle (2012) clarify stocks that tend to be small, young, volatile and composed of relatively intangible assets as opaque stocks, and recognise them to be more sensitive to investor sentiment. They report a strong relation between opaque firms and investor sentiment that is robust across narrow and expanded risk factor models. By employing the procedure of conditional marginal performance, they find that opaque firms exhibit a contrarian conditional performance. Portfolios constructed by opaque firms offer poor marginal performance after periods of high sentiment and vice versa.

Beer and Zouaoui (2012, 2013) construct portfolios based on the stock returns' exposure to sentiment. They find that portfolio returns are positively related to sentiment sensitivities. They report a significant raw profit from buying stocks with high sentiment sensitivities and selling stocks with low sensitivities. These profits cannot be attributed to the traditional size, value or moment factors. However, the inclusion of sentiment risk premium helps to explain the profit.

Ho and Hung (2013) also form portfolios based on the sentiment sensitivity of each stock. They further construct a sentiment factor defined as the long-short spreads between the returns on the two portfolios with the highest and lowest sentiment sensitivities. They employ a conditional framework to test the sentiment-augmented asset pricing model. The sentiment factor turns out to explain the size, value and momentum effects.

4.3 Data

Though investment sentiment measures have become one of the widely examined areas in behavioural finance, none of them has been fully validated. The composite investor sentiment proposed by Baker and Wurgler (2006, 2007) is employed in the last chapter and the consumer confidence provided by European Commission is used as the direct measure of sentiment for the robustness check. The two measures lead to consistent empirical results. In this chapter, these two measures are used again as two separate proxies for investor sentiment.

In this chapter, factor mimicking portfolios are constructed to explore the cross-sectional effect of investor sentiment. Firm-level accounting data are required to construct portfolios with different firm characteristics. The research period is from March 1987 to December 2012 since the sentiment measures start from March 1987. Two databases are used, the London Share Price Database (LSPD) and Datastream. Monthly data, such as returns and market values are obtained directly from LSPD. The market returns and risk free rate are calculated from LSPD and the details can be referred to Chapter 2 of this thesis. The accounting data (earnings per share, dividends per share, total fixed assets, research and development, book value per share, book to market ratios) are obtained from Datastream. The SEDOL number is used to match the companies between the two databases.[8] There are around 4,930 common stocks in the final sample.

A stock to be included for analysis must have at least 36 months of return data during the sample period for the requirement of beta estimation. The accounting variables are winsorised at the 1% and 99% level to mitigate the impact of outliers. Monthly earnings per share, dividends per share and book to market ratios are retrieved from Datastream. The rest of the accounting data are provided on an annual basis. Suppose the financial statement for a specific firm in a given year is published at month t and hence month t is the month of fiscal year end.[9] The reported annual accounting data are then used to match returns through the entire year. However, it should be noted that, following the convention, a six-month lag is adopted to allow a minimum of six months between the close of the fiscal year end and the time when the market receives the accounting information for that year. Accounting data for

[8] The unadjusted stock prices are used to further match these two databases. To check the matching, company name, previous name, base date and end date are also examined.
[9] The fiscal period end date of a stock in each year can be retrieved from Datastream.

a fiscal year end in month t are matched to equity returns during month t+6 through t+17 to ensure that the accounting information is available to investors.

Table 4.1 reports the summary statistics of firm characteristic variables and other relative variables. R represents the excess return. Size is defined as the market value of equity (in millions). *eps* and *dps* are earning and dividends per share scaled by book equity. The statistics of dummy variables eps^* and dps^* are also reported. $eps^* = \begin{cases} 1, if\ earning\ > 0 \\ 0, if\ earning \leq 0 \end{cases}$ and $dps^* = \begin{cases} 1, if\ dividend\ > 0 \\ 0, if\ dividend = 0 \end{cases}$. FA and RD are short for total fixed assets and research and development, where both are scaled by total assets. BE/ME is the ratio of book equity to market equity, and SG stands for sale growth, which is defined as the percentage change over the previous year's sales. All the variables are reported as percentages, except for size.

Table 4.1: Summary statistics of firm characteristics

	definition	Mean	Median	Std.Dev.	No. of Obs.
R	Excess return	0.303	0.00	0.19	685519
SIZE	Market capitalisation	965.16	30.92	451.55	734337
eps	Earnings per share/Book equity	14.08	6.58	13.41	37922
eps^*	$eps^* = \begin{cases} 1, if\ earning\ > 0 \\ otherwise \end{cases}$	72	1.00	41.41	37922
dps	Dividend per share/ Book equity	6.28	0.00	17.24	59157
dps^*	$dps^* = \begin{cases} 1, if\ dividend\ > 0 \\ otherwise \end{cases}$	65	1.00	48.43	59157
FA	Fixed assets/Total assets	21	0.02	9.71	34503
RD	Research and development/Total assets	4.7	0.00	10.00	20037
BE/ME	Book equity/ Market equity	2.46	1.53	5.33	64627
SG	Sales growth rate	9.98	4.75	7.11	20184

Note: All the variables are reported as percentages, except for size (in millions).

4.4 Portfolio Constructions

4.4.1 Construction and Measuring Attributes of Sentiment-prone Portfolios

This section constructs portfolios based on the exposure of stock to investor sentiment. A lot of the literature suggests that the effect of investor sentiment on stock returns may vary in the cross-section. Typically, stocks that are harder to evaluate, and also tend to be riskier to arbitrage, are more vulnerable to waves of investor sentiment. Baker and Wurgler (2006, 2007) profile the characteristics of these stocks as young stocks, small stocks, unprofitable stocks, non-dividend-paying stocks, high volatility stocks, extreme growth stocks and distressed stocks.

Berger and Turtle (2012) introduce a more direct approach to examine the relationship between investor sentiment and firm characteristics. The sentiment sensitivities are estimated within the pooled time-series cross-section of stocks, and then ten portfolios are formed according to estimated sentiment sensitivities. Average firm characteristics across portfolios are reported to investigate whether firms in the high sensitivity groups display features of volatile returns, a small equity base, low-dividends, low-earnings, high distress risk, and holding relatively more intangible assets. Berger and Turtle label these firms as opaque firms.

The sentiment sensitivities are estimated at the firm level. Following Lee et al. (1991) and Berger and Turtle (2012), the sentiment beta of each stock is estimated using the following regression,

$$R_{jt} = \alpha_j^t + \beta_{jm}^t R_t^M + \beta_{js}^t \Delta\mathrm{SENT}_t + \varepsilon_{jt} \tag{4.1}$$

for j = 1, 2,…N; t = 1, 2, …T. N is the number of cross-sectional observations (firms) available and T is the number of time-series observations available for each firm. R_{jt}, the excess return on stock j at time t, is defined as the individual stock return in excess of the risk-free rate. $\Delta\mathrm{SENT}_t$ is the monthly change in investor sentiment index. R_t^M represents the excess return of the market portfolio.

Following the convention, the above model is estimated on a rolling basis with an estimation window of 36 months[10]. At each time t, the absolute value of β_{js}^{t} represents the measure of the sensitivity of stock to sentiment factor.

Sentiment-prone portfolios are constructed based on the absolute value of sentiment betas at a given time t by equally splitting the available firms into ten portfolios which represent different levels of sentiment sensitivities[11]. At time t, estimate equation (4.1) across month t-36 through t-1, and then sort the absolute estimates of beta to 10 sentiment sensitivity portfolios. For each firm in a given portfolio at a given time t, the average firm characteristics are calculated using the previous 3 years' data. The 3 year average of characteristic variables corresponds to the estimation period for the rolling window, and this procedure ensures firm characteristics match sentiment sensitivity estimations.

The average firm characteristics from the rolling regressions are reported in Table 4.2. The F-statistics of the null hypothesis that average firm characteristics are equal across all sentiment portfolios, and t-statistics of the null hypothesis that the average of a firm's characteristic is equal between the lowest and highest sentiment-prone portfolios are reported in the last two columns of each table.

[10] Brown and cliff (2004) report that sentiment significantly predicts future returns at the 1-, 2- and 3-year horizon. An estimation window of 36 months on a rolling basis is adopted. Specifically, the sentiment beta (β_{js}^{t}) for a stock j at time t are estimated using data of month t-36 through t-1, and all the estimated betas for each available firm are assigned into ten sentiment sensitivity portfolios at time t. The absolute value of estimated β_{js}^{t} represents the sensitivity of stock to investor sentiment at time t.

[11] Berger and Turtle (2012) form the portfolios on the basis of raw beta estimates. They assign stocks with negative estimates of β_{js} to one portfolio, and then equally split the rest of the firms into nine other portfolios, where sentiment betas increase across portfolio. However, this study will use the absolute value of betas to form the ten portfolios. The argument is straightforward. The higher the absolute value of betas, the higher the responsiveness of stock returns to the shift of contemporaneous investor sentiment. Ho and Huang (2013) and Beer and Zouaoui (2012) adopt the absolute value procedure of sentiment betas.

The results strongly support the hypothesis that firms more exposed to investor sentiment incline to be relatively more volatile, smaller, less profitable, and lower-dividend-paying, less tangible assets. That is, stocks that are harder to arbitrage and more difficult to value, exhibit higher sentiment sensitivities. All the F-statistics and t-statistics are significantly rejected. Hence, differences across all portfolios and between the portfolios with the lowest and highest sentiment exposures are highly significant. For every specified firm characteristic, there is a general trend across the sentiment portfolios. For example, as the sentiment sensitivity goes up, the average standard deviation rises from 12.62% to 18.83% correspondingly. The research and development also shows an upward tendency as sentiment sensitivities become higher. On the contrary, the mean market capitalisation decreases monotonically as investor sentiment increases across portfolios. Sample averages of earnings, dividends, and tangibility all generally decrease as sentiment sensitivity increases. The patterns of BE/ME and sales growth are a bit complicated. Generally, the statistics of these two characteristics go up at first but decrease for the portfolios most impacted by sentiment. Overall, the results displayed in table 4.2 reinforce the hypothesis of the strong relation between investor sentiment and various firm characteristics, after controlling for market risk (Baker and Wurgler, 2006).

Table 4.2: Firm characteristics of sentiment-prone portfolios

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	***F***	***p-value***	***T(10-1)***	***p-value***
Std. Dev.	12.62	13.03	13.87	14.37	14.95	15.06	16.77	16.78	17.79	18.83	***437.57***	***0.00***	***-36.08***	***0.00***
size	1184.84	1166.71	1026.06	975.15	865.69	765.32	678.45	572.67	442.14	205.93	***83.80***	***0.00***	***-10.68***	***0.00***
eps	14.16	13.55	13.10	12.56	12.04	11.95	10.80	8.98	8.86	7.99	***12.08***	***0.00***	***5.42***	***0.00***
dps	9.22	7.12	7.42	5.93	5.32	4.56	4.28	4.03	3.14	1.77	***23.29***	***0.00***	***4.69***	***0.00***
eps*	85.73	82.16	83.66	82.95	80.21	78.72	75.72	73.56	69.12	67.17	***153.17***	***0.00***	***9.36***	***0.00***
dps*	86.24	84.95	83.55	80.61	78.66	76.47	71.85	68.20	66.51	63.88	***92.83***	***0.00***	***8.76***	***0.00***
fixed assets	33.79	31.87	31.33	30.81	30.87	25.54	24.25	23.23	21.59	19.76	***18.54***	***0.00***	***4.05***	***0.00***
research and development	3.73	5.45	5.94	5.10	7.47	8.66	9.50	10.01	10.21	12.94	***23.75***	***0.00***	***-4.01***	***0.00***
BE/ME	1.79	1.62	1.92	2.02	2.03	2.51	2.59	2.35	2.11	2.21	***2.96***	***0.00***	***8.79***	***0.00***
sales growth	2.08	2.23	1.91	2.19	2.15	2.51	2.37	2.82	2.66	3.03	***4.47***	***0.00***	***4.36***	***0.00***
average return	0.68	0.76	0.75	0.80	0.88	0.91	1.09	1.17	1.31	1.67	***4.58***	***0.00***	***2.41***	***0.00***

Note: The following model is estimated: $R_{jt} = \alpha_j^t + \beta_{jm}^t R_t^M + \beta_{js}^t \Delta\mathrm{SENT}_t + \varepsilon_{jt}$ on a 36-month rolling-window basis. Portfolio 1 consists of stocks least exposed to sentiment while portfolio 10 includes stocks most exposed to sentiment. All the characteristics are reported as percentages, except for size (in millions). The last row reports the average returns of each portfolio. F-statistics and t-statistics are reported testing that the given average firm characteristic is equal across all sentiment portfolios, and between the 1st and 10th sentiment respectively.

To net of the effects of other risk factors which have been well established in the literature, Berger and Turtle (2012) suggest a five-factor model to control for multiple risk sources. Three famous risk factors, small-minus-big (SMB), high-minus-low (HML) and the momentum factor (UMD) are augmented to the above model to consider sentiment sensitivities. The augmented five-factor model is written as,

$$R_{jt} = \alpha_j^t + \beta_{jm}^t R_t^M + \beta_{j,smb}^t SMB_t + \beta_{j,hml}^t HML_t + \beta_{j,umd}^t UMD_t + \beta_{js}^t \Delta\mathrm{SENT}_t + \varepsilon_{jt} \qquad (4.2)$$

Where SMB, HML and UMD represent the size, value and momentum risk factors respectively. The firm characteristics of portfolios based on model (4.2) are presented in Appendix A.1. Firm characteristics of sentiment sensitivity portfolios exhibit patterns that are consistent with those presented in table 4.2.

In conclusion, the construction of sentiment sensitivity portfolios and the calculation of firm characteristics across portfolios provide strong evidence that small, volatile, unprofitable, non-dividend paying, less tangible, and extremely growing firms are especially susceptible to sentiment risks. These firms are typically hard to value and difficult to arbitrage. The empirical results further confirm the conjecture of Baker and Wurgler (2006, 2007).

4.4.2 Construction of Characteristics-matched Portfolios and Measuring their Returns Conditional on Investor Sentiment

This part constructs portfolios on the basis of firm characteristics. In each month, all the firms are sorted into ten portfolios. Specifically, each month, all the stocks are ranked by a characteristic, such as size, and then are allocated into ten portfolios. Each portfolio has the same number of firms and the firm characteristics are increasing across portfolios. The value-weighted portfolio returns are calculated afterwards. Conditional on the last period's sentiment, the returns of the decile portfolios across firm characteristics are investigated. For each category portfolio, the average return is computed over months in which the sentiment from the previous month is positive, months in which the sentiment is negative, and the difference between these two average returns. The calculated conditional returns of each portfolio are reported in table 4.3.

Figure 4.1 reports the conditional characteristic effects in a direct, nonparametric way. The unconditional monthly returns across the decile portfolios are depicted by purple lines, while the conditional return differences are represented by green lines. The blue bars represent average monthly return after periods of positive sentiment and the red bars represent returns after periods of negative sentiment.

The second row of table 4.3 shows that when the sentiment of the last period is positive, the average return generally increases as the market capitalisation becomes larger. However, when sentiment is negative in the previous period, as presented in the third row, average return decreases as size increases. This reveals that the size anomaly exists in low sentiment periods only. When sentiment is negative, the average monthly return is 0.98% for portfolios with small firms and 0.48% for portfolios with large firms.

The next characteristic considered is age which is defined by the number of months since the firm's first appearance in the database of the LSPD. Young stocks appear to attract investors when sentiment is high and vice versa. When the sentiment of previous month is positive, firms from the top decile earn 0.43% higher average return than firms from the bottom decile.

However, when sentiment is negative, the average return of the top age decile is 0.30% less than the return of the bottom decile. In general, the conditional differences of average returns almost monotonically increase as the number of age goes up. Strikingly, the pattern of unconditional average returns is slightly ambiguous as presented in figure 4.1.

The conditional returns display the cross-sectional effect on the basis of standard deviation. When sentiment is positive, people tend to demand more volatile stocks while when sentiment is negative, people demand less volatile stocks. When sentiment is negative, stocks with the lowest standard deviation earn a 0.85% return over the following month, and stocks with the largest standard deviation enjoy a higher future return, that is 1.35% per month.

The conditional average returns are examined across earnings (dividends) deciles together with comparisons between profitable and unprofitable firms (payers and nonpayers). The average returns across profitable (dividend-paying) firms are calculated and are compared to unprofitable (non-dividend-paying) firms. When sentiment is positive, the average return of the next month is 0.45% more on profitable firms than unprofitable firms, and 0.29% more on paying firms than non-paying firms. Conversely, when sentiment is negative, the average return of the next month is 0.02% less on profitable firms than unprofitable firms, and 0.17% less on paying firms than non-paying firms. Overall, when sentiment is high, the conditional spreads of average monthly returns tend to increase as profits (dividends) become larger.

Fixed assets and research and development (RD) describe the tangibility characteristics of firms. Unlike the US market revealed by Baker and Wurgler (2006), the empirical results detect a strong pattern of conditional average returns across the fixed assets and RD decile portfolios. Firms with more intangible assets tend to be more exposed to sentiment fluctuations. When the sentiment of the last month is positive, firms with the most fixed assets enjoy 0.36% more average return compared to firms with the least fixed assets. On the other hand, firms pursuing the highest RD suffer s 0.72% return loss compared to firms with the lowest RD. When the sentiment of the last month is negative, the situation is completely the opposite. In general, the conditional spread of average returns is positively related to the proportion of fixed assets, and negatively related to the proportion of RD.

The variable BE/ME, displays the unconditional effects that the higher BE/ME is associated with higher average returns, which is well known as the value effect. However, the conditional differences exhibit a U-shaped pattern. The U-shaped pattern of conditional spread also appears in the sales growth decile portfolios. This suggests that firms with extreme values of growth and BE/ME react more to sentiment than firms with middle values. The explanation is straightforward. Firms that are greatly undervalued or growing extremely slowly are more likely to be distressed firms. On the other hand, firms that are extremely overvalued or growing tend to be high-flying firms. Both these two types of firm are very hard to value and hence risky to arbitrage and more sensitive to investor sentiment.

Table 4.3: Future monthly returns (in percentage) conditional on last period's sentiment

	sentiment	1	2	3	4	5	6	7	8	9	10	10-1	10-5	5-1
size	positive	0.71	0.71	0.77	0.80	0.80	0.82	0.85	0.86	0.91	0.87	0.16	0.07	0.16
	negative	1.58	1.51	1.39	1.35	1.36	1.32	1.33	1.30	1.26	1.07	-0.51	-0.29	-0.51
	difference	-0.87	-0.80	-0.62	-0.55	-0.56	-0.50	-0.48	-0.44	-0.35	-0.20	0.67	0.36	0.67
age	positive	0.49	0.76	0.75	0.81	0.86	0.89	0.87	0.89	0.99	0.92	0.43	0.06	0.43
	negative	1.24	1.00	0.97	1.11	1.14	1.12	1.11	1.12	1.11	0.94	-0.3	-0.2	-0.3
	difference	-0.75	-0.24	-0.22	-0.30	-0.28	-0.23	-0.24	-0.23	-0.12	-0.02	0.73	0.26	0.73
Std. Dev.	positive	1.11	0.88	0.84	0.81	0.76	0.74	0.74	0.70	0.59	0.61	-0.50	-0.15	-0.35
	negative	1.45	1.56	1.55	1.50	1.45	1.57	1.39	1.44	1.65	1.95	0.50	0.50	0.00
	difference	-0.34	-0.68	-0.71	-0.69	-0.69	-0.83	-0.65	-0.74	-1.06	-1.34	-1.00	-0.65	-0.35
eps	positive	0.71	0.73	0.74	0.82	0.91	0.87	0.92	1.01	1.05	0.95	0.25	0.04	0.21
	negative	1.48	1.17	1.26	1.21	1.10	1.04	0.98	1.02	1.04	1.12	-0.36	0.02	-0.38
	difference	-0.77	-0.44	-0.52	-0.39	-0.19	-0.17	-0.06	-0.01	0.01	-0.17	0.30	0.13	0.17
dps	positive	0.83	0.82	0.82	0.84	0.86	0.88	0.93	0.92	0.99	0.99	0.16	0.13	0.16
	negative	1.32	1.25	1.22	1.19	1.10	1.16	1.17	1.17	1.09	1.06	-0.26	-0.04	-0.26
	difference	-0.49	-0.43	-0.40	-0.35	-0.24	-0.28	-0.24	-0.25	-0.10	-0.07	0.42	0.17	0.42
eps^*	positive	0.45									0.90			
	negative	1.13									1.11			
	difference	-0.68									-0.21			
dps^*	positive	0.61									0.90			
	negative	1.28									1.11			
	difference	-0.67									-0.21			
BE/ME	positive	0.60	0.58	0.74	0.77	0.78	0.81	0.84	0.84	0.93	0.93	0.33	0.15	0.33
	negative	1.55	1.47	1.45	1.42	1.46	1.45	1.61	1.65	1.67	2.18	0.63	0.72	0.63
	difference	-0.95	-0.89	-0.71	-0.65	-0.68	-0.64	-0.77	-0.81	-0.74	-1.25	-0.3	-0.57	-0.3
FA	positive	0.75	0.76	0.79	0.81	0.90	0.83	0.98	1.06	1.11	1.11	0.36	0.22	0.15
	negative	1.12	1.09	1.09	1.11	1.08	1.06	1.03	1.00	0.99	0.95	-0.17	-0.13	-0.04
	difference	-0.37	-0.33	-0.30	-0.30	-0.18	-0.23	-0.05	0.06	0.12	0.16	0.53	0.34	0.19
RD	positive	1.12	1.01	1.03	0.98	0.86	0.71	0.66	0.69	0.89	0.40	-0.72	-0.46	-0.26
	negative	1.00	0.82	1.17	1.41	1.66	2.25	2.26	2.25	2.55	2.69	1.69	1.03	0.65
	difference	0.12	0.19	-0.14	-0.43	-0.80	-1.54	-1.60	-1.56	-1.66	-2.29	-2.41	-1.49	-0.92
SG	positive	0.49	0.61	0.72	0.90	0.94	0.97	0.92	0.83	0.75	0.67	0.18	-0.27	0.18
	negative	1.03	1.10	1.15	1.26	1.21	1.20	1.17	0.98	0.97	1.01	-0.02	-0.2	-0.02
	difference	-0.54	-0.49	-0.43	-0.36	-0.27	-0.23	-0.25	-0.15	-0.22	-0.34	0.2	-0.07	0.2

Note: For each month, stocks are ranked into 10 portfolios according to their firm size, age, total risk (Std. Dev.), earning per share (eps), dividend per share (dps), book to market ratio (BE/ME), fixed asset over total asset (FA), research and development over total asset (RD), and sales growth (SG). Specifically, stocks are ranked into 2 portfolios depending on whether they have positive earning or dividend. eps^* and dps^* are dummy variables. eps^* $(or\ dps^*)$ are equal to unity if the stocks have positive earnings (or dividends). The value-weighted portfolio returns (in percentage) when the previous month's sentiment is positive and when the sentiment is negative are reported respectively. The last three columns present the conditional spreads for portfolio 10 and 1, portfolio 10 and 5, and portfolio 5 and 1.

The average monthly return after the positive sentiment period is represented by a blue bar. The average monthly return after the negative sentiment period is represented by a red bar. The return spread between that after the positive sentiment and after the negative sentiment is depicted by a green line. The average return of each portfolio, which is the unconditional monthly return, is depicted by a purple line.

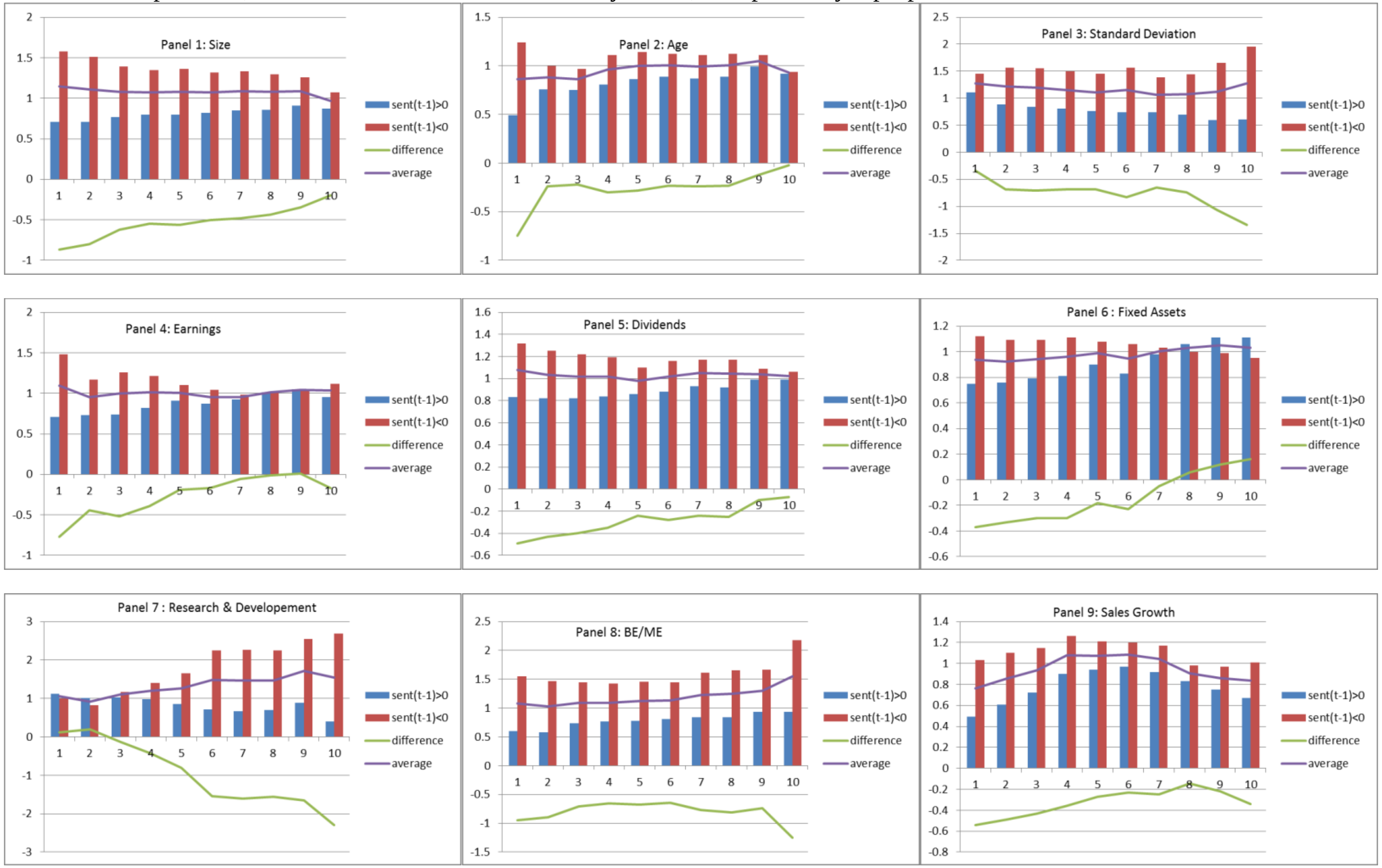


Figure 4.1: Future returns conditional on sentiment index and firm characteristics

4.5 Predictive Regressions of Long-short Portfolios

Formal quantitative approaches are applied to test the forecast power of sentiment on the cross-section. The strategy is to construct the long-short portfolios that are long on stocks with high values of a characteristic and short on stocks with low values. However, the long-short size portfolio is long on small firms and short on large firms, in accordance with the existing literature. The intuition is straightforward. For example, the last section reports that when previous sentiment is positive, firms with higher earnings seem to enjoy higher returns than firms with lower earnings. In contrast, when sentiment is negative, firms with higher earnings seem to gain less return compared to firms with lower earnings.

4.5.1 Predictive Power of Sentiment on Long-short Portfolios

To examine whether sentiment predicts long-short portfolios, the following type of regression is employed,

$$R_{X_{jt}=high,t} - R_{X_{jt}=low,t} = \alpha_1 + \alpha_2 \mathrm{SENT}_{t-1} + \varepsilon_{jt} \qquad (4.3)$$

The dependent variable is the monthly return on a long-short portfolio of each firm characteristic, where X represents the firm characteristic. For example, when exploring the conditional effect of sentiment on age decile portfolios, the dependent variable is the return spread between the oldest firms and youngest firms. The independent variable is the last period's sentiment.

To distinguish the sentiment predictability effect from traditional effects, such as size effect, value effect and momentum effect, a multivariate regression is further explored,

$$R_{X_{it}=high,t} - R_{X_{it}=low,t} = \alpha_1 + \alpha_2 \mathrm{SENT}_{t-1} + \beta R_t^M + \gamma SMB_t + \delta HML_t + \eta UMD_t + \varepsilon_{it} \qquad (4.4)$$

R_t^M is the excess market return. SMB, HML and UMD are defined in Chapter 2 and taken from the Xfi Centre for Finance and Investment website.

The empirical results of model (4.3) and (4.4) are presented in table 4.4. The estimated beta and corresponding p value of model (4.3) are presented in panel A whereas those of model (4.4) are reported in panel B. The estimates of the intercepts of each characteristic are all insignificant. The abnormal returns are statistically and economically insignificant. The empirical estimations of sentiment provide statistical evidence of the predictive power of investor sentiment on a long-short portfolio. Specifically, when the last month's sentiment is positive, returns on small, young and high volatile firms are relatively low over the following month. For example, a unit increase in sentiment is associated with a 0.825% decrease of monthly return on the small minus big portfolio, a 0.512% more monthly return on the high minus low age portfolio, and a 0.590% lower monthly return on the high minus low volatility portfolio.

For profitability and dividend payment, the analysis forms the long-short portfolios that are long on profitable (dividend-paying) stocks and short on unprofitable (non-dividend-paying) stocks. Again, the results suggest that sentiment has a significant predictive power for these portfolios. When sentiment is positive, returns of profitable and dividend-paying stocks are relatively higher over the coming month. In terms of magnitude, a unit increase in sentiment forecasts a 0.387% larger return on long-short profitability portfolio, and a 0.452% higher return on long-short dividend portfolio. The conclusions remain correct after controlling for market excess returns, size, value and momentum effects.

Baker and Wurgler (2006) report that the tangibility characteristics do not exhibit strong conditional effects in the US stock market. In contrast to their findings, the estimation of this study reveals that both the fixed assets and research and development have significant predictive power on the long-short portfolios. When sentiment is high, portfolios with more fixed assets or with less proportion of research and development, tend to earn higher return over the coming month. In particular, a unit increase in sentiment leads to a 0.594% rise in future average return on long-short portfolio formed on fixed assets, and a 0.784% fall on long-short portfolio formed on research and development.

Table 4.4: Time-series regression of Long-Short portfolio returns on the composite sentiment index (March 1987 to December 2012)

Panel A: Regressions of long-short portfolio returns on lagged sentiment only.

$$R_{X_{jt}=high,t} - R_{X_{jt}=low,t} = \alpha_1 + \alpha_2 \mathrm{SENT}_{t-1} + \varepsilon_{jt} \qquad (4.3)$$

Panel B: Regressions of long-short portfolio returns on lagged sentiment, the market risk premium, the Fama-French factor (SMB and HML), and the momentum factor (UMD).

$$R_{X_{it}=high,t} - R_{X_{it}=low,t} = \alpha_1 + \alpha_2 \mathrm{SENT}_{t-1} + \beta R_t^M + \gamma SMB_t + \delta HML_t + \eta UMD_t + \varepsilon_{it} \qquad (4.4)$$

The long-short portfolios are formed on firm characteristics (*X*): firm size, age, total risk (Std. Dev.), profitability (*eps*), dividends (*dps*), fixed asset over total asset (FA), research and development over total asset (RD), book-to-market equity (BE/ME) and sales growth (SG). The Newey-West adjusted t-values are calculated and the corresponding *p* values are reported.

		Panel A				Panel B			
		Model (4.3)				Model (4.4)			
		α_1	$p(\alpha_1)$	α_2	$p(\alpha_2)$	α_1	$p(\alpha_1)$	α_2	$p(\alpha_2)$
Size	SMB	0.001	0.788	-0.825	*0.067*	0.001	0.883	-0.743	*0.098*
Age	High-Low	0.003	0.199	0.512	*0.013*	0.001	0.574	0.403	*0.053*
Std. Dev.	High-Low	0.001	0.847	-0.590	*0.002*	0.000	0.971	-0.395	*0.026*
eps	$>0 - \leq 0$	0.004	0.081	0.387	*0.049*	0.003	0.126	0.332	*0.067*
dps	$>0 - =0$	0.003	0.260	0.452	*0.020*	0.001	0.651	0.368	*0.050*
FA	High-Low	0.002	0.466	0.594	*0.003*	0.001	0.756	0.587	*0.004*
RD	High-Low	0.002	0.527	-0.784	*0.007*	0.000	0.938	-0.415	*0.097*
BE/ME	HML	0.004	0.232	-0.434	*0.044*	0.003	0.330	-0.172	*0.398*
SG	High-Low	0.002	0.490	-0.207	*0.079*	0.002	0.556	-0.200	*0.377*
BE/ME	High-Medium	0.003	0.230	-0.414	*0.015*	0.001	0.688	-0.294	*0.086*
SG	High-Medium	0.001	0.725	-0.787	*0.000*	0.000	0.956	-0.668	*0.000*
BE/ME	Medium-Low	0.002	0.533	0.565	*0.008*	0.000	0.715	0.424	*0.051*
SG	Medium-Low	0.001	0.811	0.407	*0.010*	0.000	0.911	0.398	*0.021*

Panel B reveals that sentiment still predicts simple high minus low portfolios formed on the first seven firm characteristics after the inclusion of traditional risk factors. However, the predictive power is contaminated by the addition of size, value and momentum effects.

However, the forecast power disappears after the addition of the traditional risk factors on the HML and high-low sales growth portfolios. Since the non-parametric approach detects a U-shaped pattern of the conditional effects of the BE/ME and sales growth sorted portfolios, the predictive power on high minus medium and medium minus low portfolios formed on BE/ME and sales growth is further examined. The new portfolio strategies on BE/ME and sales growth portfolios resume the predictive power of investor sentiment, even after the addition of traditional risks.

Another strand of robustness check is to use consumer confidence as sentiment proxy and the predictive ability is consistent with the composite sentiment index; the results are reported in Appendix A.2.

4.5.2 Predictive Regression Revisited – the Conditional CAPM Framework

Lemmon and Oklahoma (2006) and Verma and Soydemir (2009) decompose their sentiment measures to fundamental prospects (rational) and sentiment component (irrational) and explore the effects of sentiment and returns of long-short portfolios based on the fundamental and sentiment components together following Lemmon and Portniaguina (2006). Their model offers a considerable benefit that it studies simultaneously the impact of economic fundamentals and the impact of investor sentiment on stock returns.

$$R_{X_{jt}=high,t} - R_{X_{jt}=low,t} = (\alpha_1 + \alpha_2 \mathrm{SENT}_{t-1}) + (\beta_1 + \beta_2 Fund_{t-1}) R_{mt} + \varepsilon_{jt} \quad (4.5)$$

Recall that the measures of sentiment are orthogonalised to various macro variables to isolate the components of business cycle variation following Baker and Wurgler (2006). Specifically, the individual economic variables, such as IPO numbers, IPO first-day returns, turnover ratios and consumer confidence are regressed on macro variables. The residuals are used to construct the composite sentiment index (*SENT*) whereas the fitted values of each regression are used to construct the composite fundamental index (*Fund*). For robustness purpose, consumer confidence is regressed on macro variables and the residual is treated as the direct proxy of sentiment index (*SENT*) whereas the fitted value is treated as the corresponding fundamental index (*Fund*).

Lemmon and Portniaguina's model extends the conditional CAPM by integrating both the psychological component reflecting investor sentiment and the rational component reflecting the economic fundamentals. This model allows the conditional market beta to be a function of economic fundamental prospects and allows the pricing errors to vary with investor sentiment.

Under the rational hypothesis, the expected returns of the long-short portfolios are related to the economic fundamentals, as investors rationally form expectations about future macroeconomic conditions. There is substantial evidence that small stocks fluctuate more with the business cycle (Chan et al, 1985; Chan and Chen, 1991; Jagannathan and Wang, 1991). The size premium is expected to be negatively related to economic fundamentals. The conditional beta of small firms should increase (decrease) after periods of negative (positive) expectation about economic fundamentals. Similarly, firms that are more volatile or experiencing high growth are more likely to be influenced by recessions in the business cycle and are expected to have a negative β_2. On the contrary, firms that are enjoying profits, paying dividends or having more fixed assets are less sensitive to contractions in the business cycle and hence are expected to have a positive β_2.

Under the behavioural hypothesis, as presented in the previous sections, investors tend to overvalue stocks that are hard to value and difficult to arbitrage when they are optimistic and to undervalue these stocks when they are pessimistic. Therefore, a variation of size premium is expected to be negatively affected by irrational sentiment and a negative α_2 is expected. Overall, firms that are more vulnerable to sentiment are expected to have a negative α_2 and *vice versa*.

Table 4.5: Time series regressions of long-short portfolio returns on the composite sentiment, using the framework of ICAPM (March 1987 to December 2012)

Panel A: Regressions of long-short portfolio returns where market beta is conditional on fundamental component of sentiment.

$$R_{X_{jt}=high,t} - R_{X_{jt}=low,t} = (\alpha_1 + \alpha_2 \mathrm{SENT}_{t-1}) + (\beta_1 + \beta_2 Fund_{t-1})R_t^M + \varepsilon_{jt} \quad (4.5)$$

Panel B: Regressions of long-short portfolio returns where market beta is conditional on fundamental component, dividend yield, inflation rate, term spread and interest rate. The market risk premium, the Fama-French factor (SMB and HML), and the momentum factor (UMD) are included to restrict the traditional risk.

$$R_{X_{jt}=high,t} - R_{X_{jt}=low,t} = (\alpha_1 + \alpha_2 \mathrm{SENT}_{t-1}) + (\beta_1 + \beta_2 Fund_{t-1} + \beta_3 DY + \beta_4 Inflation + \beta_5 TS + \beta_6 IR)R_t^M + \beta R_{mt} + \gamma SMB_t + \delta HML_t + \eta UMD_t + \varepsilon_{jt} \quad (4.6)$$

The long-short portfolios are formed on firm characteristics (*X*): firm size, age, total risk (std. dev.), profitability (*eps*), dividends (*dps)*, fixed asset over total asset (FA), research and development over total asset (RD), book-to-market equity (BE/ME) and sales growth (SG). The Newey-West adjusted t-values are calculated and the corresponding p values are reported.

		Panel A				Panel B			
		Model (4.5)				Model (4.6)			
		α_2	$p(\alpha_2)$	β_2	$p(\beta_2)$	α_2	$p(\alpha_2)$	β_2	$p(\beta_2)$
Size	SMB	-0.31	*0.00*	-0.31	*0.00*	-0.98	*0.00*	-0.89	*0.000*
Age	High-Low	0.11	*0.052*	0.14	*0.057*	0.11	*0.052*	-0.14	*0.057*
SD	High-Low	-0.45	*0.029*	-0.41	*0.00*	-0.31	*0.085*	-0.36	*0.015*
EPS	$>0 - \leq 0$	0.13	*0.024*	0.23	*0.002*	0.37	*0.026*	0.16	*0.011*
DPS	$>0 - =0$	0.27	*0.019*	0.40	*0.066*	0.35	*0.010*	0.43	*0.011*
FA	High-Low	0.11	*0.040*	0.163	*0.001*	0.22	*0.065*	0.31	*0.002*
RD	High-Low	-0.49	*0.049*	-0.21	*0.024*	-0.63	*0.006*	-0.49	*0.007*
BE/ME	HML	-0.09	*0.17*	-0.54	*0.000*	0.47	*0.017*	0.52	*0.000*
SG	High-Low	-0.03	*0.25*	-0.07	*0.511*	-0.163	*0.535*	-0.56	*0.008*
BE/ME	High-Medium	-0.12	*0.095*	-0.53	*0.000*	-0.43	*0.021*	-0.48	*0.001*
SG	High-Medium	-0.51	*0.004*	-0.15	*0.012*	-0.44	*0.009*	-0.20	*0.034*
BE/ME	Medium-Low	0.23	*0.022*	0.36	*0.000*	0.36	*0.005*	0.45	*0.000*
SG	Medium-Low	0.15	*0.044*	0.13	*0.008*	0.44	*0.081*	0.17	*0.026*

The regression results from the model (4.5) are reported in panel A of table 4.5. The composite sentiment index is used to measure investor sentiment. For size premium, the empirical results support both hypotheses and are consistent with those of Lemmon and Portniaguina (2006). The estimated coefficients of α_2 and β_2 are negative and statistically significant. A significant negative estimate of β_2 indicates that when changes in the business cycle are positive, returns of small stocks are lower relative to large stocks in the next period. On the contrary, when there are negative changes in the business cycle, the following period's returns of small stock are higher. Consistent with the behaviour hypothesis, the estimate of α_2 suggests a significant negative relationship between the lagged sentiment and size premium. This result provides support to Baker and Wurgler (2006) and Lemmon and Portniaguina (2006) and reinforces the noise trader theory that small stocks are overvalued relative to large stocks during bullish periods.

The empirical results of risk premia based on firm characteristics such as age, volatility, profitability, dividend and tangibility lend support to both the rational and behavioural hypotheses. In particular, old firms, dividend-paying firms, profitable firms and firms with a large proportion of fixed assets have positive estimates of α_2 and β_2. A positive α_2 suggests that firms with those characteristics are less affected by the downward changes of business cycles. Furthermore, a positive β_2 suggests that those firms tend to be undervalued by investors when they are optimistic under the behavioural hypothesis. Overall, the future risk premiums based on these characteristics are positively related to investor sentiment and economic fundamentals. In contrast, returns of volatile firms and firms involved in intensive research and development are negatively related to investor sentiment and economic fundamentals.

The cases of BE/ME and sales growth are more complicated. The empirical results of long-short risk premiums based on high BE/ME (or sales growth) minus low BE/ME (or sales growth) are statistically insignificant. The traditional views are that firms with high BE/ME and sales growth are hard to value and difficult to arbitrage, and they are more sensitive to fluctuations of the business cycle and investor sentiment. However, firms with low BE/ME are overvalued and low sales growth firms are often distressed firms with shrinking sales. Those firms are also risky to arbitrage and are vulnerable to economic fundamental and investor sentiment. Hence, alternative portfolios are formed based on high minus medium values of BE/ME and SG and medium minus low. It turns out that the estimates of α_2 and β_2 become statistically significant. The results are consistent with the U-shape pattern found by Baker and Wurgler (2006). It might also explain why Lemmon and Portniaguina (2006) fail to explain the value premium using portfolios that are long on firms with high BE/ME and short on firms with low BE/ME.

To assess the robustness of the results of this model, the research runs regressions that allow the market betas to vary directly with other macro variables (dividend yield, inflation rate, term spread and interest rate) in addition to the fundamental component[12]. The traditional factors, SMB, HML and UMD are also included as control variables.

$$R_{X_{jt}=high,t} - R_{X_{jt}=low,t} = (\alpha_1 + \alpha_2 \mathrm{SENT}_{t-1}) + (\beta_1 + \beta_2 Fund_{t-1} + \beta_3 DY + \beta_4 Inflation$$
$$+\beta_5 TS + \beta_6 IR)R_t^M + \beta R_t^M + \gamma SMB_t + \delta HML_t + \eta UMD_t + \varepsilon_{jt} \quad (4.6)$$

Panel B of table 4.5 displays the robustness regressions using model (4.6). The empirical results are qualitatively identical to those described in panel A. The regressions essentially confirm the significance of the patterns suggesting in the sorts, although the statistical significance of α_2 and β_2 is slightly weaker in general.

[12] A number of variables may help predict future economic conditions, such as the term spread of Stock and Watson (1989); the interest rate of Bernanke (1990); the interest rate and default spread of Jagannathan and Wang (1996); the default spread, dividend yield, T-bill yield and consumption-to-wealth ratio of Lemmon and Portniaguina (2006).

Consumer confidence is also used to proxy investor sentiment and the corresponding empirical studies are consistent with studies using composite sentiment index. The detailed results are presented in Appendix A.3.

Overall, the rational and behavioural hypotheses are both supported by empirical results. The economic fundamental component of the sentiment measures rationally forecasts changes in the business cycle and induces variations of market risk premium. Small firms, volatile firms, young firms, unprofitable firms, non-dividend-paying firms, intangible firms, firms with intensive research and development, firms with extreme BE/ME value and firms experiencing extreme high or low sales growth are more vulnerable to the business cycle after periods characterised by bad economic prospects. Furthermore, the results suggest that investor sentiment is an important factor in the return generating process of common stocks. In particular, firms that are hard to value and difficult to arbitrage earn low excess returns after periods when investors are optimistic. The same firms that are more sensitive to the business cycle after bad economic prospects also tend to be hard to value and difficult to arbitrage.

4.5.3 Systematic Risk Explanation

Despite the efforts to isolate sentiment from economic fundamentals, the possibility remains that the sentiment measure is a proxy for an omitted risk factor and the predictive power of sentiment is just compensation for systematic risk. As shown in previous sections, large, old, profitable, less volatile, dividend-paying, tangible firms and firms with stable growth require higher returns compared to small, young, unprofitable, volatile, non-dividend paying, intangible firms and firms with extreme growth. Intuitively, large, older, profitable, less volatile, dividend-paying, tangible firms and firms with stable growth are recognised as riskier according to the systematic risk explanation. While this proposition already seems counterintuitive, the analysis attempts to provide some evidence to rule out the possibility more rigorously.

Table 4.6: Conditional Market betas (March 1987 to December 2012)

Regressions of long-short portfolio returns where market beta is conditional on investor sentiment.

$$R_{X_{it}=high,t} - R_{X_{it}=low,t} = \alpha_1 + \alpha_2 \mathrm{SENT}_{t-1} + (b_1 + b_2 \mathrm{SENT}_{t-1}) R_t^M + \varepsilon_{it} \qquad (4.7)$$

Panel A uses composite sentiment index as the measure of sentiment and panel B uses consumer confidence.

The long-short portfolios are formed on firm characteristics (*X*): firm size, age, total risk (std. dev.), profitability (*eps*), dividends (*dps*), fixed asset over total asset (FA), research and development over total asset (RD), book-to-market equity (BE/ME) and sales growth (SG). The Newey-West adjusted t-values are calculated and the corresponding p values are reported.

		Panel A		Panel B	
		Composite Sentiment Index		Consumer Confidence	
		b_2	$p(b_2)$	b_2	$p(b_2)$
Size	SMB	-0.0294	*0.213*	-0.0162	*0.331*
Age	High-Low	-0.052	*0.260*	-0.037	*0.578*
SD	High-Low	0.045	*0.495*	0.020	*0.546*
eps	$>0 - \leq 0$	0.033	*0.333*	0.076	*0.251*
dps	$>0 - = 0$	0.036	*0.605*	-0.014	*0.846*
FA	High-Low	-0.333	*0.000*	-0.172	*0.000*
RD	High-Low	0.584	*0.000*	0.300	*0.000*
BE/ME	HML	0.014	*0.212*	0.021	*0.231*
SG	High-Low	-0.161	*0.067*	-0.089	*0.049*
BE/ME	High-Medium	0.371	*0.000*	0.210	*0.000*
SG	High-Medium	-0.003	*0.969*	0.009	*0.840*
BE/ME	Medium-Low	-0.236	*0.000*	-0.137	*0.000*
SG	Medium-Low	-0.146	*0.017*	-0.081	*0.010*

There are two basic stories of systematic risk explanations. One is that the systematic risks of stocks with certain characteristics vary with the sentiment measures. Baker and Wurgler (2006) propose a simple model to investigate this possibility.

$$R_{X_{it}=high,t} - R_{X_{it}=low,t} = \alpha_1 + \alpha_2 \mathrm{SENT}_{t-1} + (b_1 + b_2 \mathrm{SENT}_{t-1}) R_t^M + \varepsilon_{it} \qquad (4.7)$$

In the framework of the conditional CAPM model, the systematic risk and beta loadings, are correlated to the sentiment measures. If sentiment coincides with time variation in market betas, then the estimates of b_2, should have the same sign as the estimates of α_2 in table 4.4. However, as reported in table 4.6, when the estimates of b_2 is significant, the sign is wrong.

The second story of the systematic risk explanation is to keep beta fixed, but to allow the market risk premium to vary with investor sentiment. This story implies that the difference in required returns between different beta stocks varies in proportion. However, the long-short portfolio returns reveal that the predictive power of several characteristics varies not just in magnitude over time, but also in sign.

4.6 The Sentiment Strategy

The patterns of firm characteristics and portfolio returns obtained from models (4.1) and (4.2) are consistent. According to the existing literature, model (4.1), on a rolling window basis, is used to analyse sentiment portfolio returns. Table 4.7 presents the summary statistics of sentiment-prone portfolio returns. The portfolio returns in excess of risk free rate generally increase with the portfolio sentiment sensitivities. Portfolio that is most influenced by sentiment earns the highest monthly excess return of 1.67% and portfolio that is least influenced by sentiment obtains 0.68% monthly excess return. The T-statistic suggests that the difference between portfolio 10 and portfolio 1 is statistically significant. The strategy of buying portfolio 10 and selling portfolio 1 leads to an annual profit of 11.9%.

Table 4.7: Summary statistics of the sentiment-prone portfolio excess returns per month

	Port 1	Port 2	Port 3	Port 4	Port 5	Port 6	Port 7	Port 8	Port 9	Port 10
Mean	0.68	0.76	0.75	0.80	0.88	0.91	1.09	1.17	1.31	1.67
Min	0.311	0.159	0.129	0.131	0.298	0.175	0.133	0.274	0.136	0.136
Max	-0.314	-0.202	-0.198	-0.152	-0.212	-0.127	-0.165	-0.170	-0.172	-0.185
Returns of (Port10 – Port1)					t-statistic: 2.41					

Note: The reported portfolio returns are subtracted by risk free rate and displayed in percentages.

There are numerous papers attempting to estimate transaction costs in the stock market. The research typically reveals that the transaction costs are higher for firms with a bad performance whereas they are lower for firms with a good performance. Basing on different strategies, Lesmond et al. (2004) report that the transaction costs for weak performers rank from 3.419% to 6.099%; those are from 4.317% to 5.049% for strong performers and from 2.893% to 4.163% for medium performers from 1980 to 1998. Groot et al. (2012) report that the average transaction costs are 1.6% for most liquid stocks and 6.0% for most illiquid stocks from 1990 to 2009. Thapa et al. (2010) show that the total cost of the US market is 1.562% and that of the UK market is 4.724% from 2001 to 2006. Li et al. (2009) demonstrate that the transaction cost is 3.4% for winners and around 6.6% for losers in UK stock markets. All the transaction costs reported above are the round-trip costs based on full turnover. Hence, it is reasonable to believe that the strategy based on long-short sentiment-prone portfolios is able to achieve significant profits even after the consideration of transaction costs.

The analysis starts with the exploration of the source of this profit by examining the impact of traditional risk to see whether the traditional risk factors help explain the high returns of the portfolio most sensitive to sentiment. In additional to the Fama and French 3 risk factors and the momentum factors, the liquidity risk factor (LIQ) is adopted to further rule out the impact of liquidity. Appendix A.4 provides a full description of the construction procedure of the liquidity risk factor. The simple model as follows is utilised:

$$R_{pt} = \alpha_p + \beta_{pm} R_t^M + \beta_{p,smb} SMB_t + \beta_{p,hml} HML_t + \beta_{p,umd} UMD_t + \beta_{p,liq} LIQ_t + \varepsilon_{pt} \qquad (4.8)$$

R_{pt} is the portfolio excess return and other notations are defined as before. The intercept, α_p, measures the average monthly abnormal return. The regression results are shown in table 4.8.

The values of adjusted R^2 are relatively low for the three portfolios that are most influenced by investor sentiment. These portfolios, especially the last two portfolios, exhibit the largest alpha coefficients. The corresponding t-statistics indicate that the abnormal returns on portfolios most exposed to sentiment are significantly different from zero. Therefore, the reasonable conclusion is that the traditional risk factor does not explain the returns of portfolios with high sentiment sensitivities.

Table 4.8: Time-series regressions of monthly excess returns of sentiment-prone portfolios on traditional risk factors

Regressions of excess returns of the ten sentiment portfolios on the four traditional risk factors.

$$R_{pt} = \alpha_p + \beta_{pm} R_t^M + \beta_{p,smb} SMB_t + \beta_{p,hml} HML_t + \beta_{p,umd} UMD_t + \beta_{p,liq} LIQ_t + \varepsilon_{pt} \qquad (4.8)$$

R_{pt} is the portfolio excess returns. The four factors are the market risk premium, the Fama-French factor (SMB and HML), the momentum factor (UMD) and the liquidity factor (LIQ). Portfolio 1 consists of stocks least sensitive to sentiment while portfolio 10 consists of stocks most sensitive to sentiment. The adjusted R^2 are reported in the last column. The Newey-West adjusted t-values are calculated and the corresponding *p* values are reported in the parentheses.

Portfolio	alpha	Rm	SMB	HML	UMD	LIQ	Adjusted R^2
1.	-0.0013	0.911	-0.065	0.141	-0.023	0.007	0.793
p-value	*(0.749)*	*(0.000)*	*(0.017)*	*(0.040)*	*(0.541)*	*(0.842)*	
2	-0.00021	0.993	-0.0057	0.102	0.039	0.016	0.817
p-value	*(0.927)*	*(0.000)*	*(0.095)*	*(0.044)*	*(0.374)*	*(0.734)*	
3	-0.0003	0.934	0.0119	0.099	0.091	0.018	0.778
p-value	*(0.880)*	*(0.000)*	*(0.075)*	*(0.068)*	*(0.029)*	*(0.665)*	
4	0.0007	0.928	0.0147	0.083	-0.120	0.016	0.776
p-value	*(0.856)*	*(0.000)*	*(0.079)*	*(0.090)*	*(0.231)*	*(0.734)*	
5	0.0020	0.9351	0.035	-0.164	-0.031	0.027	0.770
p-value	*(0.210)*	*(0.000)*	*(0.044)*	*(0.069)*	*(0.413)*	*(0.523)*	
6	0.0021	0.940	0.045	-0.225	-0.031	0.024	0.747
p-value	*(0.236)*	*(0.000)*	*(0.036)*	*(0.000)*	*(0.414)*	*(0.622)*	
7	0.0022	0.975	0.055	-0.319	0.0458	0.112	0.735
p-value	*(0.193)*	*(0.000)*	*(0.023)*	*(0.000)*	*(0.511)*	*(0.031)*	
8	0.0029	1.0168	0.072	0.024	0.223	0.143	0.685
p-value	*(0.174)*	*(0.000)*	*(0.025)*	*(0.634)*	*(0.000)*	*(0.014)*	
9	0.0045	1.112	0.087	0.0258	0.1015	0.291	0.708
p-value	*(0.001)*	*(0.000)*	*(0.009)*	*(0.670)*	*(0.002)*	*0.000*	
10	0.0051	1.215	0.165	0.074	0.0401	0.351	0.662
p-value	*(0.006)*	*(0.000)*	*(0.000)*	*(0.192)*	*(0.386)*	*(0.001)*	

The third column describes the market beta of model (4.8) which measures the exposure to systematic risk. The regression results show that the portfolios most sensitive to sentiment have a higher systematic risk than the portfolios less sensitive to sentiment. The exposure to market risk is 0.887 for the portfolio least impacted by sentiment, while it is 1.215 for the portfolios most impacted by sentiment.

The fourth, fifth and sixth columns present the beta loadings of size, value and liquidity risk factors respectively. Portfolios that are least exposed to sentiment are negatively related to SMB but positively related to HML and LIQ. On the contrary, portfolios that are most exposed to sentiment are positively related to SMB but negatively related to HML. The factor loadings on SMB and LIQ generally increase. The results corroborate that the portfolios which are most sensitive to sentiment contain more firms of small capitalisation and low liquidity. There is no clear pattern of the factor loadings on HML which is consistent with conjecture that firms with extremely high and low values of BE/ME are all sensitive to investor sentiment.

Unfortunately, there isn't a clear implication from the regression coefficients for the momentum factor and only three out of them are significant. The abnormal return, described by alpha coefficients, is significantly different from zero for the two portfolios that are most sensitive to sentiment. Overall, it may be concluded that neither the three risk factors of Fama and French (1993) nor the momentum factor nor the liquidity factor can explain the abnormal returns of portfolios that are susceptible to investor sentiment.

4.7 The Sentiment Risk Factor Explanation

Section 4.5 suggests that sentiment predicts returns on long-short portfolios constructed from various firm characteristics and that the predictive power cannot be justified by systematic risk. The empirical results support the hypothesis that investor sentiment is an important factor in the return generating process. In accordance with Fama and French (1993), the sentiment risk premium is constructed and the effects of this risk premium are explored in this section.

4.7.1 Construction of Sentiment Risk Premium

It is well-known that the separately-identified size and value effects are not independent phenomena because the security characteristics all share a common variable – price per share of the firm's common stock. Fama and French (1993) propose a double-sort portfolio from the intersections of the BE/ME and size groups and then construct the SMB and HML factors.

The sentiment sensitivity may be correlated with other variables that might also affect the risk and return relationship. As reported earlier, small firms and firms with extreme values of BE/ME are more sensitive to sentiment compared with firms that are large and fairly valued. Therefore, a portfolio constructed using high sentiment sensitivity may include a large number of small stocks or stocks with extreme BE/ME ratios. As a result, returns of such portfolios could be affected by the size effect or value effect. In spirit with the construction of SMB and HML factors by Fama and French (1993), a triple-sorting procedure is proposed to orthogonalise the sentiment effect from the size and value effects.

Every month, all stocks in the sample are ranked by size and split into two groups, small and big (S and B). These stocks are also broken into three book-to-market equity groups on the break points for the bottom 30% (low), middle 40% (Medium), and top 30% (High) according to their BE/ME ratios.

Similarly, stocks are sorted by their sensitivities to investor sentiment using the absolute value of their sentiment betas as described in model (4.1). The stocks are broken into three portfolios. The low-sensitivity (LS) portfolio consists of the stocks least exposed to sentiment, whose absolute sentiment betas are the bottom 30% of the ranked values. The medium-sensitivity (MS) portfolio includes stocks whose absolute sentiment betas are the medium 40%

of the ranked values and the high-sentiment (HS) portfolio includes stocks with the top 30% absolute sentiment betas.

Eighteen portfolios (S/L/LS, S/L/MS, S/L/HS, S/M/LS, S/M/MS, S/M/HS, S/H/LS, S/H/MS, S/H/HS, B/L/LS, B/L/MS, B/L/HS, B/M/LS, B/M/MS, B/M/HS, B/H/LS, B/H/MS, B/H/HS) are constructed from the intersection of independent sorts of stocks into size, BE/ME and sentiment sensitivity. Monthly value-weighted returns are calculated for each portfolio from 1987m03 to 2012m12.

The value-weighted returns of each portfolio are calculated. The sentiment risk premium factor, denoted as SRP, is defined as the average return on the six high-sentiment portfolios minus the average return on the six low-sentiment portfolios,

$$SRP = \frac{1}{6}(\mathrm{S/L/HS} + \mathrm{S/M/HS} + \mathrm{S/H/HS} + \mathrm{B/L/HS} + \mathrm{B/M/HS} + \mathrm{B/H/HS}) - \frac{1}{6}(\mathrm{S/L/LS} + \mathrm{S/M/LS} + \mathrm{S/H/LS} + \mathrm{B/L/LS} + \mathrm{B/M/LS} + \mathrm{B/H/LS}) \quad (4.9)$$

Table 4.9: Properties of the investigated risk factors

	Rm	SMB	HML	UMD	LIQ	SRP
Panel A: summary statistics monthly returns of portfolio risk factors						
Mean (%)	0.36	0.09	0.28	0.79	0.49	0.60
Median (%)	0.81	0.05	0.19	0.80	0.17	0.58
Min (%)	-13.61	-11.44	-18.49	-24.40	-12.57	-29.26
Max (%)	9.89	16.49	12.15	13.77	14.91	34.29
Panel B: correlation of portfolio risk factors						
Rm	1					
SMB	0.10	1				
HML	-0.13	-0.09	1			
UMD	-0.23	-0.12	0.54	1		
LIQ	-0.60	-0.14	0.01	0.29	1	
SRP	0.17	0.35	-0.26	0.01	-0.26	1

Note: Rm is the market factor which is the market portfolio return minus the risk free rate. SMB, HML, UMD, LIQ and SRP are size, value, momentum, liquidity and sentiment risk factors.

Table 4.9 summarises the properties of the sentiment risk factor (SRP) and of the market (Rm), size (SMB), BE/ME (HML), momentum (UMD), and liquidity (LIQ) factors for comparison. The correlation matrix presented in panel B shows that the risk premium related to sentiment is weakly related to the market risk premium and momentum premium. The correlations between sentiment risk factor and the other three factors, SMB, HML and LIQ are moderate. These low correlations indicate the inability of the traditional risk factors to capture the sentiment effect and appear to confirm the hypothesis that the sentiment risk factor contains information that is not connected to the other risk factors.

4.7.2 The Impact of Sentiment Risk Premium

To test whether sentiment risk is a priced risk factor and requires a risk premium for any stocks exposed to it, the sentiment risk premium is augmented to the multi-factor model of equation (4.8). The following model is examined:

$$R_{pt} = \alpha_p + \beta_{pm} R_t^M + \beta_{p,srp} SRP_t + \beta_{p,smb} SMB_t + \beta_{p,hml} HML_t$$
$$+ \beta_{p,umd} UMD_t + \beta_{p,liq} LIQ_t + \varepsilon_{pt} \qquad (4.10)$$

Table 4.10 presents the estimation results of this sentiment-augmented multi-factor model. The factor loadings of sentiment risk factor are significant for the three portfolios most exposed to sentiment at the 1% significance level and are significant for the seventh portfolio at the 10% level. Therefore, the portfolios that are more sensitive to investor sentiment are more influenced by the sentiment risk premium. The inclusion of a sentiment risk premium raises the explanatory power of these portfolio returns from 1.9% to 5.3%. In contrast, the increments of explanatory power of the rest of the portfolios are much less, only from -0.2% to 0.4%. The returns of the portfolio least exposed to sentiment are negatively related to sentiment risk premium while returns of the portfolio most exposed to sentiment are positively related to the sentiment risk premium.

Table 4.10: Time-series regressions of monthly excess returns of sentiment-prone portfolios on traditional risk factors

Regressions of excess returns of the ten sentiment portfolios on the sentiment risk factor and the four traditional risk factors.

$$R_{pt} = \alpha_p + \beta_{pm} R_t^M + \beta_{p,srp} SRP_t + \beta_{p,smb} SMB_t + \beta_{p,hml} HML_t + \beta_{p,umd} UMD_t + \beta_{p,liq} LIQ_t + \varepsilon_{pt} \quad (4.10)$$

R_{pt} is the portfolio excess returns. The factors are the market risk premium, the sentiment risk factor (SRP), the Fama-French factor (SMB and HML), and the momentum factor (UMD). Portfolio 1 consists of stocks least sensitive to sentiment while portfolio 10 consists of stocks most sensitive to sentiment. The adjusted R^2 and Δ adjusted R^2 are reported in the last two columns. Δ adjusted R^2 is the increment of adjusted R^2 in table 4.9 over those reported in table 4.8 and shows the improvement of the adjusted R^2 after the addition of the sentiment risk factor. The Newey-West adjusted t-values are calculated and the corresponding p values are reported in the parentheses.

Portfolio	alpha	Rm	SRP	SMB	HML	UMD	LIQ	Adj.R^2	Δ adj.R^2
1.	0.0043	0.986	-0.042	0.132	-0.091	0.011	0.001	0.793	0
p-value	*(0.011)*	*(0.000)*	*(0.302)*	*(0.012)*	*(0.111)*	*(0.791)*	*(0.831)*		
2	0.0044	1.128	-0.033	-0.023	0.046	-0.032	0.015	0.819	0.2%
p-value	*(0.001)*	*(0.000)*	*(0.429)*	*(0.612)*	*(0.367)*	*(0.385)*	*(0.676)*		
3	0.0019	0.913	0.0141	0.093	0.069	0.038	0.014	0.776	-0.2%
p-value	*(0.105)*	*(0.000)*	*(0.456)*	*(0.091)*	*(0.250)*	*(0.396)*	*(0.734)*		
4	0.0024	0.936	0.028	0.063	0.081	0.087	0.026	0.707	0
p-value	*(0.408)*	*(0.000)*	*(0.253)*	*(0.221)*	*(0.150)*	*(0.038)*	*(0.600)*		
5	0.0027	0.954	0.032	0.106	0.107	-0.232	0.027	0.773	0.3%
p-value	*(0.210)*	*(0.000)*	*(0.160)*	*(0.104)*	*(0.133)*	*(0.000)*	*(0.732)*		
6	-0.0019	0.940	0.031	0.056	0.004	-0.036	0.037	0.748	0.4%
p-value	*(0.226)*	*(0.000)*	*(0.189)*	*(0.246)*	*(0.946)*	*(0.344)*	*(0.391)*		
7	-0.0018	0.898	0.040	0.081	0.076	-0.038	0.048	0.738	0.3%
p-value	*(0.253)*	*(0.000)*	*(0.078)*	*(0.090)*	*(0.145)*	*(0.325)*	*(0.266)*		
8	0.00029	0.963	0.059	-0.0154	-0.042	0.051	0.158	0.704	1.9%
p-value	*(0.862)*	*(0.000)*	*(0.000)*	*(0.860)*	*(0.662)*	*(0.467)*	*(0.001)*		
9	0.00056	1.021	0.095	0.021	-0.025	-0.104	0.157	0.764	2.6%
p-value	*(0.713)*	*(0.000)*	*(0.001)*	*(0.599)*	*(0.560)*	*(0.001)*	*(0.001)*		
10	0.00018	0.986	0.181	0.132	-0.091	0.011	0.168	0.715	5.3%
p-value	*(0.920)*	*(0.000)*	*(0.000)*	*(0.012)*	*(0.111)*	*(0.791)*	*(0.004)*		

The research is interested in the magnitude and significance level of abnormal returns. It is observed that the inclusion of the sentiment risk premium reduces the magnitude of the alpha estimates and they are no longer significant. The null hypothesis that the alpha coefficients are zero, cannot be rejected for portfolios 9 and 10 after the addition of the sentiment risk premium. Together with the increments of the adjusted R^2, the addition of a risk sentiment premium contributes to better explain the abnormal returns of portfolio 9 and 10.

4.7.3 The Impact of Sentiment Risk Premium on Size and BE/ME Portfolios

The last section indicates that sentiment risk premium helps to explain returns of sentiment portfolios. This section further examines whether this risk factor helps to explain returns of size and BE/ME portfolios.

Panel A of Table 4.11 presents the regression results of model (4.8) where the dependent variables are portfolio excess returns sorted by firm market capitalisation. The adjusted R^2 are high in all cases expect for three portfolios with the lowest capitalisation. These portfolios also exhibit relatively larger abnormal returns compared with the rest of the portfolios. The abnormal returns tend to be less as the firm capitalisations become larger. Panel B shows the results of model (4.10). For the three portfolios with the smallest stocks, the inclusion of the sentiment risk premium increases the explanatory power from 3.0% to 5.9%. The portfolios with the least market capitalisations are most impacted by the sentiment risk factor. The abnormal returns are substantially reduced and are no longer significant after the addition of the sentiment risk premium.

When turning to portfolios sorted by BE/ME values, there is no surprise that the addition of a sentiment risk factor improves the explanatory power of the portfolios with large BE/ME values. For portfolios 9 and 10, the increments of explanatory power are 1.3% and 2.1% and the abnormal returns become very small and not significantly different from zero. Furthermore, the adjusted R^2 also increases by 1.1% and 0.8% for portfolios 1 and 2. The abnormal returns of these two portfolios are reduced by the addition of the sentiment risk factor. This finding confirms the previous results that there is a U-shaped pattern in returns conditional on investor sentiment. Stocks with low BE/ME are considered to be greatly overvalued and are vulnerable to investor sentiment. The detailed results are shown in Appendix A.5.

Table 4.11: Time-series regressions of monthly excess returns of size portfolios

Panel A: Regressions of excess returns of the ten sentiment portfolios on the four traditional risk factors.

$$R_{pt} = \alpha_p + \beta_{pm}R_t^M + \beta_{p,smb}SMB_t + \beta_{p,hml}HML_t + \beta_{p,umd}UMD_t + \beta_{p,liq}LIQ_t + \varepsilon_{pt} \quad (4.8)$$

Panel B: Regressions of excess returns of the ten sentiment portfolios on the sentiment risk factor the four traditional risk factors.

$$R_{pt} = \alpha_p + \beta_{pm}R_t^M + \beta_{p,srp}SRP + \beta_{p,smb}SMB_t + \beta_{p,hml}HML_t + \beta_{p,umd}UMD_t + \beta_{p,liq}LIQ_t + \varepsilon_{pt} \quad (4.10)$$

R_{pt} is the size portfolio excess returns. The factors are the market risk premium, the sentiment risk factor (SRP), the Fama-French factor (SMB and HML), and the momentum factor (UMD). The adjusted R^2 and Δ adjusted R^2 are reported. Δ adjusted R^2 is the increment of adjusted R^2 in table 9 over those reported in table 8 and shows the improvement of the adjusted R^2 after the addition of the sentiment risk factor. The Newey-West adjusted t-values are calculated and the corresponding p values are reported.

Panel A:	Portfolio	alpha	*p-value*	Rm	*p-value*	SMB	*p-value*	HML	*p-value*	UMD	*p-value*	LIQ	*p-value*	Adj. R^2
	1.	0.0118	*0.000*	1.005	*0.000*	1.088	*0.000*	0.140	*0.063*	0.080	*0.164*	0.156	0.015	0.750
	2	0.0079	*0.000*	1.007	*0.000*	1.054	*0.000*	0.225	*0.000*	-0.073	*0.114*	0.102	0.048	0.761
	3	0.0057	*0.000*	0.986	*0.000*	1.073	*0.000*	0.229	*0.000*	-0.052	*0.212*	0.154	0.001	0.799
	4	0.0044	*0.005*	1.006	*0.000*	1.089	*0.000*	0.105	*0.036*	-0.045	*0.239*	0.110	0.003	0.838
	5	0.0024	*0.081*	0.998	*0.000*	1.020	*0.000*	0.186	*0.000*	-0.008	*0.816*	0.083	0.052	0.863
	6	0.004	*0.002*	0.972	*0.000*	0.999	*0.000*	0.201	*0.000*	-0.079	*0.013*	0.066	0.009	0.894
	7	0.0015	*0.203*	0.938	*0.000*	0.947	*0.000*	0.103	*0.005*	-0.065	*0.022*	0.064	0.094	0.912
	8	0.0011	*0.313*	0.908	*0.000*	0.792	*0.000*	0.094	*0.009*	-0.049	*0.075*	0.013	0.714	0.913
	9	0.0019	*0.088*	0.817	*0.000*	0.509	*0.000*	-0.019	*0.607*	-0.169	*0.000*	0.011	0.739	0.907
	10	0.0017	*0.075*	0.912	*0.000*	0.092	*0.001*	-0.015	*0.612*	-0.059	*0.009*	0.032	0.299	0.903

Panel B:

Port.	alpha	*p-value*	Rm	*p-value*	SRP	*p-value*	SMB	*p-value*	HML	*p-value*	UMD	*p-value*	LIQ	*p-value*	Adj.R^2	Δ adj.R^2
1.	0.0016	*0.238*	1.004	*0.000*	0.090	*0.000*	1.084	*0.000*	0.143	*0.058*	0.077	*0.182*	0.159	0.014	0.809	5.9%
2	0.0015	*0.211*	1.006	*0.000*	0.088	*0.0003*	1.012	*0.000*	0.266	*0.000*	-0.063	*0.172*	0.121	0.019	0.796	3.5%
3	0.0015	*0.179*	0.987	*0.000*	1.073	*0.000*	1.016	*0.000*	0.286	*0.000*	-0.038	*0.352*	0.180	0.000	0.829	3.0%
4	0.0020	*0.094*	1.006	*0.000*	1.089	*0.000*	1.031	*0.000*	0.163	*0.001*	-0.030	*0.410*	0.113	0.000	0.849	1.1%
5	0.0026	*0.054*	0.997	*0.000*	0.050	*0.012*	0.987	*0.000*	0.218	*0.000*	0.0001	*0.998*	0.108	0.009	0.866	0.3%
6	0.0042	*0.001*	0.982	*0.000*	0.058	*0.024*	0.969	*0.000*	0.231	*0.000*	-0.072	*0.023*	0.079	0.039	0.896	0.2%
7	0.0011	*0.352*	0.951	*0.000*	0.051	*0.009*	0.941	*0.000*	0.108	*0.003*	-0.069	*0.013*	0.068	0.008	0.914	0.2%
8	0.0011	*0.315*	0.907	*0.000*	0.047	*0.011*	0.792	*0.000*	0.094	*0.009*	-0.049	*0.077*	0.026	0.468	0.912	-0.1%
9	0.0019	*0.114*	0.806	*0.000*	-0.002	*0.958*	0.507	*0.000*	-0.018	*0.632*	-0.171	*0.000*	0.001	0.793	0.907	0
10	0.0014	*0.145*	0.910	*0.000*	-0.023	*0.024*	0.088	*0.001*	-0.012	*0.686*	-0.063	*0.006*	0.031	0.318	0.905	0.2%

Note: Portfolio 1 contains smallest stocks and portfolio 10 consists of largest firms.

4.7.4 Price of Sentiment Risk Factor

Table 4.12: Pricing the cross-section of portfolios sorted by sentiment, size, BE/ME and size and BE/ME-sorted portfolios, respectively

This table reports the summary statistics of the cross-sectional Fama and MacBeth regressions for the sentiment-prone portfolios, size portfolios, BE/ME portfolios and size and BE/ME sorted portfolios. In the first stage, portfolio returns are regressed on the pricing factors (market excess return, SMB, HML, UMD, LIQ and SRP) to obtain factor loadings. In the second stage, for each month, portfolio returns are regressed on the loadings, resulting in an estimate of the price of risk for each factor. The *t*-ratios are calculated using the Jagannathan and Wang (1998) and Newey and West (1987) procedures to account for the estimation errors in the first-stage estimation and correct for the possible heteroskedasticity and autocorrelation. The corresponding *p*-values are reported in the parentheses according to the adjusted *t*-ratios. Adjusted R^2 and root-mean-squared pricing errors (RMSPE) are reported.

	10 Sentiment-prone Portfolio		10 Size Portfolio		10 BE/ME Portfolio		25 Size and BE/ME Portfolio	
	5-factor	6-factor	5-factor	6-factor	5-factor	6-factor	5-factor	6-factor
Rm	0.164	0.586	0.206	0.266	0.214	0.208	0.304	0.322
p-value	*(0.088)*	*(0.000)*	*(0.006)*	*(0.001)*	*(0.063)*	*(0.083)*	*(0.261)*	*(0.191)*
SMB	0.173	0.025	0.271	0.201	0.159	0.165	0.258	0.0076
p-value	*(0.042)*	*(0.535)*	*(0.003)*	*(0.083)*	*(0.009)*	*(0.091)*	*(0.000)*	*(0.942)*
HML	0.178	0.234	0.414	0.301	0.194	0.185	0.916	0.639
p-value	*(0.082)*	*(0.004)*	*(0.063)*	*(0.101)*	*(0.000)*	*(0.077)*	*(0.000)*	*(0.000)*
UMD	0.072	0.061	0.371	0.224	0.021	0.021	0.640	0.550
p-value	*(0.036)*	*(0.130)*	*(0.000)*	*(0.017)*	*(0.015)*	*(0.066)*	*(0.081)*	*(0.234)*
LIQ	0.131	0.069	0.334	0.090	0.192	0.197	0.379	0.345
p-value	*(0.105)*	*(0.249)*	*(0.139)*	*(0.734)*	*(0.074)*	*(0.819)*	*(0.005)*	*(0.107)*
SPR		0.589		0.492		0.229		0.298
p-value		*(0.000)*		*(0.008)*				*(0.042)*
Adjusted R^2	0.264	0.823	0.847	0.934	0.831	0.906	0.765	0.881
RMSPE	0.301	0.114	0.131	0.113	0.138	0.124	0.123	0.112

To test whether investor sentiment is priced in the cross-section of the stock market, the Fama-MacBeth two-stage regression is performed on models (4.8) and (4.10). The variables to be explained are the excess returns on the ten sentiment-prone portfolios, the ten size-sorted portfolios, the ten BE/ME-sorted portfolios and the twenty five size and BE/ME-sorted portfolios. The estimation results are displayed in table 4.12. The regression results suggest that investor sentiment has a significant positive price for the portfolios sorted by four criteria. This suggests that, on average, investing in stocks exposed to more sentiment risk is rewarded with higher returns. In general, the inclusion of sentiment risk premium attenuates the impacts of the traditional risk factors (SMB, HML and UMD) and liquidity risk factor (LIQ) and reduces the significant levels of these factors. The adjusted R^2 and root-mean-squared pricing error (RMSPE) of the sentiment-augmented factor model compares favourably to the traditional factor model with market excess return, size, value, momentum and liquidity premiums.

4.8 Conclusion

Using all the non-financial firms listed on London Stock Exchange from March 1987 to December 2012, portfolios are constructed based on the exposure of stock returns to investor sentiment. The study finds that the sensitivities of investor sentiment vary monotonically with certain firm characteristics in the cross-section. Specifically, small firms, volatile firms, unprofitable firms, non-dividend-paying firms, less intangible firms, and extremely growing firms are more sensitive to market sentiment. The results are consistent with the predictions of noise traders' models that the returns of stocks are hard to value and difficult to arbitrage and are especially susceptible to market sentiment. The results indicate that measures revolving around reducing limits to arbitrage would be efficient in reducing the negative effect that noise traders have on the market.

The research shows that the cross-section of future stock returns is conditional on previous measures of investor sentiment. Sentiment exerts a predictive power on long-short portfolios and the predictive power cannot be regarded as compensation for systematic risk. The empirical results provide evidence that investors appear to overvalue stocks with certain characteristics (small, volatile, unprofitable, non-dividend-paying, less intangible, and extremely growing) during periods when investor sentiment is high, and vice versa. The results are consistent with predictions of models in which limits of arbitrage and correlated trading by noise traders can cause the prices of assets to deviate from economic fundamentals.

The empirical findings imply that investors should consider the impact of noise trading when making investment decisions. First, investors should take a contrarian investment strategy to gain excess returns. Second, stocks that are more vulnerable to market sentiment are more suitable for investors who can bear larger risks.

Given the predictive power of investor sentiment, this chapter explores the profitability of the strategy that is long on stocks most exposed to sentiment and short on stocks least exposed to sentiment. This strategy generates a significant profit which cannot be fully explained by the traditional risk factors, such as market excess return, size factor (SMB), value factor (HML), momentum factor (UMD) or liquidity factor (LIQ).

A new risk factor, the sentiment risk factor, is established following a triple-sort procedure. The risk factor helps to explain the abnormal returns of portfolios including stocks of the smallest market capitalisation and those of portfolios including stocks with extreme values of BE/ME ratios. The empirical evidence from the two-stage Fama-MacBeth procedure suggests that the sentiment risk factor is significantly priced in the cross-section, which reveals that risk-averse investors require risk compensation for exposure to sentiment risk. Sentiment risk shall be a priced risk factor in asset pricing, for example, it might be a potential factor in the framework of the ICAPM model and arbitrage pricing model. The inclusion of this new factor reduces the risk premium of the traditional risk factors mentioned above.

Appendix A

Table A.1: The time-series averages of each firm characteristics are calculated, and then these averages are pooled across sentiment sensitivity portfolios

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	***F***	***p-value***	***T(10-1)***	***p-value***
Std. Dev.	10.91	11.28	11.50	11.70	11.96	12.62	13.50	14.79	17.40	23.49	842.351	0.000	-49.099	0.000
size	1446.63	1305.65	1489.15	1269.94	1175.14	1065.62	904.59	769.38	529.97	176.42	96.723	0.000	19.757	0.000
eps	17.02	15.41	14.79	12.92	14.26	13.36	12.35	13.68	12.64	10.15	4.503	0.000	4.405	0.000
pps	5.79	5.71	5.67	5.31	5.15	4.09	4.77	4.75	4.41	2.72	3.846	0.000	3.257	0.000
*eps**	83.47	83.97	83.43	82.80	81.70	80.95	79.46	75.24	66.26	49.00	432.232	0.000	-34.877	0.000
*dps**	78.19	80.06	79.91	78.58	78.19	75.52	71.91	66.71	56.07	35.47	257.441	0.000	-29.908	0.000
fixed assets	32.33	31.46	31.44	31.27	31.48	31.00	29.91	29.30	29.24	29.21	8.056	0.000	3.575	0.000
research and development	4.57	4.58	4.60	4.61	4.64	4.79	4.94	5.41	7.06	9.57	9.405	0.000	3.780	0.000
BE/ME	1.36	2.16	2.13	2.10	2.35	2.78	2.81	2.56	2.28	2.68	3.426	0.000	3.363	0.000
sales growth	2.09	2.63	4.17	4.77	5.26	6.35	10.29	10.49	8.67	7.03	3.529	0.000	3.678	0.000

Note: The following model is estimated: $R_{jt} = \alpha_j^t + \beta_{jm}^t R_t^M + \beta_{j,smb}^t R_{smb,t} + \beta_{j,hml}^t R_{hml,t} + \beta_{j,umd}^t R_{umd,t} + \beta_{js}^t \Delta\mathrm{SENT}_t + \varepsilon_{jt}$ on a 36 rolling-window basis. Portfolio 1 consists of stocks least exposed to sentiment while portfolio 10 includes stocks most exposed to sentiment. The F-statistics and t-statistics are reported testing that the given average firm characteristic is equal across all sentiment portfolios, and between the 1st and 10th sentiment respectively.

Table A.2: Time-series Regression of Long-Short Portfolio returns on consumer confidence, March 1987 to December 2012 of Section
Panel A: Regressions of long-short portfolio returns on lagged sentiment only.

$$R_{X_{jt}=high,t} - R_{X_{jt}=low,t} = \alpha_1 + \alpha_2 \mathrm{SENT}_{t-1} + \varepsilon_{jt} \qquad (4.3)$$

Panel B: Regressions of long-short portfolio returns on lagged sentiment, the market risk premium, the Fama-French factor (SMB and HML), and the momentum factor(UMD).

$$R_{X_{it}=high,t} - R_{X_{it}=low,t} = \alpha_1 + \alpha_2 \mathrm{SENT}_{t-1} + \beta R_t^M + \gamma SMB_t + \delta HML_t + \eta UMD_t + \varepsilon_{it} \qquad (4.4)$$

The long-short portfolios are formed on firm characteristics (X): firm size, age, total risk (std. dev.), profitability (eps), dividends (dps), fixed asset over total asset (FA), research and development over total asset (RD), book-to-market equity (BE/ME) and sales growth (SG). The Newey-West adjusted t-values are calculated and the corresponding p values are reported.

		Panel A		Panel B	
		Model (4.3)		Model (4.4)	
		α_2	$p(\alpha_2)$	α_2	$p(\alpha_2)$
Size	SMB	-0.684	*0.050*	-0.601	*0.095*
Age	High-Low	0.348	*0.053*	0.323	*0.081*
SD	High-Low	-0.992	*0.008*	-0.554	*0.078*
eps	$> 0 - \leq 0$	0.719	*0.035*	0.705	*0.046*
dps	$> 0 - = 0$	0.753	*0.044*	0.599	*0.099*
FA	High-Low	0.879	*0.009*	0.893	*0.011*
RD	High-Low	-0.587	*0.026*	-0.492	*0.026*
BE/ME	HML	-0.920	*0.056*	-0.309	*0.499*
SG	High-Low	-0.617	*0.066*	-0.428	*0.187*
BE/ME	High-Medium	-0.898	*0.026*	-0.797	*0.072*
SG	High-Medium	-0.961	*0.000*	-0.668	*0.000*
BE/ME	Medium-Low	0.746	*0.024*	0.648	*0.052*
SG	Medium-Low	0.567	*0.063*	0.553	*0.056*

Table A.3: Time series regressions of long-short portfolio returns on the consumer confidence (using the framework of ICAPM, March 1987 to December 2012)

Panel A: Regressions of long-short portfolio returns where market beta is conditional on fundamental component of sentiment.

$$R_{X_{jt}=high,t} - R_{X_{jt}=low,t} = (\alpha_1 + \alpha_2 \mathrm{SENT}_{t-1}) + (\beta_1 + \beta_2 Fund_{t-1})R_t^M + \varepsilon_{jt} \quad (4.5)$$

Panel B: Regressions of long-short portfolio returns where market beta is conditional on fundamental component, dividend yield, inflation, term spreadand interest. The market risk premium, the Fama-French factor (SMB and HML), and the momentum factor(UMD) are included to restrict the traditional risk.

$$R_{X_{jt}=high,t} - R_{X_{jt}=low,t} = (\alpha_1 + \alpha_2 \mathrm{SENT}_{t-1}) + (\beta_1 + \beta_2 Fund_{t-1} + \beta_3 DY + \beta_4 Inflation$$
$$+\beta_5 TS + \beta_6 IR)R_t^M + \beta R_t^M + \gamma SMB_t + \delta HML_t + \eta UMD_t + \varepsilon_{jt} \quad (4.6)$$

The long-short portfolios are formed on firm characteristics (*X*): firm size, age, total risk (std. dev.), profitability (eps), dividends (dps), fixed asset over total asset (FA), research and development over total asset (RD), book-to-market equity (BE/ME) and sales growth (SG). The Newey-West adjusted t-values are calculated and the corresponding p values are reported.

		Panel A				Panel B			
		Model (4.5)				Model (4.6)			
		α_2	$p(\alpha_2)$	β_2	$p(\beta_2)$	α_2	$p(\alpha_2)$	β_2	$p(\beta_2)$
Size	SMB	-0.29	*0.00*	-0.16	*0.049*	-0.63	*0.00*	-0.16	*0.049*
Age	High-Low	0.10	*0.070*	0.11	*0.095*	0.10	*0.070*	0.11	*0.095*
SD	High-Low	-0.11	*0.014*	-0.43	*0.00*	-0.11	*0.014*	-0.43	*0.00*
eps	$>0 - \leq 0$	0.14	*0.017*	0.22	*0.001*	0.14	*0.017*	0.22	*0.001*
dps	$>0 - =0$	0.53	*0.023*	0.20	*0.078*	0.53	*0.023*	0.20	*0.078*
FA	High-Low	0.48	*0.001*	0.170	*0.000*	0.48	*0.001*	0.170	*0.000*
RD	High-Low	-0.11	*0.041*	-0.21	*0.011*	-0.11	*0.041*	-0.21	*0.011*
BE/ME	HML	-0.07	*0.24*	-0.47	*0.000*	-0.07	*0.24*	-0.47	*0.000*
SG	High-Low	-0.06	*0.24*	-0.02	*0.832*	-0.06	*0.24*	-0.02	*0.832*
BE/ME	High-Medium	-0.73	*0.014*	-0.47	*0.000*	-0.73	*0.014*	-0.47	*0.000*
SG	High-Medium	-0.54	*0.032*	-0.16	*0.008*	-0.54	*0.032*	-0.16	*0.008*
BE/ME	Medium-Low	0.477	*0.005*	0.26	*0.000*	0.477	*0.005*	0.26	*0.000*
SG	Medium-Low	0.44	*0.028*	0.11	*0.011*	0.44	*0.028*	0.11	*0.011*

Appendix A.4

This paper follows Liu (2006)'s approach of constructing liquidity measure. Amihud (2002) and Pastor and Stambaugh (2003) propose various ways to measure liquidity (or illiquidity). Despite the fact that Amihud and Pastor and Stambaugh approaches are popular in liquidity literature, they use dollars volume of individual stocks. Since the pounds volumes of individual stocks in UK stock market are not available before 2011, Liu's approach which requires trading volumes in number rather than pounds volumes is adopted in this thesis. In fact, Liu(2006) demonstrate his measure of illiquidity is highly correlated with Aminud measure.

The liquidity measure of a security, LM, as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months, that is,

$$LM = \left[Number\ of\ zero\ daily\ volume\ in\ prior\ 12\ month + \frac{1/12\ month\ turnover}{deflator}\right] * 21 * 12/NoTD$$

where 12-month turnover is turnover over the prior 12months, calculated as the sum of daily turnover over the prior 12 periods, daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day, NoTD is the total number of trading days in the market over the prior 12 months, and Deflator is chosen such that

$$0 < \frac{1/12\ month\ turnover}{deflator} < 1$$

for all sample stocks. A deflator of 860000 is used to constructing LM.

Individual stocks are sorted into 10 portfolios in an ascending order based on their liquidity measure (LM). Hence, portfolio 10 is consisted of stocks that are least liquid and portfolio 1 is consisted of stocks that are most liquid. Equal-weighted returns of each portfolio are calculated. Then, the mimicking liquidity factor (LIQ) is constructed. LIQ is constructed as the monthly return difference of portfolio 10 and portfolio 1.

Table A.5: Time series regressions of monthly excess returns of BE/ME sorted portfolios (Portfolio 1 contains lowest BE/ME stocks and portfolio 10 consists of highest BE/ME firms)

Panel A: Regressions of excess returns of the ten sentiment portfolios on the four traditional risk factors.

$$R_{pt} = \alpha_p + \beta_{pm} R_t^M + \beta_{p,smb} SMB_t + \beta_{p,hml} HML_t + \beta_{p,umd} UMD_t + \beta_{p,liq} LIQ_t + \varepsilon_{pt} \quad (4.8)$$

Panel B: Regressions of excess returns of the ten sentiment portfolios on the sentiment risk factor the four traditional risk factors.

$$R_{pt} = \alpha_p + \beta_{pm} R_t^M + \beta_{p,srp} SRP_t + \beta_{p,smb} SMB_t + \beta_{p,hml} HML_t + \beta_{p,umd} UMD_t + \beta_{p,liq} LIQ_t + \varepsilon_{pt} \qquad (4.10)$$

R_{pt} is the BE/ME portfolio excess returns. The factors are the market risk premium, the sentiment risk factor (SRP), the Fama-French factor (SMB and HML), and the momentum factor (UMD). The adjusted R^2 and Δ adjusted R^2 are reported. Δ Adjusted R^2 is the increment of adjusted R^2 in table 4.9 over those reported in table 4.8 and shows the improvement of the adjusted R^2 after the addition of the sentiment risk factor. The Newey-West adjusted t-values are calculated and the corresponding p values are reported.

Panel A:

Portfolio	alpha	*p-value*	Rm	*p-value*	SMB	*p-value*	HML	*p-value*	UMD	*p-value*	LIQ	*p-value*	Adj. R^2
1.	0.003	0.068	1.047	0.000	0.793	0.000	-0.601	*0.000*	-0.108	*0.006*	0.031	*0.488*	0.855
2	0.0022	0.066	0.958	0.000	0.756	0.000	-0.285	*0.000*	-0.022	*0.451*	0.031	*0.350*	0.889
3	0.003	0.024	0.906	0.000	0.668	0.000	-0.018	*0.649*	-0.063	*0.032*	0.044	*0.177*	0.876
4	0.0021	0.063	0.833	0.000	0.795	0.000	0.123	*0.001*	-0.003	*0.899*	0.047	*0.126*	0.891
5	0.003	0.006	0.835	0.000	0.850	0.000	0.219	*0.000*	-0.063	*0.038*	0.021	*0.530*	0.881
6	0.0027	0.031	0.805	0.000	0.783	0.000	0.260	*0.000*	-0.034	*0.261*	0.022	*0.529*	0.867
7	0.0041	0.001	0.779	0.000	0.845	0.000	0.372	*0.000*	-0.006	*0.833*	0.037	*0.378*	0.881
8	0.0044	0.002	0.805	0.000	0.899	0.000	0.433	*0.000*	-0.014	*0.685*	0.068	*0.008*	0.857
9	0.0068	0.000	0.070	0.000	0.935	0.000	0.376	*0.000*	-0.129	*0.001*	0.067	*0.009*	0.835
10	0.0112	0.000	0.776	0.000	1.025	0.000	0.473	*0.000*	-0.108	*0.047*	0.077	*0.002*	0.741

Panel B:

Port.	alpha	*p-value*	Rm	*p-value*	SRP	*p-value*	SMB	*p-value*	HML	*p-value*	UMD	*p-value*	LIQ	*p-value*	Adj. R^2	Δ adj. R^2
1.	0.0021	*0.163*	1.013	*0.000*	-0.121	*0.000*	0.714	*0.000*	-0.523	*0.000*	-0.089	*0.017*	0.001	*0.983*	0.866	1.1%
2	0.0017	*0.152*	0.944	*0.000*	-0.051	*0.003*	0.723	*0.000*	-0.252	*0.000*	-0.014	*0.629*	0.018	*0.582*	0.897	0.8%
3	0.0023	*0.057*	0.920	*0.000*	-0.079	*0.011*	0.662	*0.000*	-0.013	*0.735*	-0.068	*0.019*	0.021	*0.543*	0.879	0.3%
4	0.0022	*0.042*	0.822	*0.000*	-0.039	*0.014*	0.769	*0.000*	0.148	*0.000*	0.003	*0.916*	0.022	*0.212*	0.893	0.2%
5	0.0032	*0.010*	0.843	*0.000*	0.043	*0.187*	0.847	*0.000*	0.222	*0.000*	-0.066	*0.030*	0.050	*0.133*	0.881	0
6	0.0026	*0.044*	0.890	*0.000*	0.008	*0.794*	0.781	*0.000*	0.262	*0.000*	-0.036	*0.240*	0.058	*0.057*	0.867	0
7	0.0020	*0.104*	0.780	*0.000*	0.027	*0.419*	0.874	*0.000*	0.373	*0.000*	-0.007	*0.820*	0.079	*0.019*	0.887	0.6%
8	0.0016	*0.242*	0.796	*0.000*	0.036	*0.079*	0.878	*0.000*	0.454	*0.000*	-0.009	*0.802*	0.076	*0.023*	0.865	0.8%
9	0.0013	*0.396*	0.687	*0.000*	0.062	*0.004*	0.894	*0.000*	0.416	*0.000*	-0.119	*0.001*	0.129	*0.001*	0.848	1.3%
10	0.0014	*0.548*	0.794	*0.000*	0.122	*.019*	1.017	*0.000*	0.479	*0.000*	-0.115	*0.035*	0.133	*0.000*	0.822	2.1%

Chapter 5 Conclusion

5.1 Concluding Remarks

Classical finance theory, which is based on the EMH, has been questioned for many years. Its assumptions of the rationality of agents and unlimited arbitrage opportunities have been undermined by recent empirical research. New evidence suggests a novel area in finance which considers human psychology as a predictor of market changes; so called behavioural finance.

Numerous bodies of literature have indicated that investor sentiment is related to time-series and cross-sectional stock returns. DSSW (1990) provides a formal model to address the relations between investor sentiment and stock returns and volatility. This thesis investigates the roles that sentiment plays in standard asset pricing models. At the market level, it explores the risk-return relation affected by sentiment by augmenting sentiment to the EGARCH component model. The study further examines the risk premia of sentiment-affected volatility components in the cross-section. At the firm level, this study explores the relation of sentiment and stock returns based on certain firm characteristics. The sentiment risk premium is developed on the basis of the sensitivity of stock returns to investor sentiment. The research then examines whether the sentiment risk factor is priced. Furthermore, the research examines whether the sentiment risk factor, either standing alone or working with other risk factors, helps to explain portfolio abnormal returns.

The thesis reveals that investor sentiment is positively related to market returns. The sentiment of the last period has the opposite effect on short- and long-run volatility and hence the overall effect of sentiment on future aggregate volatility is unclear. However, since the effects of short- and long-long run volatility on market excess returns are also the opposite, the final effect of sentiment on market return is that the bullish (bearish) sentiment (or changes of sentiment) results in higher (lower) future market return. Recent studies find that sentiment can predict returns (Simon and Wiggins, 2001; Wang, 2001). The result is consistent with Wang et al. (2006) in the sense that market excess returns are contemporaneously positively correlated with shifts in sentiment and that the bullish (bearish) changes of sentiment lead to higher (lower) future returns. However, they demonstrate that changes in sentiment negatively forecast aggregate volatility without ambiguity.

The existing literature demonstrates that investor sentiment exhibits a cross-sectional effect. Investor sentiment helps to explain various anomalies, such as size and value anomalies (Neal and Wheatley, 1998; Brown and Cliff, 2005; Lemmon & Portniaguina, 2006). Besides the size and value anomalies, empirical research further considers investor sentiment to explain other financial anomalies, such as firms without profits, paying dividends, or that low fixed assets earn higher future returns on average than firms with profits, paying dividends or with high fixed assets (Baker and Wurgler, 2006; Berger and Turtle, 2012; Stambaugh et al. ,2012). The study confirms that investor sentiment helps to explain the abnormal returns of small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks and distressed stocks.

Although some studies show that financial markets do not price psychological factors (Elton et al., 1998; Sias et al., 2001; Glushkov, 2006), a large number of studies find that sentiment is an important factor in the return generating process of US common stocks (Lee et al., 2002; Kumar and Lee, 2006; Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Ho and Hung, 2008; Berger and Turtle, 2012; Stambaugh et al., 2012). The study suggests that investor sentiment is a priced factor in the cross-section of the UK stock markets. The pricing ability is robust to the inclusion of size, value, momentum and liquidity risk factors. Hence, investor sentiment is a potential risk factor and it should be priced as other factors in the frameworks of intemporal CAPM or arbitrage pricing theory.

5.2 Summary Findings

The main results of each chapter are given as follows.

Chapter 2 applies Adrian and Rosenberg's decomposition of market risk to the UK stock market. The short- and long-run components of volatility have the opposite effects on market returns. In the cross-section, the empirical results indicate that the short- and long-run volatility components have significantly negative prices of risk. However, the performance of the decomposition model is inferior to the Fama-French three factor model.

The DSSW model suggests that stock returns and volatility are all related to investor sentiment. The inferior performance of the volatility decomposition model in Chapter 2 may be caused by the ignorance of investor sentiment. Therefore, Chapter 3 improves the EGARCH component model by including investor sentiment. By augmenting sentiment to the mean of Adrian and Rosenberg's EGARCH component model, or to both the mean and variance equations, market excess returns are significantly positively related to investor sentiment and the changes of investor sentiment in the time-series estimations.

The study detects significantly negative prices of short- and long-run components of volatility in the cross-sectional estimations. The sentiment-augmented model outperforms the FF 3 factor model in explaining the cross-sectional stock returns. The incorporation of sentiment enhances the pricing ability of short- and long-run volatilities. This chapter provides empirical evidence that investor sentiment has impacts on stock returns and volatility at the market level.

Chapter 4 turns to investigate the sentiment effects on individual stock returns, at the firm level. All the non-financial firms listed on the London Stock Exchange from March 1987 to December 2012 are included to construct portfolios based on sentiment sensitivities and firm characteristics, respectively. The study finds that the sensitivities of investor sentiment vary monotonically with certain firm characteristics in the cross-section. Small firms, volatile firms, unprofitable firms, non-dividend-paying firms, less intangible firms, and extremely growing firms are more responsible to investor sentiment.

The research shows that the cross-section of future stock returns is conditional on previous measures of investor sentiment. Sentiment exerts predictive power on long-short portfolios based on certain firm characteristics. Given the predictive power of investor sentiment, the research attempts to explain the profits of the strategy that is long on stocks most exposed to sentiment and short on stocks least exposed to sentiment. However, the significant profit generated by the long-short strategy cannot be fully explained by the traditional risk factors, such as the FF three factors.

The thesis establishes a triple-sort procedure to construct the sentiment risk factor. The risk factor helps to explain the size and value anomalies. The empirical evidence from the two-stage Fama-MacBeth procedure suggests that the sentiment risk factor is significantly priced in the cross-section. This implies that investors require compensation for bearing noise trader risk. The inclusion of the sentiment risk factor actually reduces the risk premium of the traditional risk factors, such as the market risk premium, the size, value, and momentum and liquidity risk premiums.

5.3 Problems and Future Research

Despite the great effort that has been devoted to investigating the effects that investor sentiment could possibly have on stock returns and volatility, this thesis does not address several interesting issues due to data availability and time constraints. There is possible scope in the following directions for future research to enhance the understanding of the role of investor sentiment in asset pricing.

First, the thesis measures investor sentiment in two ways: the composite sentiment index proposed by Baker and Burgler (2006, 2007) and consumer confidence. Although these two measures provide consistent results, there is yet no definite measure of investor sentiment that is universally accepted. Furthermore, the macro variables used to construct the composite sentiment vary due to data availability. A number of measures have been developed in the literature without having been fully validated and therefore leaving to question which measure should be used for empirical exploration. It would be important to establish a standard approach to measure investor sentiment or at least set up a criterion to evaluate various sentiment measures.

Second, the thesis focuses on the effect of sentiment on stock returns. It is argued that noise traders act in concert on noise and drive price away from fundamentals. Hence, sentiment of irrational investors is a systematic risk that should be priced. It’s been well known in behavioural finance that irrational investors suffer from psychological biases, such as representative bias, overconfidence bias, cognitive bias and hindsight bias. The thesis neglects the theory that investors' psychological biases drive their sentiment. It would be interesting to explore the relationship between investor sentiment and their psychological biases and investigate whether sentiment measures could be built from their psychological biases.

Third, most existing studies of investor sentiment, including this thesis, focus on short investment horizons. It would be interesting to explore the long-run relation between investor sentiment, market volatility and stock returns.

Fourth, this thesis constructs the sentiment-prone portfolios based on the absolute value of the sentiment beta of individual stocks. Alternatively, it could be based on the raw value of sentiment beta where the sign of sentiment beta is considered (Berger and Turle, 2012). The results of the UK market are consistent with Berger and Turtle's results of the US market. It is still worth examining whether using the raw value of sentiment beta leads to similar conclusions in the UK market.

Fifth, as shown on the website of the Office for National Statistics, investors from rest of the world hold significantly more shares (in terms of value) than any other sector. Rest of the world ownership stood at an estimated 53.2% of the value of the UK stock market at the end of 2012. Specifically, about 25.5% of the value of the UK stock market is owned by North American investors. This might suggest that the UK stock market is greatly influenced by the sentiment of North American investors. Therefore, it would be interesting to investigate the impact sentiment of North American investors on the UK stock market.

Sixth, the existing literatures and this paper all demonstrate that stocks that are hard to value are more vulnerable to waves of investor sentiment. Therefore, the approach helping to value this type of stock should be efficient to minimise the impact of market sentiment. It would be of practical importance for future research to examine whether the use of analyst coverage and analyst forecast dispersion as possible variables helps to measure the difficulty in valuing stocks.

Seventh, the existing literature and this thesis confirm that stocks that are hard to arbitrage and hard to value are more exposed to investor sentiment. Further research could concentrate on the particular reasons why these stocks are vulnerable to sentiment. For instance, it may be interesting to see whether the difficulties of valuation and arbitrage are due to high arbitrage costs or low institutional ownership.

Finally, the thesis suggests the cross-sectional pricing ability of sentiment risk in the UK stock market. Existing research also demonstrates the effects of sentiment risk in the US and European markets. It is worth investigating the cross-sectional effects of sentiment on emerging stock markets. Furthermore, it would be intriguing to ask whether investor sentiment would have larger effects in the emerging market than the developed market; or in markets in which the participation of individual investors is relatively more than institutional investors.

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