The Role of Investor Sentiment in Asset Pricing

CHIEN-WEI HO

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Chienwei Ho

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Dedication

To my loving mother in heaven and father, for their lifetime sacrifice to support my study.

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"It is a long road when you're on your own…" Dan Hill's lyrics of the soundtrack for the movie *First Blood* deeply touches me as I recall the journey of my Ph.D. study in the past years. I am like a soldier who has to fight day and night in order to win the battle. Obviously, no war can be won by a single soldier. My wife Chunling has been accompanying me during the entire process. She quit her Ph.D. study at Purdue and moved to Durham with me in order to provide the best possible care for our sons Daniel and Joseph. Without her sacrifice, the completion of this thesis is impossible. My parents have sacrificed significantly their own enjoyment to fully support my study. It is a pity for me that I will not be able to present this fruit to my mother in person, but I believe she will be happy to know in heaven that I have completed my Ph.D., especially the good news arrived on her birth date. My brother Weili's looking after my parents in Taiwan allowed me to concentrate on my study overseas.

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Abstract

This thesis investigates various roles that investor sentiment may play in asset pricing. The empirical analysis consists of three main parts based on the role of investor sentiment in the stock markets. The first part discusses the role of investor sentiment as conditioning information. It aims to examine its ability to explain the dynamic nature of the expected returns for individual stocks and its explanatory power capture the financial market anomalies such as the size, value, liquidity, and effects. The second part focuses on the role of investor sentiment as a risk factor. The purpose is to construct a risk factor on the basis of investor sentiment and test whether this proposed sentiment factor is priced and helps to explain the aforementioned financial market anomalies. The third part explores the role of investor sentiment in different international stock markets. It attempts to assess the extent to which investor sentiment affects the stock market volatility and returns of different regions.

The results suggest that investor sentiment exhibits explanatory power for cross section of stock returns in the U.S. market. Acting as conditioning information or a risk factor, investor sentiment can generally capture the size and value effects. Furthermore, it can also capture the momentum effect under certain model specifications. The thesis shows that investors require compensation for bearing noise traders; in other words, investor sentiment is a priced factor. At the market level, the impacts of investor sentiment on stock volatility and returns vary across countries. For some countries investor sentiment affects both volatility and returns while for the others investor sentiment has less influence on stock price behaviour.

Overall, the findings of the thesis provide empirical evidence that overlooking the role of investor sentiment in classical finance theory could lead to an imperfect picture of describing the stock price behaviour.

Declaration

The material contained in this thesis has not been submitted in support of an application for another degree or qualification in this or any other University.

Chienwei Ho (2012)

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CHAPTER 1 INTRODUTION

1.1 Background

The efficient market hypothesis (EMH) has been one of the central pillars of finance since the 1960s. Extensive academic research on whether stock markets are efficient has been widely seen in finance journals and conferences in the past decades. The idea of market efficiency was developed independently by Samuelson and Fama in the 1960s. According to Fama (1970, p.383), an efficient market is "a market in which prices always fully reflect available information."

The EMH has become a widely accepted belief among financial economists since its inception. For example, Jensen (1978, p.95) claims that "there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis." One of the primary implications of the EMH with respect to investment strategies is that average investors, both individual and institutional, cannot consistently beat the market if markets are efficient. Investors are advised to passively buy-and-hold the market portfolio rather than waste time and effort to engage in active investment strategies because all information has been fully incorporated into prices and hence financial assets are always priced correctly.

Despite its early theoretical and empirical success, the EMH subsequently faces both theoretical and empirical challenges and gradually loses its ground just as other once-fully supported economic theories must encounter at some stage. The first challenge to the EMH, probably also the most fatal one, results from its theoretical assumption that investors in general are fully rational. According to the EMH, investors' shifts in demand for financial assets are their reactions to the information associated with the fundamental values of the underlying assets. Consequently, changes in prices simply reflect the random arrivals of fundamental news. This argument becomes difficult to sustain according to Black's (1986) seminal discussion about noise trading. Black (1986) points out that there are some investors who trade on "noise" as if it were profitable information associated with fundamentals. Nevertheless, he emphasizes the importance of existence of noise traders in making transaction happen in asset markets. The impact of noise traders is first theorised by De Long, Shleifer, Summers, and Waldmann (1990) (DSSW, 1990). Assuming a market in which both informed traders – investors who trade on information, and noise traders – investors who trade on noise as if it were information coexist, they show that the unpredictable changes in noise traders' beliefs would deter informed traders from take opposite positions against noise traders and hence prices of risky assets may deviate further from their fundamental values as noise traders become more bullish or bearish. The deviation of price from fundamental value could be prolonged than anticipated by informed traders, depending on the strength and proportion of noise traders in the market. They term this risk caused by noise traders as "noise trader risk".

In addition to the theoretical challenges, the EMH falls in a vulnerable position after the publication of Shiller's (1981) and Leroy and Porter's (1981) volatility tests. They provide empirical evidence that stock market is too volatile to be justified by changes in dividends, suggesting investors are not fully rational and stock prices could be affected by factors irrelevant to fundamental information.

The EMH predicts that stock price should follow a random walk due to the random arrivals of new information. If the EMH fully describes stock price behaviour, predictability of returns from past data or firm characteristics should be impossible. However, a large number of studies have identified abnormal returns are associated with firm's past performance, market capitalization, and firm-specific financial ratios. For example, DeBondt and Thaler (1985) find that stocks with low returns in the past three to five years have higher average returns than stocks with high returns in the same past period – the reversal effect. On the other hand, Jegadeesh and Titman (1994) show that movements in individual stock prices over the period of six to twelve months tend to predict future movements in the same direction – the momentum effect. Researchers also find that stocks with small capitalization or those with prices that are low relative to accounting magnitudes like book values, earnings, and cash flows yield higher average returns (Banz, 1981; Basu, 1977; Fama and French, 1988; Lakonishok, Shleifer, and Vishny, 1993; Chan, Hmao, and Lakonishok, 1991). These empirical results that seem to be inconsistent with theories are called "anomalies". The existence of anomalies implies either financial markets are inefficient or traditional asset pricing models are inadequately specified.

The unexplained volatility in the stock market and the anomalies call into question the foundation of the EMH and call for the demand for a new paradigm for modern financial theory. In the recent decades, financial economists have attempted to return to the original point to understand how human psychology influences investors' financial decisions. This evolution leads to the emergence of a new paradigm of financial research – behavioural finance.

Being a relatively new field in finance, behavioural finance applies psychology to the study of financial behaviour. It attempts to study why people buy or sell financial assets based on the psychological principles of decisions making. Instead of completely replacing traditional finance, behavioural finance plays a complementary role in understanding the issues that traditional finance appears to fail to provide satisfactory answers to the questions such as: (i) Why do individual investors trade? (ii) How do they perform? (iii) How do they choose their portfolios? (iv) Why do returns vary across stocks for reasons other than risk[1]? Behavioural finance focuses on how investors interpret and act on information during their

[1] See Subrahmanyam (2007) for detailed review of behavioural finance.

investment decision making. The standard assumption underlying traditional finance that investors are always behave in a rational, predictable, and an unbiased manner is relaxed in behavioural finance. Behavioural financial economists have documented plenty of evidence that investors' emotions and cognitive errors are associated with various financial market anomalies.

Despite behavioural finance is a relatively new approach in finance research, the topics that behavioural finance covers have grown rapidly in the past decades. One of the important areas that researchers have devoted to learn is the role that noise traders play in determining asset prices. This issue is also the focus of this thesis. The noise trader approach to finance is a vis-à-vis alternative to the efficient markets approach. This thesis adopts the noise trader approach to examine whether investor sentiment helps to better describe individual stock returns and can explain the well-documented financial market anomalies. This thesis also explores the impacts of investor sentiment on stock volatility and returns at the market level for different countries.

Compared to the EMH, the assumptions of the noise trader approach are more plausible as a description of investor behaviour and stock markets. They are also the two building blocks of behavioural finance. Shleifer and Summers (1990) summarise the basic assumptions of the noise trader approach as follows. First, the noise trader approach assumes that some investors are not fully rational and their demand for risky asset is affected by their beliefs or sentiments that are not fully justified by fundamental values. Second, arbitrage – defined as trading by fully rational investors not subject to such sentiment – is risky and therefore limit. These two critical assumptions are also employed in this thesis. Consequently, the trading behaviour of noise traders causes deviations of stock price from fundamental value because changes in investor sentiment are not fully countered by rational investors.

1.2 Objectives

Despite the existing literature documents that investor sentiment exhibits certain degree of predictability for both time-series and cross-sectional stock returns, few studies address the issues with respect to the relationship of investor sentiment and financial market anomalies and the interactive impacts of investor sentiment on stock volatility and return. This thesis attempts to shed light on how investor sentiment can help to enhance our understanding of stock price behaviour when it plays various roles in the asset pricing models.

The role that investor sentiment is adopted in the existing empirical studies is quite limited. Researchers normally use raw investor sentiment measures as an explanatory variable in the empirical framework. They test whether these raw investor sentiment measures predict time-series or explain cross-sectional stock returns. Commonly-used investor sentiment measures in the literature include survey-based data such as consumer confidence or transaction-based data such Baker and Wurgler's (2006.

Using the University of Michigan Consumer Sentiment Index (MS) and the Conference Board Consumer Confidence Index (CCI), respectively, Fisher and Statman (2003) find a positive relationship between the monthly *change* in the investor sentiment and *contemporaneous* S&P 500 stock returns, and a negative relationship between the *level* of the investor sentiment in one month and the stock returns over the *next* month and the next 6 and 12 months. Brown and Cliff (2005) use the Investors Intelligence sentiment index (II), which reflects the sentiment of the newsletter writers, to examine the long-run sentiment-return relation. They find that returns over future multiyear horizons are negatively associated with investor sentiment. These studies show that investor sentiment can predict future stock returns.

Baker and Wurgler (2006) find that investor sentiment has larger effects on stocks whose valuations are highly subjective and difficult to arbitrage. Their results show that when beginning-of-period sentiment is low (high), subsequent returns are relatively high (low) for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. Lemmon and Portniaguina (2006) find that investor sentiment forecasts the returns of small stocks and stocks with low institutional ownership. These findings suggest that investor sentiment can also affect the cross section of individual stocks.

A handful of studies also detect sentiment-return relation for the non-U.S. markets. Jansen and Nahuis (2003) find that changes in investor sentiment, proxied by the European Commission's consumer confidence indicators, are positively associated with contemporaneous stock returns in nine European countries. Schmeling (2009) finds that consumer evidence and subsequent aggregate stock returns are negatively correlated in most of the eighteen industrialised countries. Consumer confidence has larger impacts on stock returns for countries with incomplete markets and more subjected to herding behaviour. This evidence shows that investor sentiment effect exists globally.

Despite numerous studies on the effect of investor sentiment in stock markets, few researchers address this issue in the asset pricing contexts. Traditional asset pricing models such as the Capital Asset Pricing Model (CAPM) or Fama-French model (FF) rarely consider behavioural component such as investor sentiment in model specifications. If investor sentiment plays a critical role in investors' decisions making, incorporating investor sentiment into model specification could potentially help to better describe stock price behaviour and may explain the financial market anomalies such as size effect (Banz, 1981), value effect (Chan, Hamao, and Lakonishok, 1991), and momentum effect (Jegadeesh and Titman, 1993).

The purpose of this thesis is to propose new directions of the roles of investor sentiment that researchers could adopt in the analysis of the explanatory power of investor sentiment for stock price behaviour.

1.3 Research Questions

Despite the literature has provided some interesting findings about sentiment-price relation, our understanding about the role of investor sentiment in asset pricing models is still limited. A number of key questions have yet been answered. For example, how investor sentiment is associated with financial market anomalies? What might be the roles that investor sentiment plays in determining cross-section stock returns? Is investor sentiment a priced factor? In other words, do markets compensate investors for bearing noise trader risk? To what degree could investor sentiment affect stock price behaviour in different countries? These are the main questions that this thesis attempts to address.

Specifically, the first question concerns the role of investor sentiment as conditioning information in asset pricing models. Two important issues are investigated: first, I investigate whether conditional models completely explain conditional expected returns and examine whether conditional alphas are unrelated to the conditioning instruments as in Bauer, Cosemans, and Schotman (2010); second, I assess whether incorporating investor sentiment into the information asset of the asset pricing models helps to capture the financial market anomalies. One of the criteria when selecting conditioning variables in asset pricing models is that they should reflect investors' perception of future market returns or business cycle conditions. Studies have shown that investor sentiment not only predicts stock returns but also leads business cycle. Hence, it is nature to consider investor sentiment as a good candidate for conditioning variable since Furthermore, adding investor sentiment as conditioning information to an asset pricing model transforms a traditional rational model to a more behavioural-oriented model that considers the possible human emotion effect that may involve in investment decisions.

The second question explores the role that investor sentiment plays as a risk factor in determining stock prices. DSSW (1990) claim that noise trading could cause the market to misprice the risky asset if limits of arbitrage are present. Baker and Wurgler (2006) find that stocks whose values are hard to value and difficult to arbitrage tend to be more responsive to investor sentiment. Their empirical work suggests that investor sentiment exhibits cross-sectional influence on individual stock returns. Motivated by these findings, thesis attempts to construct a factor on the basis of noise trader risk and test whether this factor is prices. The search for risk factors that accurately describe differences in expected returns across assets has been one of the primary research tasks in the finance literature. Given the numerous empirical findings that investor sentiment exhibits time-series and cross-sectional stock returns, it would be natural to develop a risk factor based on investor sentiment and test whether such sentiment-based factor is priced.

This thesis also investigates to what extent investor sentiment could potentially explain the financial market anomalies using the two-pass regression framework proposed by Avramov and Chordia's (2006). In their model specifications, they allow the factor loadings of various asset pricing models to vary with default spread and firm-specific variables over time. Their models can successfully capture both the size and value effects. However, they fail to capture the momentum effect, just as Fama and French fail to explain in their three-factor model. In their paper, Avramov and Chordia's conjecture that it is possible that there exists a yet undiscovered risk factor related to the business cycle that may capture the impact momentum on the cross-section of individual stock returns (*p*.1034). Since the literature has shown that investor sentiment is closely related to business cycle, investor sentiment has potential to explain not only the size and value effects but also the momentum effect. Hence, the thesis asks whether investor sentiment risk factor can also explain these anomalies, especially the momentum effect.

The third question investigates the role of investor sentiment at the market level. Using the data for the U.S., European, and Asia-Pacific regions, the thesis asks whether investor sentiment has different effects on the stock markets in different countries. Apart from investigating the impact of investor sentiment on stock market returns, the thesis also asks whether investor sentiment affects the volatility of stock returns. DSSW (1990) argue that noise traders' misperceptions are stochastic and they have the worst possible market timing. The more variable noise traders' beliefs are, the more damage their poor market timing does to their returns. In other words, price risk increases as noise traders' beliefs become more variable. Despite their noise trader model has become one of the important theories in behavioural finance, relevant empirical studies are limited, particularly the tests on the impact of investor sentiment on stock volatility. Lee, Jiang, and Indro (2002) utilise the GARCH-M model to test the four effects that DSSW (1990) theorise but it fails to control for the macroeconomic variables which are also related to stock market returns and its analysis is focused on the U.S. market. Hence, this thesis intends to fill this gap by exploring the role of investor sentiment in international stock markets by assessing its impacts on both stock returns and volatility using a framework similar to Lee, Jiang, and Indro (2006)[2].

1.4 Structure of the Thesis

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

Chapter 2 provides a literature review of the financial market anomalies examined in this thesis and the relationship between investor sentiment and stock price behaviour. This chapter begins by reviewing the size, value, and momentum effects: the empirical evidence that conflicts the prediction of the EMH and cannot be explained by the traditional asset

[2] Compared to their model, my model adopts monthly consumer confidence as investor sentiment proxies, controls for macroeconomic variables in the mean equation, and considers the lead-lag relation between investor sentiment and returns.

pricing models. Then, it provides an overview of the relationship between investor sentiment and stock price behaviour. It discusses the features of the noise trader approach which is perceived to be a more plausible description for stock markets. A section is then devoted to reviewing the important empirical evidence regarding the relationship between investor sentiment, stock returns, and volatility.

Chapter 3 describes the data used followed by the discussion of the methodology employed in this thesis. This chapter provides the information on the investor sentiment proxies used in the analysis, the macroeconomic variables, and stock return data. It then describes the empirical frameworks of the two-pass regression model proposed by Avramov and Chordia (2006), the formation of conditional asset pricing models, the construction of investor sentiment risk factor, and the GARCH-M model.

Chapter 4 investigates the role of investor sentiment as conditioning information in asset pricing models. The primary purpose of this chapter is to answer whether incorporating investor sentiment as a conditioning variable in the Capital Asset Pricing Model (CAPM), Fama-French three factor model, and Fama-French based models helps to capture the size, value, liquidity, and momentum effects on the risk-adjusted returns of individual stocks in the U.S. market.

Chapter 5 examines the role of investor sentiment as a risk factor in asset pricing. This chapter starts with constructing an investor sentiment factor followed by a test on whether the sentiment factor commands a risk premium. Then, this chapter focuses on the pricing ability of the sentiment-augmented modes for the financial market anomalies.

Chapter 6 studies the role of investor sentiment in international stock markets by examining how investor sentiment is related to stock market returns and volatility in the U.S., European, and Asia-Pacific markets. In addition, this chapter also explores the degree to which macroeconomic variables affect the market returns.

Chapter 7 summarises the findings of this thesis and proposes some directions for future research.

CHAPTER 2 REVIEW OF LITERATURE

2.1 Financial Market Anomalies

One of the primary purposes of this thesis is to study whether incorporating investor sentiment in asset pricing models helps to capture the financial market anomalies. In this section, I provide an overview of the major financial anomalies that this thesis intends to examine. Anomalies are simply the empirical results that appear, until adequately explained, to run counter to market efficiency. These empirical phenomena are called anomalies because they are inconsistent with maintained theories of asset pricing behaviour.

It is worth noting that empirical tests of the EMH are by their very nature joint hypothesis tests which involve testing the EMH and the underlying asset pricing model such as the CAPM. Rejections of the tests suggest that either the market examined is not efficient or the asset pricing model used for risk adjustment fails to properly describe stock price behaviour.

In the past decades, researchers have identified a handful of facts that one group of stocks earns higher average returns than another. Many of the anomalies indentify predictable stock returns related to individual firm-specific characteristics. This chapter focuses on the three anomalies: the size, value, and momentum effects.

2.1.1 Size Effect

Banz (1981) finds the size effect, also called the "small-firm" effect in the literature. He finds that firms with low levels of market capitalisation on the New York Stock Exchange (NYSE) tend to earn higher average returns than is predicted by the Sharpe – Lintner (1965) capital asset pricing model over 1936-1977. A trading strategy of buying very small firms results in an average return of 19.8% annually compared to one of buying very large firms over the same sample period. The international evidence on the size effect is also well-documented in the literature. In his recent paper that reviews the size effect, Dijk (2011) reports that small firms outperform large firms in 18 of the 19 countries investigated, and also in a sample of emerging markets and in Europe, suggesting that data mining is unlikely to be the reason why the size effect arises.

The size effect is one of the first anomalies that relate firm characteristics to stock returns. Following Banz's finding and conjecture that higher returns on small stocks might be attributable to the fact that many investors are less willing to hold small stocks due to relatively insufficient information as opposed to large stocks, there have been numerous studies into possible explanations. Several studies show that the January effect is related to the size effect. Kleim (1983) reports that almost 50% of the small firm effect occurs in January. Horowitz, Loughran, and Savin (2000) observe that the average return of the size decile varies across months in a year – the average return of the smallest size decile of stocks is significantly higher than the average return of the largest size decile in January while this relation reverses in the other 11 months. This evidence suggests that the size effect is actually a manifestation of the January effect. Similarly, Pettengill, Sundaram, and Mathur (2002) provide evidence that the size effect is actually asymmetric: it is more pronounced in down markets compared to up markets, suggesting that the assumption that beta should be the same in up and down markets could cause an underestimation of the size effect.

Another line of explanation for the observed size effect focuses on the betas estimated for the small firms. Some researchers argue that small firms earn higher average returns than predicted by the CAPM because the betas estimated for small firms are incorrectly too low, as a result, the difference between the actual returns on small firms and the expected returns predicted by the CAPM is biased upwards. Roll (1970) and Reinganum (1981) claim that the underestimation of beta for small firms is due to their less trade compared to large firms and nonsynchronous trading. Christie and Hertzel (1981), however, argue that beta of small firms is downward biased because the estimation of beta uses historical returns and the estimated beta for small firms fails to recognise the fact that small firms have become riskier as their economic characteristics have changed over time. Other researchers attribute the failure of the CAPM in describing equity returns to the static nature of beta. They content that a dynamic version of the CAPM which allows beta to be time-varying with available information over time could provide a superior description of stock price behaviour. Jagannathan and Wang (1996) show that a conditional CAPM can explain about 30% of the cross-sectional return variation as opposed to the static CAPM for 100 size-beta sorted portfolios of NYSE and American Stock Exchange (AMEX) stocks over 1962-1990. Motivated by the evidence that the conditional asset pricing models outperform the unconditional models, this thesis adopts the time-varying beta model to explore the explanatory power of investor sentiment for the financial market anomalies.

Another group of researchers claim that the size effect arises because the single factor CAPM is an inappropriate pricing model for estimating expected equity returns and propose a multifactor model should do a better job in explaining expected returns. Using the APT model, Chan, Chen, and Hsieh (1985) find that the difference in return between the smallest portfolios and the largest portfolio shrinks to 1.5% per year compared to 11.5% obtained by the standard CAPM. Similarly, Vassalou and Xing (2004) and Hwang, Min, McDonald, Kim, and Kim (2010) document that the size effect is associated with the factors related to default risk and credit spread, respectively. This implies that the size effect may be captured if more appropriate models with multiple risk factors are used to estimate expected returns, hence, this thesis attempts to construct a risk factor based on investor sentiment and examine whether this factor can explain the anomalies.

Finally, some researchers show that the size effect arises because investors of small stocks would require compensation for holding stocks with less liquidity (Amihud and

Mendleson, 1991). The literature shows that small stocks tend to have larger bid-ask spreads and large transactions would cause larger price impacts for small stocks.

Interestingly, despite investor behaviour is often used to explain the value effect, similar explanations for the size effect are relatively rare (Dijk, 2011). By introducing investor sentiment into asset pricing models, the thesis is the first that examines the size effect in this line.

2.1.2 Value Effect

The second anomaly this thesis intends to examine is the value effect, noted by Basu (1977) that firms with high earning-price (E/P) ratios earn positive abnormal returns than predicted by the CAPM[3]. In his seminal paper, Basu (1977) groups the sample stocks into quintiles on the basis of P/E ratios. A strategy of forming these portfolios at the beginning of each year and then holding for 12 months reveals that high P/E portfolios yield lower returns than do low P/E portfolios. Investment strategies of this type involve classifying stocks into "value stocks" and "growth stocks". Value stocks are those with low prices relative to earnings, book value, or cash flows while growth stocks are those with high scaled-price ratios.

Similarly, after controlling for risk, researchers later find stocks with high book-to-market ratios (B/M) or dividend yields (D/P) outperform those with low B/M or D/P. Fama and French (1992) divide stocks listed on the NYSE, AMEX, and NASDAQ over 1963-1990 into 10 portfolios each year based on their B/M ratios, and then calculate the average return of each portfolio over the next year. They report that value stocks (stocks with high B/M) additionally earn 1.53% per month compared to growth stocks (stocks with low B/M) and this return difference is much higher than can be justified based on the differences in beta between these two groups of stocks. A similar result but with a slightly lower return

[3] Reinganum (1981) shows that the E/P effect is highly correlated with the size effect.

difference of 0.68% between the two extreme portfolios is found when using E/P to group stocks. To control for the size effect, Lakonishok, Shleifer, and Vishny (1994) first group stocks into 5 quintiles based on size, then within each size quintile, they divide stocks into 10 deciles according to market-to-book ratio. Their finding shows that high B/M stocks (i.e., low market-to-book ratio) outperform low B/M stocks by 7.8% per year. Furthermore, they examine whether this difference in returns between these two extreme B/M portfolios is caused by the difference in risk between portfolios. Instead of estimating betas for the B/M portfolios like most researchers do to measure the corresponding risks of portfolios, they differentiate periods of good markets from bad markets. They argue that a stock would be perceived to be less risky if it performs well in bad markets. No evidence is found that high B/M stocks provide a higher return than low B/M stocks in bad market periods. Hence, they conclude that the value effect is not linked to the level of risk. As the size effect, the value effect is evident not only in the U.S. markets but also prevalent in an international context. For example, Fama and French (1998) document that, besides the U.S., the value effects are also observed in Japan, the U.K., France, and Germany over 1975-1995 when using B/M, E/P, and cash flow-to-price (C/F) ratios to classify stocks into value and growth groups.

Now the question is what causes the value effect. Why stocks with high B/M, E/P, or C/F consistently earn higher average returns than stocks with low B/M, E/P, or C/F? Two competing explanations for this phenomenon exist in the literature. The first explanation focuses on the link of the value effect to risk compensation. For example, Fama and French (1992) argue that value stocks are fundamentally riskier than growth stocks. Hence, investors in values stocks would require higher expected returns for bearing higher fundamental risk.

The second line of explanations involves some degree of investor irrationality that leads to mispricing of extreme B/M portfolios. Lakonishok, Shleifer, and Vishny (1994) claim that the value advantage is mainly due to investors' errors of expectation about future earnings on growth and value stocks that cause investors' preference of growth stocks over value stocks[4]. Investors extrapolate past growth rate too far into the future: some investors are overly excited about stocks that have done very well in the past and buy them up and this causes the growth stocks to be overpriced while they overreact to stocks that have done very poorly, overselling them and hence these stocks are underpriced. In particular, growth stocks are the firms whose earnings growth rates are expected to lie above the market average while value stocks are those whose growth rates are anticipated to fall below the market average in the future. People in general make forecasts based on the past information. As a result, a series of unexpected good news related to a firm's earnings may cause investors to think that this favourable pattern will keep continuing in the future and hence forecast a period of significant growth, and vice versa. If the market overreacts to such information and extrapolates it too far into the future, the growth stocks are overpriced and the value stocks are underpriced. When the stock prices revert to a mean later, the value stocks will outperform the growth stocks. Lakonishok, Shleifer, and Vishny's (1994) view receives supportive empirical evidence of La Porta, Lakonishok, Shleifer, and Vishny's (1997) and Skinner an Sloan (2002) who also show that investors underestimate future earnings for value stocks and overestimate future earnings for growth stocks.

Another behavioural explanation for the value effect considers the differences in firm characteristics such as volatility, arbitrage costs, and ownership by sophisticated investors for value portfolios and growth portfolios. Ali, Hwang, Trombley (2003) show that the value effect is greater for stocks with higher idiosyncratic return volatility, higher transaction costs, and less ownership by sophisticated investors. Their finding supports Shliefer and Vishny's (1997) view that the value effect reflects market mispricing caused by arbitrage risk. According to Shliefer and Vishny's (1997), volatility deters arbitrage activities. Since

[4] They propose four reasons why individual investors, and even institutional investors, prefer to hold growth stocks over value stocks in their paper.

arbitrageurs are risk averse and are concerned about the idiosyncratic risk of their portfolios, high arbitrage risk due to the volatility of arbitrage returns deters arbitrage activity and explains the existence of the value effect. Furthermore, arbitrageurs tend to avoid stocks with high transaction costs. Stocks with lower sophisticated investor ownership are more likely to be mispriced because noise traders, compared to sophisticated investors, are prone to suffering systematically biased expectations about future firm earnings.

Interestingly, the firm-specific characteristics of stocks – high volatility, large transaction costs, and low sophisticated investor ownership – reported to have greater value effect in Ali, Hwang, Trombley (2003) coincide with the characteristics of stocks which are considered to be highly subjective and difficult to arbitrage in Baker and Wurgler (2006). In their seminal paper on the impact of investor sentiment on the cross-section of future stock returns, Baker and Wurgler (2006) find that more volatile stocks, unprofitable stocks, distressed, and those which are less attractive to arbitrageurs are likely to be more affected by shifts in investor sentiment. Also, the low sophisticated investor ownership argument in Ali, Hwang, Trombley (2003) is consistent with Lemmon and Portniagunia (2006) that stocks held predominantly by individual investors are more prone to mispricing arising from changes in investor sentiment.

The empirical evidence provided by Ali, Hwang, Trombley (2003), Baker and Wurgler (2006), Lemmon and Portniagunia (2006) implies that stocks with greater value effect tend to have hard-to-value and difficult-to-arbitrage features and are more likely to be mispriced. This thesis proposes that investor sentiment could play a potential role in explaining the existence of the value effect because investor sentiment has a greater impact on the returns of stocks whose values are hard to value and difficult to arbitrage and these stocks are also the ones reported to have larger value effect due to mispricing.

2.1.3 Momentum effect

The third anomaly this thesis attempts to examine is the momentum effect reported by Jegadeesh and Titman (1993) who find that stocks with high returns over the past three to twelve months (winners) continue to outperform stocks with low returns (losers) over the next three to twelve months. For example, investors who long winners and short losers of the past six months are expected to earn an average excess return of 0.95% per month over the next six months. They show that this momentum profit cannot be explained by the CAPM or other risk factors and propose that underreaction to firm-specific information might be the reason why this patter in stock returns is present. Subsequently, researchers find that the momentum effect is also present at the level of industry. Moskowitz and Grinblatt (1999) find momentum works extremely well among industry and sector portfolios. Compared to individual stock momentum, they find that industry momentum works quickly and at a shorter horizon. Industry momentum investment strategies, which buy stocks from past winning industries and sell stocks from past losing industries, are highly profitable even after controlling for size, B/M, individual stock momentum, the cross-section dispersion in mean returns, and potential microstructure influences. Furthermore, numerous studies show that momentum is present in international markets and hence make the data snooping criticism weakened (Rouwenhorst, 1998; Griffin, Ji, and Martin, 2003, 2005) For example, Rouwenhorst (1998) report that momentum profit of 1% per month is present in the 12 European countries. Griffin, Ji, and Martin (2003, 2005) show that momentum is virtually a global phenomenon.

A number of explanations for momentum have emerged since its detection by Jegadeesh and Titman (1993). Efficient-markets-based explanations focus on the risk nature of momentum. Chordia and Shivakuman (2002) show that lagged macroeconomic variables can explain profits to momentum strategies, and once stock returns are adjusted for their predictability based on these macroeconomic variables such momentum profits vanish. They argue that momentum profits are conditional on business cycle: momentum profits are positive during expansionary periods while become negative during recessions. Their result shows that dividend yield, default spread, yield on three-month T-bills, and term structure spread can predict one-month-ahead stock returns which constitute the primary component of the observed momentum profits. Another notable explanation for momentum is proposed by Conrad and Kaul (1998) who claim that momentum profits could be entirely due to cross-sectional variation in expected returns rather than to any predicable time-series variation in stock returns. They show that stocks with high unconditional expected rates of return in adjacent time periods are expected to have high realised rates of returns in both periods, and vice versa. They claim that profits to momentum strategies are positive on average even though the expected returns are constant over time. Lesmond, Schill, and Zhou (2004) argue that momentum profits are simply an illusion induced by trading cost because momentum strategies involve stocks that are highly trading intensive, expensive, and risky (small, high beta, illiquid, off-NYSE extreme performers). Pastor and Stambaugh (2003) show that their liquid risk factor explains half of momentum profits and Bansal, Dittmar, and Lundblad (2005) that consumption risk embodied in cash flows explains the average return differences across momentum portfolios. Some researchers argue that momentum profits are related to time-variation in expected returns (Chordia and Shivakuman, 2002; Wu, 2002; Wang, 2003; Li, Miffre, Brooks, and O'sSullivan, 2008).

Behavioural financial economists' explanations for momentum are centred on psychology and market inefficiency (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshlifer, and Subrahmanyam, 1998; Hong and Stein, 1999). They propose that momentum profits arise because of investors' cognitive errors when incorporating information into prices.

Several cognitive errors are claimed to be the cause of the momentum effect. The "conservatism bias", proposed by Barberis, Shleifer, and Vishny (1998), causes momentum because it leads investors to underreact to information when salient news initially arrives. Investors tend to underweigh new information and hence update their beliefs slowly. Stocks prices gradually reflect this information until the information is fully incorporated. They propose that investors also suffer from the "representative heuristic" which is the tendency that investors to identify an uncertain event, or a sample, by the degree to which it is similar to the parent population. Investors who behave in this manner would mistakenly conclude that firms with extraordinary earnings growths in the past will continue to experience similar extraordinary growth in the future. Together with the conservatism bias, the profitability of momentum strategies arises.

Daniel, Hirshleifer, and Subrahmanyam (1998) claim that the "self-attribution bias" is responsible for momentum. They argue that informed investors are overconfidence about the signal received. Investors who suffer from a "self-attribution" bias tend to attribute the performance of ex post winners to their stock selection skills but blame the performance of ex post losers for their bad luck. As a result, these investors may overestimate the precision of the signals and drive the prices of the winners above fundamental values. Together with their delayed overreaction, momentum profits are present.

Hong and Stein (1999) attribute momentum profits to the bounded rationality of investors, who use partial information when updating their information. They assume two groups of investors who act on different sets of information in the market. The informed investors possess signals about future cash flows but overlook information in the past history of prices. The other investors act on a limited history of prices but fail to observe fundamental information. The informed traders tend to underreact to the information obtained and hence the prices gradually reflect the contained information, resulting in momentum profits. The investors who trade on past information but ignore fundamental information may extrapolate the future price pattern based on the past pattern and push prices of past winners higher than fundamentals. As a result, the past winners continue to outperform the past losers in the future period.

Despite extensive literature on momentum, its relationship with investor sentiment receives little attention. Motivated by the findings of the following studies, this thesis conjectures that momentum profits could be associated with investor sentiment. First, in their evaluation of various explanations for momentum, Jegadeesh and Titman (2001) conclude that behavioural stories are more promising in explaining momentum than do risk-based or trading cost stories. Investor sentiment concerns investor psychological and emotional conditions and has become one of the important fields in behavioural finance research. Second, investor sentiment could lead to momentum through the sentiment-liquidity (or sentiment-volume) and liquidity-return (or volume-return) channels. For the sentiment-liquidity channel, Hong and Stein (2007) argue that trading volume appears to be an indicator of investor sentiment. Baker and Stein (2004) and Liu (2006) show that investor sentiment is positively related to stock market liquidity. For the liquidity-return channel, Chan, Hameed, and Tong (2000) find that momentum profits tend to be higher when the trading volume of the previous period is higher. The findings of these studies suggest that investor sentiment could lead to momentum profits firstly through its positive impact on trading volume and then push stock prices with the increased trading volume.

Among the anomalies mentioned so far, the momentum effect is the only anomaly that Fama and French's three factors (Fama and French, 1996) and Avramov and Chordia's (2006) conditional versions of asset pricing models fail to successfully capture. Capturing the momentum effect hence becomes one of the most important challenges to this thesis.

2.2 Investor Sentiment in Stock Market

A growing body of research shows that investor sentiment influences stock price behaviour, suggesting that the issue now facing financial economists is not whether investor sentiment affects prices but to what extent can investor sentiment impact stock market. Studies that explore the impact of investor sentiment on stock market rest on three critical re-examinations of the assumptions underlying market efficiency: investor rationality, uncorrelated errors, and unlimited arbitrage.

This section starts with an overview of the noise trader approach, an alternative to the efficient markets approach. The noise trader approach questions the plausibility of the assumptions of investor rationality, uncorrelated errors, and unlimited arbitrage in describing investor behaviour and market. Subsequently, this section reviews the empirical evidence of the various relationships between investor sentiment and stock price behaviour.

2.2.1 The Noise Trader Approach

Economists of behavioural finance suggest that investors exhibit excessive optimism or pessimism in assessing asset values (DSSW, 1990), and have the propensity to speculate (Baker and Wurgler, 2006). Individuals also often trade on noise not related to fundamentals (Black, 1986), and buy or sell stocks in concert (Kumar and Lee, 2006). The unpredictable fluctuation of investor sentiment deters arbitrage activities, and may create a risk that is not diversifiable and is unrelated to fundamental risk (DSSW, 1990). Furthermore, a broad-based wave of sentiment affects the prices of individual stocks differently, and impacts the cross-section of returns (Baker and Wurgler, 2006). Recently, Yu and Yuan (2011) document that at the aggregate market level sentiment significantly influences the mean-variance trade-off, and thus they suggest the integration of investor sentiment into models of stock prices and the risk-return relation.

The findings of these studies directly challenge the assumptions of market efficiency. According to the EMH, investors are always rational. Rationality means two things. First, investors update their beliefs correctly by following Bayes' law when receiving new information. Second, investors make choices that are normatively acceptable in the sense that they are consistent with Savage's notion of Subjective Expected Utility (Barberis and Thaler, 2003). Hence, the EMH predicts that prices are always right in the sense that stock price equals its fundamental value. However, behavioural finance argues that some investors are irrational. For example, Black (1986) indicates that people sometimes trade on noise as if it were information. Noise represents the information that has no fundamental component and hence rational investors should not use noise to value financial assets. DSSW (1990) describe two groups of investors in their noise trader model: noise traders and rational arbitrageurs. Noise traders form erroneous beliefs about the future distribution of returns on a risky asset. Noise traders feature several characteristics. First, they are subject to behavioural biases such as overconfidence, conservatism, overreaction or underreaction in processing information and forecasting stock returns. Second, they perceive risks incorrectly. Third, they form portfolios based on noise rather than information. As a result, noise traders may drive prices away from fundamentals. In contrast, rational arbitrageurs are sophisticated investors who have rational expectation. They buy when noise traders depress prices and sell when traders push prices up. Compared to noise traders, rational arbitrageurs are assumed to be risk averse and have reasonably short investment horizons. Trading of rational arbitrageurs helps to bring prices back to fundamentals and keeps markets efficient.

The second assumption underlying the EMH is that investors' errors are uncorrelated. Proponents of the EMH argue that investors' trading behaviours are random and will be cancelled out. As a result, the impact of noise traders is insignificant. However, researchers show that investing in risky assets could be a social activity, investors' transactions are systematically correlated, and investors are subject to the same kinds of judgment errors. In reality, investors are exposed to information, often times rumours or noise, provided by their family, friends, colleagues, and neighbours in casual chats. Shiller (1984) emphasises the importance of social influences on investing in our daily lives as follows:

> *Investing in speculative assets is a social activity. Investors spend a substantial part of leisure time discussing investments, reading about investments, or gossiping about others successes or failures in investing. It is thus plausible that investors' behaviour (and hence prices of speculative assets) would be influenced by social movements.*

Such social influence embodies in behaviour of investors in two aspects. First, apart from fundamental information, psychology or investor sentiment may affect the decisions of investors and drive asset prices. Second, transactions of individual investors, including professional investors, could be systematically correlated. When investors buy or sell stocks in concert, stock returns tend to move in lock-step. Using the trading records of individual investors in the U.S. market, Kumar and Lee (2006) find that systematic trading by retail investors leads to stock comovements beyond the usual risk factors. Retail trades do aggregate across individuals and that collective action of these individuals can influence stock returns. Their result also shows that small firms, lower-priced firms, firms with lower institutional ownership, and value (high B/M) firms have strong retail concentration and disproportionately high retail trading activities.

The third assumption of the EMH is that there are no limits to arbitrage, which has long been an essential concept in traditional finance. Alexander, Sharpe, and Bailey (2001) define arbitrage as

> *Arbitrage is the process of earning riskless profits by taking advantage of differential pricing for the same physical asset or security....., arbitrage typically entails the sale*

of a security at a relatively high price and the simultaneous purchase of the same security (or its functional equivalent) at a relatively low price.

The EMH states that mispricing cannot occur because arbitrageurs, who form fully rational expectations about stock prices, can always bring prices to fundamentals by taking opposite positions against noise traders. If the price of the stock falls below that of the substitute portfolio, arbitrageurs sell the substitute portfolio and buy the stock until these two assets reach the same price, and vice versa.

The noise trader model predicts that the impact of noise traders on stock prices would not be entirely countered by rational arbitrageurs because rational arbitrageurs face two types of risk – fundamental risk and noise trader risk. These risks would deter the willingness of arbitrageurs from betting against noise traders and limit the size of the arbitrageurs' initial positions, leaving the price deviating from its fundamental value.

Fundamental risk exists because new fundamental information may unexpectedly arrive after an arbitrageur has taken his initial position. For example, an arbitrageur who believes that a particular stock is selling above the stocks' present value of expected future dividends is selling short this stock in hopes of making profits when closing his position by buying back the stock at a lower price in the future. The arbitrageur is bearing the risk that the realisation of dividends may turn out to be better than expected or new fundamental information of positive nature may suddenly arrive. The arbitrageur would suffer a loss on his position in either case. In the first scenario in which the realised dividends are higher than expected, the arbitrageur who sells short are responsible for the payment of the dividends to the investor from whom he borrowed the stock for short selling. Miscalculation of the future dividends would result in an additional cash crunch for the arbitrageur. In the second scenario in which new fundamental information unexpectedly arrives, the arbitrageur is likely to suffer a loss if this new information is positive and causes the price to rise above his short-selling price for his initial position. As a result, fear of such a loss limits arbitrageurs' trading against noise traders even arbitrageurs believe that the current market price is not in line with its fundamental value.

The second risk that deters arbitrageurs from taking opposite positions against noise traders is noise trader risk. Noise trader risk arises from the unpredictability of the future resale price caused by the unpredictability of noise traders' future opinions or investor sentiment (DSSW 1990). Suppose an arbitrageur is short selling an overpriced stock and will liquidate his position in the future, he must bear the risk that at that time the stock will be even more overpriced than it is today because of the increasing bullishness of noise traders later. If he for some reasons has to liquidate his short position before the price returns to the fundamental value, he would suffer a loss. The more unpredictable the future resale price is, the higher the noise trader risk can bring to the market. The possibility that the mispricing being exploited by the arbitrageur worsens in the short run limits the arbitrageur's initial position and hence keeps him from driving the price entirely back to its fundamental value.

In real-world trading, there are some other factors that further limit arbitrage and hence noise traders can create an extensive effect on stock price and arbitrageurs' efforts to bring price back to fundamental value may become in vain.

The first factor is the length of the arbitrageurs' horizon (DSSW, 1990; Shleifer and Summers, 1990). Noise trading can more effectively drive prices away from fundamentals when arbitrageurs have shorter horizons. In general, arbitrageurs have finite horizons. Several reasons explain why arbitrageurs have short horizons. For example, arbitrage is costly. Arbitrageurs must pay per period fees in order to borrow cash or securities to implement their trades. The longer period they take to close out their positions, the higher amount of such fees accumulates. Costly real-world arbitrage discourages arbitrageurs to trade and hence they fail to completely eliminate the long-term price divergence from fundamental values caused by noise trading.

The second factor is the ownership of the money that arbitrageurs use to engage in arbitrage (Shleifer and Vishny, 1997). In the real world, professional managers who engaged in arbitrage act as agents for their investors: they manage other people's money. Arbitrageurs with highly specialized knowledge of financial markets usually engage in arbitrage using the money from wealthy individuals, banks, endowments, and other investors who are perceived to have a limited knowledge of these markets. Investors quite often allocate their money to the funds managed by such arbitrageurs based on their past returns – performance-based arbitrage. When prices further diverge far away from fundamental values, the performance of arbitrageurs can get worse. It is the time that arbitrageurs require more capital to exploit such profit opportunities. However, investors might withdraw their money from the arbitrageurs because of the observed bad performance of the arbitrageurs. As a result, arbitrageurs can become most constrained when they have the best opportunities to bet against this mispricing. This phenomenon gives more room for noise traders to increase the effectiveness of their trading on stock prices. Performance-based arbitrage helps boost the force of noise trading in the market, especially when prices are significantly out of line and arbitrageurs are fully invested.

Finally, market structure can also influence the effect of investor sentiment on the behaviour of stock prices. Deuskar (2008) provides empirical evidence that in a market with a specialist market maker investor sentiment does not affect return continuation because there is no underreaction to information in the order flow while in a market without a specialist market marker, higher investor sentiment is associated with higher return continuation because noise traders underreact to the information in the order flow.

The discussion so far indicates that investor sentiment or noise trading can affect stock prices and stock markets are not efficient. In their seminal work, DSSW (1990) develop a noise trader risk model which shows that irrational noise traders with erroneous beliefs not only affect prices but also earn higher expected returns than rational arbitrageurs. Consequently, prices can prices can diverge significantly from fundamentals even though there is no uncertainty about fundamentals. They study the equilibrium stock prices under the assumption that arbitrage is risky and limited. Their theory shows that investor sentiment affect stock prices through four effects. The "price pressure" effect states that as noise traders become more bullish, their demand for stock increases and push up its price. They reduce the return to risk bearing and, hence, the differential between their returns and those of arbitrageurs. The "hold more" effect states that when noise traders on average become more bullish they would hold more stock and earn a larger share of the rewards to risk bearing. Noise traders' expected returns relative to those of arbitrageurs increase. The buy high-sell low effect or Fried effect is associated with the misperceptions of noise traders. Noise traders tend to buy the most of stock just when other noise traders are doing so, together with their poor market timing, they are most likely to suffer a capital loss. The damage caused by noise traders' poor market timing to their returns increases with the variability of their beliefs. The last effect is the "create space" effect. This effect is associated with the variability of noise traders' beliefs. The more variable noise traders' beliefs are, the higher the price risk is. Since arbitrageurs are risk averse, higher price risk is a deterrent to arbitrage. DSSW (1990) show that the price pressure and buy high-sell low effects will have lower damage to noise traders' average returns relative to arbitrageurs' returns, suggesting that noise traders' relative expected returns will rise when the variability of noise traders' beliefs increases. The "hold more" and "create space" effects tend to raise noise traders' relative expected returns while the "buy high-sell low" and "price pressure" effects tend to lower noise traders' relative expected returns.

2.2.2 Investor Sentiment and Stock Price Behaviour

Over the past decade, a large of body of literature has provided empirical evidence that investor sentiment is closely related to stock price[5]. Early studies focus on the time-series relationship between investor sentiment and stock price and document that investor sentiment is a contrary indicator of future stock returns. Fisher and Statman (2000) find both American Association of Individual Investors' sentiment index and Wall Street strategists' sentiment are negatively correlated with the S&P 500 returns in the following month[6]. In their later study, Fisher and Statman (2003) examine whether consumer confidence proxies investor sentiment and predicts stock returns. Their result shows that increases in consumer confidence about the economy are accompanied by statistically significant increases in the bullishness of individual investors about the stock market. Similar to their earlier findings in Fisher and Statman (2000), their results indicate that high consumer confidence is generally followed by low subsequent S&P 500, NASDAQ, and small stock returns. Contemporaneously, changes in consumer confidence move in the same direction with the S&P 500 returns.

Using a sentiment measure based on Investors Intelligence sentiment index, Brown and Cliff (2005) find the market pricing errors predicted by their valuation model increases with investor sentiment. High investor sentiment level is followed by low returns at horizons of two and three years for large and growth stocks[7]. Charoenrook (2005) uses the University of

[5] The review here focuses on the studies that use survey-based investor sentiment indicators because the sentiment measures adopted in thesis such as consumer confidence and investor sentiment indicators are survey data. Readers who are interested in other investor sentiment proxies can find detailed discussion in Baker and Wurgler (2007).
[6] Their result shows that the relationship between the level of Investors Intelligence sentiment indicator and S&P 500 returns is also negative but not statistically significant. Furthermore, the level of sentiment does not exhibit predictive power for the returns of small stocks.
[7] In contrast, their earlier study (Brown and Cliff, 2004) shows that their investor sentiment constructed differently exhibits little power for near-term future stock returns despite sentiment levels and changes are strongly correlated with contemporaneous market returns.

Michigan Consumer Sentiment Index to investigate its explanatory power for market returns. Similarly, she finds that changes in consumer sentiment are positively related to contemporaneous excess market returns and are negatively related to future excess returns at one-month and one-year horizons.

These findings reveal two distinctive sentiment-return relationships. First, the positive contemporaneous sentiment-return relationship shows that stock price tends to be overvalued in a bullish market, especially when the excessive optimism of investors is unwarranted by fundamentals and there are limits to arbitrage in the market. Second, the negative relationship between current investor sentiment and subsequent stock returns indicates that the market tends to revert to its fundamental value after gradual corrections occur over a longer horizon.

Early studies on investor sentiment and stock price mainly focused on the U.S. market. Recently, researchers have investigated whether investor sentiment affects stock returns internationally. Due to the lack of indicators specifically compiled to measure the sentiment of stock investors, most empirical tests employ consumer confidence to proxy for investor sentiment. For example, Jansen and Nahuis (2003) use the consumer confidence indicators compiled by the European Commission to investigate the short-run relationship between investor sentiment and stock returns for 11 European countries. Their findings indicate that stock returns and changes in sentiment are positively correlated for most of the countries in the sample, with Germany as the main exception[8]. Using consumer confidence indices of 18 industrialised countries, Schmeling (2009) shows that investor sentiment is a contrarian indicator for the future stock returns across countries: high (low) investor sentiment tends to be followed by lower (higher) stock returns. They show that this negative sentiment-return relationship holds for not only the aggregate market returns but also for returns of value,

[8] However, they find that stock returns generally Granger-cause consumer confidence over two-week to one-month horizons, but consumer confidence does not Granger-cause stock returns for the same horizons. This finding is in line with Otoo (1999) for the U.S. that changes in stock prices and changes in investor sentiment are contemporaneously correlated and stock price performance raises consumer confidence with a lag. Using different sentiment measures, Wang, Keswani, and Taylor (2006) also find that their sentiment measures are caused by returns and volatility rather than vice versa.

growth, and small stocks for different forecasting horizons. The effects of sentiment on stock returns are more pronounced in countries with low institutional development or countries which are prone to herd-like behaviour and overreaction. Akhtar, Faff, Oliver, and Subrahmanyam (2011) even find when a lower than previous month consumer confidence is announced, the Australian stock market suffers a significant negative announcement day effect.

Another line of research investigates how investor sentiment influences people's investment decisions and subsequently affects returns of stocks with different firm characteristics. Lee, Shleifer, and Thaler (1991) document that small stocks are disproportionately held by individual investors, a group of people who are more likely to trade on noise as if it were information, as opposed to institutional investors. Nagel (2005) finds that institutional investors tend to hold large stocks and stocks with low institutional ownership misreact to news about future cash flows. Also, Zweig (1973), Lee, Shliefer, and Thaler (1991), and Neal and Wheatley (1998) argue that because closed-end funds are disproportionately held by individual investors, closed-end fund discount is an appropriate proxy for investor sentiment. They show that the discount increases as investors become bearish. Based on this evidence, it is nature to conjecture that there is a close relationship between (retail) investor sentiment and the returns of certain groups of stocks. Kumar and Lee (2006) find that the trades of individual investors are systematically correlated: they buy or sell stocks in concert. Small, value (high B/M), and low institutional ownership stocks have stronger retail concentrations and disproportionately high retail trading activities. The combination of the systematic trading of individual investors and high retail concentration for certain stocks explains why the returns of these stocks tend to move together closely.

Using consumer confidence to proxy for investor sentiment, Lemmon and Portniaguina (2006) provide additional supportive evidence that stocks predominantly held by individual investors such as small stocks are more prone to mispricing arising from changes in investor sentiment. They also find that high sentiment level predicts lower future returns on value stocks. In their seminal paper, Baker and Wurgler (2006) show that their investor sentiment measure has cross-sectional effects on stock returns. They find that stocks whose valuations are highly subjective and difficult to arbitrage are more likely to be affected by shifts in investor sentiment. In particular, they show that newer, smaller, more volatile, unprofitable, non-dividend paying, distressed or with extreme growth potential stocks earn relatively lower (higher) subsequent returns when investor sentiment is high (low).

Motivated by the findings of these studies, this thesis proposes that investor sentiment, if used as a conditioning variable or a risk factor, may help to capture the size, value, and momentum anomalies. This is the primary issue that the first two essays of this thesis intend to address. This thesis is the first that directly tests the explaining power of investor sentiment for these anomalies by using sentiment as a conditioning variable or a risk factor in various dynamic asset pricing models.

Finally, despite DSSW (1990) theorise that investor sentiment or noise trading can affect the volatility of stock returns through the Friedman and the "creates space" effects, existing empirical evidence on this line of research is scarce as opposed to the well-documented sentiment-return evidence. Supportive evidence mainly focuses on the U.S. market. For example, Brown (1999) shows that individual investor sentiment is related to increased volatility of close-end funds, suggesting that irrational investors acting in concert on noise not only influence asset prices but also generate additional volatility. Lee, Jiang, and Indro (2002) use Investors Intelligence sentiment index to examine its relationship with stock market volatility and excess returns. They find that the magnitude of bullish (bearish) changes in investor sentiment leads to downward (upward) revisions in volatility and higher (lower) future excess returns.

The third essay of this thesis adopts the framework of Lee, Jiang, and Indro (2002) to investigate the impacts of investor sentiment, proxied by consumer confidence, on volatility and excess returns in the eight international markets. This essay not only extends its study to the non-U.S. markets but also considers the following issues that Lee, Jiang, and Indro (2002) fail to consider in their analysis. First, I control for the macroeconomic variables in the mean equation of the GARCH model when examining the direct impact of investor sentiment on excess returns. Second, the sentiment variable is lagged one period in the mean equation in order to clearly demonstrate the lead-lag relationship between investor sentiment and stock returns.

Overall, the existing literature shows that investor sentiment is a vital component in the formation of stock prices. Investor sentiment is positively related to contemporaneous stock returns but negatively related to subsequent returns. Investor sentiment also affects cross section of stock returns. Some stocks are more prone to changes in investor sentiment than the others, depending on the firms' characteristics such as market capitalisation, price multiples, and ownership concentration. Studies also show that investor sentiment influences stock volatility at the market level. Despite plenty of evidence that investor sentiment exhibits explanatory power for stock returns and volatility, to my best knowledge, no studies assess the performance of sentiment in capturing financial market anomalies in the asset pricing context. Contrary to most of the existing empirical studies that simply use the raw sentiment index to explore the sentiment-return relation, the first two essays of this thesis attempt to understand this issue from the perspective of asset pricing framework by treating investor sentiment as a conditioning variable or a risk factor in the models. Also, using an empirical framework that is superior to the existing studies in terms of its model specification, the third essay contributes to the knowledge by extending the sentiment-volatility-return to the international markets beyond the U.S. evidence.

CHAPTER 3 DATA AND METHODOLOGY

3.1 Investor Sentiment Measures

Despite a growing body of empirical studies on the influence of investor sentiment on stock market has emerged dramatically over the last two decades, there is no consensus on investor sentiment measures in the literature.

The investor sentiment measures employed in previous studies fall into two categories: survey-based and market-based sentiment indices. Survey-based investor sentiment indices are obtained by polling the opinions or perceptions of household investors or financial experts on a regular basis – usually weekly or monthly. The respondents are requested to express their beliefs about the prospect of the economy, personal financial situation, or the predicted move of the stock market. Examples of survey-based sentiment indices are the University of Michigan Consumer Sentiment Index, the Conference Board Consumer Confidence Index, and the Investors Intelligence sentiment index. Some researchers use or develop market-based investor sentiment indices which are calculated based on stock market transaction activities. These investor sentiment measures, for example, include put-call ratio and the Volatility Index (VIX). Bake and Wurgler (2006) develop a composite index of sentiment based on the common variation in six underlying proxies for sentiment: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. Despite various indices are used to proxy investor sentiment, they reflect and capture different aspects of information. The selection of investor sentiment proxy in empirical work is sometimes arbitrary, depending on the purpose of the study and the data availability.

This thesis employs both survey-based and market-based investor sentiment indices. For the tests of the U.S. market, I use the University of Michigan Consumer Sentiment Index, the Conference Board Consumer Confidence Index, the Investors Intelligence sentiment index, and Baker and Wurgler's composite sentiment index. When examining the impact of investor sentiment on the performance of the international stock markets, I use mainly the country-specific consumer confidence index – an index that is similar to the University of Michigan Consumer Sentiment Index. The literature, for example, Jansen and Nahuis (2003) and Schmeling (2009), that investigates the sentiment-return relation in international stock markets uses consumer confidence as a measure of investor sentiment due to the lack of direct investor sentiment like Investors Intelligence sentiment index that is particularly focused on the beliefs of the specific stock market in a country. Fisher and Statman (2003) show that consumer confidence moves with investor sentiment in the U.S. market. Therefore, this thesis uses consumer confidence for the non-U.S. stock markets to proxy the investor sentiment of each market. The consumer confidence indices used in this study are either provided by the governments or institutions of these countries.

This section introduces each investor sentiment measure used in this thesis, including the contents of each index and the method used to compose its overall score or index.

3.1.1 The University of Michigan Consumer Sentiment Index

The University of Michigan Consumer Sentiment Index has been published on a quarterly basis for months 3, 5, 8, and 11 since 1947 and became on a monthly basis since 1978. It polls via telephone approximately 500 respondents representing all U.S. households based on their opinions regarding buying major household items, current financial position, the twelve-month conjecture of business conditions, and the five-year forecast of the economy prospects as well as unemployment conditions. In particular, the overall consumer confidence index is based on the following five questions: (1) Do you think now is a good time for people to buy major household items? (good time to buy/uncertain, depends/bad time to buy). (2) Would you say that you (and your family living there) are better off or worse off financially than you were a year ago? (better/same/worse). (3) Now, turning to business conditions in the country as a whole—do you think that during the next 12 months, I'll have good times financially or bad times or what? (good times/uncertain/bad times). (4) Looking ahead, which would you say is more likely—that in the country as a whole I'll have continuous good times during the next 5 years or so or that I'll have periods of widespread unemployment or depression, or what? (good times/uncertain/bad times). (5) Looking ahead—do you think that a year from now, you (and your family living there) will be better off financially, or worse off, or just about the same as now? (better/same/worse).

For each question a "diffusion measure" is calculated as 100 plus the difference between the percent of favorable replies and the percent of unfavorable replies. Then, an index is constructed by dividing the level of diffusion measure by the base-period level of 110 and multiplying by 100 (i.e., diffusion measure times 0.909). Finally, Michigan obtains an overall consumer confidence index by averaging the diffusion indices into a composite diffusion index and then converting the results to a base-period index.

3.1.2 The Conference Board Consumer Confidence Index

The Conference Board Consumer Confidence Survey started on a bimonthly basis in 1967 and became available on a monthly basis in 1977. The Conference Board mails out the survey questionnaires to 5,000 households designed to represent all US households. The index results are based on approximately 3,500 responses. The questions surveyed by the Conference Board are designed to track the respondents' perceptions or forecast on the present business conditions, current job availability, business conditions over the next six months, job availability over the next six months, and family income prospects over the next six months. The questions – somewhat different from those in the Michigan survey – are (1) How would you rate present general business conditions in your area? (good/normal/bad). (2) What would you say about available jobs in your area right now? (plentiful/not so many/hard to get). (3) Six months from now, do you think business conditions in your area will be (better/same/worse)? (4) Six months from now, do you think there will be (more/same/fewer) jobs available in your area? (5) How would you guess your total family income to be 6 months from now? (higher/same/lower).

Slightly different from the Michigan survey, the Conference Board calculates its diffusion measure by dividing the positive response percentage by the sum of the positive and negative response percentages. Then, the index is obtained by dividing the diffusion measure by 62.5 (the diffusion measure in the base period)[9]. The Conference Board calculates an overall index from the question-level indices by converting each diffusion index to a base-year index and then averaging the indices together.

3.1.3 The Investors Intelligence Sentiment Index

The Investors Intelligence sentiment index, published by Chartcraft, has become available since 1963. The survey was monthly for 1963, then bi-weekly through June 1969 when it was shifted to the weekly schedule, that continues through the present. It reflects the outlook of independent financial market newsletter writers. Investors treat this index as a contrarian indicator in the sense that extremes of the index in either direction are signals of reversal of the market's current trend[10]. Investors are advised to act opposite to the balance of expert opinion since most advisory services are trend followers: they are most bearish at market bottoms, and least bearish at market tops (Investors Intelligence, November, 1984).

Unlike consumer confidence that is mainly designed to track consumer attitudes and expectations, Investors Intelligence sentiment index directly reflects the opinions of the stock market participants. Each week, the editor of Investors Intelligence reviews approximately 150 market newsletter writers and classifies their opinions into three categories. "Bullish" represents , among the total number of the bullish and bearish newsletter writers, the

[9] The Michigan and the Conference Board use different base periods – 1966:Q1 and 1985. Therefore, the index levels of the two surveys are not comparable since the response patterns on which the indices are based are different.
[10] The "normal range" Investors Intelligence considers to be 45% bulls, 35% bears, and 20% correction.

percentage of the bullish advisors who recommend stock for purchase or predict that the stock market will rise; "Bearish" indicates the proportion of the advisory services that recommend closing long positions or opening short ones because the market is predicted to decline; "Correction" denotes the ratio of the newsletter writers who predict a bull market but advises clients to hold off buying, or predicts a bear market but sees a short-term rally in the near future.

3.1.4 The European Commission Consumer Confidence Index

For each examined EU country I use the consumer confidence survey composed by the European Commission. The monthly European consumer confidence surveys began in 1985. The survey is conducted by various national institutes on behalf of the European Commission. The consumer confidence survey is one of the surveys used to construct the Economic Sentiment Indicator. The sample sizes for consumer confidence surveys are: 2,000 for UK, 3,300 for France, 2,000 for Germany, and 2,000 for Italy. The European consumer confidence surveys are harmonized, thus, the questionnaires are identical in all countries.

The respondents express their economic or financial expectations over the next twelve months in the following areas: the general economic situation, unemployment rate, personal household financial position, and personal savings. Specifically, they are asked to answer the following questions: (1) How do you expect the general economic situation in this country to develop over the next 12 months? It will (get a lot better (PP) /get a little better (P) /stay the same/get a little worse (N) /get a lot worse (NN) /don't know). (2) How do you expect the number of people unemployed in this country to change over the next 12 months? The number will (increase sharply (NN) /increase slightly (NN) /remain the same/fall slightly (P) /fall sharply (PP) /don't know). (3) How do you expect the financial position of your household to change over the next 12 months? It will (get a lot better (PP) /get a little better (P) /stay the same/get a little worse (N) /get a lot worse (NN) /don't know). (4) Over the next

12 months, how likely is it that you save any money? (very likely (PP) /fairly likely (P) /not likely (N) /not at all likely (NN) /don't know). The relative score for each question is calculated as the difference between the percentages of positive (PP and P) and negative (NN and N) answers with the weight of 1 on PP and NN, and of 0.5 on P and N. (i.e., $CC_i = (PP_i + 0.5P_i) - (NN_i + 0.5N_i), i = 1,2,3,4$). The overall consumer confidence index that captures the degree to which how the consumers are confident about the prospect of the future economy is then obtained as the unweighted average of the four relative scores.

The consumer confidence surveys conducted by the University of Michigan, the Conference Board, and the European Commission are designed to measure the same concept but are different in terms of sample size, survey methodology, index construction, and questions asked. Some differences in the contents among these three surveys are noted. First, the European consumer confidence survey focuses exclusively on the respondents' expectations about the future, while the U.S. surveys also look at perceptions of present economic conditions. Second, the Michigan survey seeks some backward-looking information because the respondents are asked whether their financial positions have improved over the past year. Third, the Conference Board survey focuses on the economic conditions of the specific residential areas of the respondents while the other two surveys concern about the economic condition in the country as a whole. Fourth, the Conference Board asks about expectations over a relatively short horizon of six months, while the other two surveys look further out, to twelve months or five years.

3.1.5 The Japanese Consumer Confidence Index

To measure the investor sentiment in the Japanese stock market, this thesis adopts the consumer confidence index published by the cabinet office of Japan. The Japanese consumer confidence survey became available on a monthly basis after 1982. It surveys the perceptions of 6,720 households in overall livelihood, income growth, employment, and willingness to buy durable goods. The sample households are asked to evaluate on a scale of one to five based on their beliefs in the following four questions. (1) Do you think your family's life will get better in the coming 6 months? (improve/improve slightly/no change/ worsen slightly/worsen). (2) Do you think your family will receive more revenue in the coming 6 months? (improve/improve slightly/no change/ worsen slightly/worsen). (3) Do you think the employment situation (stabile employment and easy in finding a job) will get better in the coming 6 months? (improve/improve slightly/no change/ worsen slightly/worsen). (4) Do you think the condition to purchase consumer durables will get better in the coming 6 months? (improve/improve slightly/no change/ worsen slightly/worsen).

After the consumers' perceptions of the above questions are obtained, points are then allotted in accordance with the one-to-five scale for each question based on the anticipated effects on consumption. The consumer perception index is calculated by computing the weighted average of the points of the results (component ratio). (The following evaluation points in the five response categories are multiplied by the component ratio (%) and added: positive responses (improve +1), (improve slightly +0.75); neutral response (no change +0.5); negative responses (worsen slightly +0.25), (worsen +0). The consumer confidence index (original figure) is then calculated by simply averaging the four consumer perception indices (original figures).

3.1.6 The Australian Westpac-Melbourne Institute Survey of Consumer Sentiment

I use the Westpac-Melbourne Institute Consumer Sentiment Index, published by the Melbourne Institute of Applied Economic and Social Research, to measure the investor sentiment of the Australian stock market. The survey began in 1974 to provide an indication of the level and shifts in consumer sentiment over time. The indicator reflects consumers' opinions by combining their replies to five internationally standardized questions, originating from the U.S. survey. The survey that polls 1,200 households in Australian covers consumers' personal financial position and expectations, national economic expectations (over the next 12 month and over the 5 next years) and attitudes to major purchases. The survey contains five questions. (1) Are you better or worse off financially now than a year ago? (better off/the same/worse off). (2) Do you expect to be better or worse off financially this time next year? (better off/the same/worse off). (3) Do you expect good or bad economic times over the next 12 months in Australia? (good times/uncertain/bad times). (4) Do you expect good or bad economic times over the next 5 years in Australia? (good times/uncertain/bad times). (5) Is it a good or bad time to buy major household items? (good time to buy/uncertain, depends/bad time to buy).

The Westpac-Melbourne Consumer Sentiment Index is calculated as the balance of optimism regarding five questions about the general economic outlook. The calculation of the overall score of the index is simple. Each question can be represented by an index that is equal to the percentage of optimists minus percentage of pessimists plus 100. The Consumer Sentiment Index is an average of the five component indices.

3.1.7 The New Zealand Westpac-McDermott Miller Consumer Confidence Survey

For the New Zealand market, I use the Westpac-McDermott Miller Consumer Confidence Index surveyed by Westpac Banking Corporation in New Zealand. The survey initiated in 1988. The questions are the same as those asked in the Australian survey. The data are collected via a random sample of at least 1,500 New Zealanders by means of computer aided telephone interviews. The index is calculated as 100 plus the unweighted average of the difference between positive/optimistic responses and negative/pessimistic responses. A score above 100 denotes more optimism than pessimism and a score below 100 denotes more pessimism than optimism. McDermott Miller Limited claims that "The Index can be compared directly with the Australian Westpac-Melbourne Institute Index of

Consumer Sentiment ... It can also be compared with similar United States and European indices."

3.1.8 The European Commission Economic Sentiment Indicator

In addition to consumer confidence, for the European Union (EU) markets, I also include the European Commission Economic Sentiment Indicator (ESI) in order to analyze impact of the sentiment of the consumer and manufacturers on the European stock markets. The ESI is constructed as a weighted average of monthly survey results from five sectors: industry (with a weight of 40%), services (30%), consumers (20%), retail trade (5%) and construction (5%). Most of the ESI surveys started in 1985 with the exception of the services sector, which started later. Approximately 125,000 firms and almost 40,000 consumers are surveyed across the EU. For the countries examined in this paper, the total sample sizes are 5,800 for the UK, 18,550 for France, 10,460 for Germany, and 9,600 for Italy.

The ESI reflects the confidence of the consumers and manufactures of each EU country. The basic idea behind the ESI is that, if consumers and manufacturers feel confidence about the prospects of the general economic and own financial situation, they are more willing to increase their consumption and production, respectively. As a result, the stock markets should reflect such economic activities if economy-wide sentiment influences stock price behaviour.

3.1.9 Baker and Wurgler Composite Investor Sentiment Index

Apart from the aforementioned survey-based measures of investor sentiment, this thesis also adopts a composite investor sentiment index developed by Baker and Wurgler (2006). Using the constructed sentiment index, Baker and Wurgler (2006) find that investor sentiment exhibit cross-sectional impacts on individual stock returns. Their result shows that when the beginning-of-period sentiment is low (high), subsequent returns are relatively high (low) for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks.

Baker and Wurgler (2006) use principal component analysis to construct this sentiment index based on the common variation in six underlying investor sentiment proxies: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium[11]. They argue that this constructed sentiment index can isolate the common sentiment component from idiosyncratic, non-sentiment-related components existing in these sentiment proxies.

Alternatively, Baker and Wurgler (2006) provide a cleaner constructed sentiment index in the sense that it removes business cycle from the sentiment proxies. They first regress each of the six raw sentiment proxies on the growth in the industrial production index, the growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions. Then the first principal component of the residuals from these regressions is used as the alternative sentiment index.

When constructing a sentiment-based risk factor in the second essay of this thesis, I use sentiment measures compiled by Investors Intelligence and Baker and Wurgler composite sentiment indices, respectively. These indices capture distinct information about investor sentiment due to their differences in sentiment construction. The index proposed by Baker and Wurgler (2006) attempts to extract investor sentiment from the trading-related variables in the stock market while the Investors Intelligence index captures the psychological attitudes and forecasts of the experts towards the future movement of the stock market. Using different sentiment measures helps to examine whether my results are sensitive to the choice of sentiment proxy.

3.2 Market Data

This thesis employs both the firm-level and market-level stock returns data. In the first and second essays that explore the role of investor sentiment in determining the cross-section

[11] The sentiment index used in Baker and Wurgler (2006) is annual data. Baker and Wurgler publish the monthly sentiment index later at their website http://pages.stern.nyu.edu/~jwurgler/.

of stock returns and the ability of investor sentiment to capture the financial market anomalies, I use the firm-level data. In the third essay that investigates the direct and indirect impacts of investor sentiment on stock market returns in different countries, I adopt the market-level data.

3.2.1 Firm-Level Data

I use the monthly transaction data of the common stocks listed on the NYSE, AMEX, and the NASDAQ for the period from July 1964 through December 2005. The firm-level variables for the equity data are retrieved from the Centre for Research in Security Price (CRSP) and COMPUSTAT datasets.

A stock must meet the following criteria in order to be included for analysis: First, the return in the current month, t, and over the past 36 months must be available. Second, observations on stock prices and shares outstanding for calculating firm size and the month $t - 2$ trading volume for calculating turnover must be available. Third, B/M as of December of the previous calendar year must be available from the COMPUSTAT dataset. The analysis only includes stocks with positive B/M as in Fama and French (1992). The first two years of COMPUSTAT data for every firm are dropped to control for the COMPUSTAT survival bias as in Fama and French (1992) and Kothari, Shanken, and Sloan (1995). As in Fama and French (1992), the value of B/M for July of year t to June of year $t + 1$ is computed using accounting data as of the end of year $t - 1$. Following Avramov and Chordia (2006), B/M values greater than the 0.995 fractile or less than the 0.005 fractile are set to be the values of the 0.995 and 0.005 fractiles, respectively. The CRSP value-weighted return is employed to proxy for the market return.

3.2.2 Market-Level Data

When investigating the channels through which investor sentiment affect stock market performance in the third essay, I adopt the major market index of each examined country as a measure of the stock market performance. These market indices are widely reported in the medium and draw close attention of the public.

The monthly stock market return indices are collected from Datastream and include S&P500 (the U.S.), FTSE100 (the U.K.), CAC40 (France), DAX30 (Germany), MIB30 (Italy), NIKKEI225 (Japan), ASX20 (Australia) and NZ50CAP (New Zealand). I use each country's one-month T-bill rate to proxy for the risk-free rate except for Australia and New Zealand which the one-month interbank rates are used because the one-month T-bill rates are not available for these two countries in Datastream. The sample start dates vary across countries due to data availability but all end in September 2006[12].

3.3 Methodology

3.3.1 The Two-Pass Regression Framework

Avramov and Chordia (2006) propose a two-pass regression framework that applies to single securities to test whether various conditional versions of the asset pricing model specified in the first-pass regression can successfully explain the financial market anomalies examined in the second-pass regression. Their framework is particularly suitable for the purpose of my study on the role of investor sentiment as conditioning information or as a risk factor in explaining the financial market anomalies.

This section introduces the two-pass regression framework based on which I develop the sentiment-augmented asset pricing model that includes investor sentiment as a conditioning variable in the information set or one that contains a risk factor constructed based on the sensitivity of stock returns to the change in investor sentiment.

The exact pricing specification of a conditional version of a *K*-factor model is

[12] The starting months for the sample periods are 01. 1985 for U.S., 01. 1986 for U.K., 01. 1989 for France, 01. 1991 for Germany, 12. 1994 for Italy, 03. 1993 for Japan, 06. 1992 for Australia, and 01. 2001 for New Zealand.

$$E_{t-1}(R_{jt}) = R_{Ft} + \sum_{k=1}^{K} \lambda_{kt-1}\,\beta_{jkt-1} \tag{3.1}$$

where E_{t-1} is the conditional expectations operator, R_{jt} is the return on stock *j* at time *t* and R_{Ft} is the risk-free rate. λ_{kt-1} is the risk premium for factor *k* at *t – 1* and β_{jkt-1} is the conditional beta corresponding to factor *k*. This pricing specification imposes the theoretical restrictions ex ante that the zero-beta return equals the risk-free rate and that the factor premium is equal to the excess return on the factor, in line with Lewellen, Nagel and Shanken (2008). Using an econometric model derived from Equation (3.1), I attempt to understand whether asset-pricing anomalies might exert impacts on risk-adjusted returns – the parts of stock returns left unexplained by pricing models.

The two-pass regression framework that considers investor sentiment, default spread and firm characteristics as conditioning variables to form a dynamic asset pricing model can be summarised in a generic form as

$$R_{jt}^{*} \equiv R_{jt} - [R_{Ft} + \beta(\theta; S_{t-1}, z_{t-1}, X_{jt-1})' F_t] = c_{0t} + c_t Z_{jt-1} + e_{jt} \tag{3.2}$$

where R_{jt}^{*} is the estimated risk-adjusted return on stock *j* for time *t* and is equal to the sum of the intercept and the residual obtained from a first-pass time-series regression that contains the risk factors under examination. θ denotes the parameters that capture the dependence of β on investor sentiment (S_{t-1}), default spread (z_{t-1}), and firm characteristics (X_{jt-1}). F_t is the vector of risk factors specified in the asset pricing model. The vector of the conditional beta is estimated by the first-pass time-series regression over the entire sample period. Z_{jt-1} is the vector of the financial market anomalies – the size, value, liquidity, and momentum effects – that the traditional asset pricing models fail to capture. c_t is the vector of characteristics rewards. Equation (3.2) is a cross-sectional regression by which I run, in each month, the estimated risk-adjusted returns of individual stocks on the variables of size, B/M, liquidity, and prior returns. I test the null hypothesis that the second-pass cross-sectional slopes on the financial market anomalies are zero and statistically insignificant, that is, $\hat{c}_t = (Z_{t-1}^{'}Z_{t-1})^{-1} Z_{t-1}^{'}R_{jt}^{*} = 0$. The adjusted R squared ($\overline{R}^2$) in the second-pass regression serves as an indicator for comparing the relative overall performance of the conditional specifications of the asset pricing model. A *smaller* cross-sectional $\overline{R}^2$ indicates a higher overall explanatory power of the asset pricing model specified in the first-pass regression for stock returns.

Following Avramov and Chordia (2006), I use the deviations of the firm-specific characteristics from the cross-sectional means in a given month rather than the raw values of the firm characteristics as the regressors in the second-pass cross-sectional regression. This implies that the average stock will have a value of zero for each of the non-risk firm characteristics, so only the risk factors can determine its expected return. The variables of firm characteristics are also lagged one more period to get around the possibility that the estimate of the risk-adjusted return may be biased due to bid-ask effects and thin trading.

3.3.2 Conditional Specifications of Asset Pricing Models

The traditional asset pricing models used to form the sentiment-augmented models in my study are: (i) the CAPM, (ii) the Fama-French (1993) three-factor model (FF), (iii) the FF model augmented by the Pastor-Stambaugh (2003) liquidity factor (FFP), (iv) the FF model augmented by the winners-minus-losers portfolio (WML) which proxies for the momentum factor (FFW), and (v) the FF model augmented by both the liquidity and the momentum factors (FFPW).

The most parsimonious traditional asset pricing model examined is the CAPM which contains only a single risk factor – the excess market return. To illustrate the approach to forming the conditional models used in the first-pass regression in the two-pass regression framework, I use the single-factor CAPM as an example. Assuming the beta of the excess market return, β_{jt-1}, can be expressed as a function of investor sentiment (S_{t-1}), default spread (z_{t-1}), and firm characteristics ($SIZE_{jt-1}$ and B/M_{jt-1}) as[13]

$$\begin{aligned}\beta_{jt-1} = \beta_{j1} + \beta_{j2} z_{t-1} + \beta_{j3} S_{t-1} + \beta_{j4} z_{t-1} S_{t-1} \\ + (\beta_{j5} + \beta_{j6} S_{t-1} + \beta_{j7} z_{t-1}) SIZE_{jt-1} \\ + (\beta_{j8} + \beta_{j9} S_{t-1} + \beta_{j10} z_{t-1})(B/M)_{jt-1}\end{aligned} \tag{3.3}$$

Substitute Equation (3.3) into the CAPM, the conditional version of the CAPM that contains these three conditioning variables is

$$\begin{aligned}r_{jt} = \alpha_j + \beta_{j1} r_{mt} + \beta_{j2} z_{t-1} r_{mt} + \beta_{j3} S_{t-1} r_{mt} + \beta_{j4} z_{t-1} S_{t-1} r_{mt} \\ + \beta_{j5} SIZE_{jt-1} r_{mt} + \beta_{j6} S_{t-1} SIZE_{jt-1} r_{mt} + \beta_{j7} z_{t-1} SIZE_{jt-1} r_{mt} \\ + \beta_{j8} B/M_{jt-1} r_{mt} + \beta_{j9} S_{t-1} B/M_{jt-1} r_{mt} + \beta_{j10} z_{t-1} B/M_{jt-1} r_{mt}\end{aligned} \tag{3.4}$$

where the firm characteristics, investor sentiment and default spread are all lagged one period to stock returns and risk factors. The estimated risk-adjusted return on stock j at time t to be used in the second-pass regression as in Equation (3.2) is $R^*_{jt} = \alpha_j + u_{jt}$.

This approach can be applied to other examined models to form the corresponding conditional version of the pricing model with more risk factors like the one that contains all the considered risk factors like the FFPW model as follows

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + \beta_{jSMB} SMB_t + \beta_{jHML} HML_t + \beta_{jPS} PS_t + \beta_{jWML} WML_t + u_{jt} \tag{3.5}$$

where $r_{jt} = R_{jt} - R_{Ft}$ and r_{mt} is the excess return on the (CRSP value-weighted) market index at time t. u_{jt} is the error term. *SMB* denotes the monthly return difference between the average return on the three small size portfolios minus the average return on the three big size portfolios. *HML* denotes the monthly return difference between the average return on the two

[13] One can form different specifications by considering the beta to be a function of different conditioning variables. This will be further discussed in Chapters 4 and 5.

value portfolios minus the average return on the two growth portfolios. *PS* is the Pastor-Stambaugh (2003) liquidity factor constructed by the difference between the value-weighted return on the high liquidity sensitive portfolios and the value-weighted return on the low liquidity sensitive portfolios. *WML* is the momentum factor that represents the difference between the returns on the winner and the loser portfolios of the momentum strategies depicted by Jegadeesh and Titman (1993).

3.3.3 Construction of Investor Sentiment Risk Factor

The previous sections illustrate how various versions of the conditional asset pricing models can be formed in order to test their ability to capture the financial market anomalies. Using this framework, Chapter 4 tests the role of investor sentiment as a conditioning variable in the information set in investigating the financial market anomaly issue. The second role of investor sentiment that Chapter 5 of this thesis intends to explore is its role as a risk factor in asset pricing. This requires the construction of a risk factor based on investor sentiment measures.

This section discusses how the investor sentiment factor is constructed and is used to form the unconditional and conditional versions of the asset pricing models. My approach of constructing the sentiment factor is in the spirit of the SMB and HML factors constructed by Fama and French (1993) and the liquidity factor of Pastor and Stambaugh (2003). In particular, SMB, HML, and the liquidity factors are the payoffs on the long-short spreads constructed by sorting stocks according to market capitalization, B/M, and the sensitivity of stock returns to liquidity (the liquidity beta), respectively. Similarly, the sentiment factor SMN (sensitive minus non-sensitive) in my study represents the payoffs on the long-short spreads constructed by sorting stocks according to the sensitivity of stock returns to investor sentiment (the sentiment beta).

I start with the estimation of the sensitivity of the excess returns on individual stocks to the changes in the market-based investor sentiment index. Prior studies that explore the relation between investor sentiment and stock returns use sentiment measures based on either survey indices or market data[14]. I consider both the raw sentiment index and the index that is orthogonalized to macroeconomic variables by Baker and Wurlgler (2006). I also use the survey-based sentiment index – the Investors Intelligence sentiment index which reflects the perceptions of investment newsletter writers about the stock market. Using different sentiment measures in the construction of the investor sentiment factor allows us to examine whether the empirical results are influenced by the choice of the sentiment measures.

The estimation for sentiment beta is performed on the 25-month window rolled 1 month forward based on the following equation

$$\begin{aligned} R_{jt}^{e} &\equiv R_{jt} - R_{Ft} \\ &= \alpha_j + \beta_j^{s}\Delta SENT_t + \beta_j r_{mt} + \beta_j^{SMB} SMB_t + \beta_j^{HML} HML_t + \varepsilon_{jt} \end{aligned} \quad (3.6)$$

For each stock in turn, the sentiment beta β_j^s at time t is estimated using the monthly observations from months t through t-24. For each month I then break the stocks into five sentiment beta groups based on the absolute values of the monthly sentiment beta[15]. The monthly returns on the SMN factor are obtained by subtracting the returns on the equally weighted portfolio of the lowest sentiment beta group (non-sensitive portfolio) from the returns on the equally weighted portfolio of the highest sentiment beta group (sensitive portfolio).

The rationale underpinning the construction of the sentiment factor according to the sentiment beta is inspired by the empirical findings of Baker and Wurgler (2006) that investor

[14] For example, Fisher and Statman (2000) find that the sentiment level of Wall Street strategists is a reliable contrary indicator for future S&P 500 index returns. Others use the closed-end fund discount, e.g., Lee, Shleifer and Thaler (1991), Chopra et al. (1993), Swaminathan (1996), and Neal and Wheatly (1998).

[15] The absolute value of the sentiment beta rather than its raw value is used because the former represents the degree to which stock returns move in response to the change in the raw investor sentiment index. The higher the absolute value of the sentiment beta, the higher the responsiveness of stock returns to the change in sentiment.

sentiment not only has explanatory power for the time series of stock returns but also has a significant role in determining the cross section of average return on stocks. They document that when sentiment is low, smaller, younger, more volatile, unprofitable stocks, non-dividend-paying, extreme growth and distressed stocks earn higher subsequent returns, while these stocks earn relatively low subsequent returns when sentiment is high. Similarly, Glushkov (2006) finds that high sentiment beta stocks tend to be smaller, more volatile stocks with greater short-sales constraints and lower dividend yields that do not earn higher average returns in the short-run but require a premium in the long-run. He also provides theoretical justification that the correlation of a stock with investor sentiment increases as the proportion of irrational sentiment traders in a stock, which is reflected by the value of the sentiment beta.

Incorporating the constructed sentiment factor into the traditional asset pricing models allows me to form sentiment-augmented pricing models to investigate the explanatory power of the sentiment factor for the size, value, turnover and momentum effects. This investigation is conducted in the two-pass regression framework that has been discussed previously. If the sentiment factor helps to explain the financial market anomalies, it is expected to see that the anomalies variables in the second-pass regression become statistically insignificant once the sentiment factor appears in the asset pricing model specified in the first-pass regression.

Sorting stocks into groups based on certain firm-specific characteristics has been widely adopted as a standard approach in the finance literature to informally test the relation between the interested firm-level variables and stock price behaviour (Fama and French, 1992; Pastor and Stambaugh, 2003) The approach to constructing the sentiment risk factor in my study is in the same spirit as the literature. It is worth some discussion about the reason why I sort stocks into five quintiles based on the absolute value of the sentiment beta of each stock rather than its raw value. My approach relies on two critical assumptions that underpin behavioral finance. First, some investors, if not all, are subject to investor sentiment (DSSW, 1990). Baker and Wurgler (2007) define investor sentiment as "a belief about future cash flows and investment risks that is not justified by the facts at hand". Second, the limits of arbitrage exist because betting against sentimental investors is costly and risky. Based on these two assumptions, DSSW (1990) theorise that sentimental investor who trade on noise, i.e., the noise traders as they dub in their paper, can affect stock prices and create a risk in the price of the asset that deters rational arbitrageurs who trade on information from aggressively betting against them. As a result, stock prices can deviate from fundamental values dramatically in an unpredicted way depends on the sensitivity of stock returns to the change in investor sentiment, which can be measured by the absolute value of the sentiment beta β_j^s in Equation (3.6).

Researchers in behavioural finance claim that stock price contains at least two components: fundamental risk and noise trader risk. Assuming stocks A, B, and C have the same fundamental risk. Consider two stocks with the same absolute value of sentiment beta but have opposite signs, for example, stock A has a positive sentiment beta of 1 and stock B has a negative sentiment beta of -1. Assuming stock C has a zero-sentiment beta which suggests that its price is not affected by investor sentiment but determined completely by its fundamental value. Which stock is more affected by investor sentiment and hence perceived to be riskier by rational arbitrageurs? For rational arbitrageurs, stocks A and B are equally risky because their returns are equally sensitive to the change in investor sentiment. With a sentiment beta of 1, the return of stock A would increase by 1% as investor sentiment goes up by 1%. This suggests that whenever investor sentiment increases by 1% the stock price would be driven away positively by investor sentiment from its fundamental value by 1%. For arbitrageurs who would like to bet against stock A, they bear noise trader risk as described in DSSW (1990) because the price may not return to its fundamental value as expected in their investment horizon. If the price goes extremely, it can further deviate in a positive direction from the fundamental value in a prolonged period of time and causes capital loss for arbitrageurs. Would the arbitrageurs face less risk and suffer less loss had they bet against stock B? The answer is “No”. With a sentiment beta of -1, stock B simply suggests that its price will be driven to the other direction, i.e., negatively, from the fundamental value when investor sentiment goes up. For stocks A and B, the magnitude of the price deviations from their fundamental values is actually identical because their prices respond to the change in investor sentiment equally though in different directions. Any traders who have taken opposite positions on stock A or stock B against noise traders’ are expected to bear the same amount of the noise trader risk created by the unpredictability of noise traders’ beliefs. By contrast, stock C with a zero-sentiment beta contains no noise trader risk because its price is assumed to be determined by fundamental risk only and is unaffected by investor sentiment. Hence, for rational investors, stocks A and B are equally risky and stock C has the smallest risk given the equal fundamental risk for all three stocks.

To the contrary, using the raw value of the sentiment beta to form stock groups would *mistakenly* conclude that stock B is the least risky investment followed by stock C, and stock A has the highest risk. Sorting the stocks into quintiles by the *raw* sentiment beta would lead to conceptually incorrect sentiment-beta portfolios because the purpose is to form portfolios on the basis of the sentimental risk caused by noise trading which can be properly captured by the sentiment beta in absolute terms. Therefore, it would be more appropriate to use the absolute value of the sentiment beta rather than its raw value.

3.3.4 The GARCH-M Model

Chapter 6 modifies the framework of Lee, Jiang, and Indro (2002) to test the channels by which investor sentiment affects stock returns. According to DSSW (1990), investor sentiment either directly influences stock returns or indirectly affects stock returns by changing the volatility of returns. DSSW (1990) theorise that the direct effect of investor sentiment on stock returns is the result of the "hold more" and the "price pressure" effects while the indirect effect is determined by the Fried and the "create space" effects. Lee, Jiang, and Indro (2002) propose that GARCH-M model can be used to capture these four impacts of noise trading on stock price.

Following Lee, Jiang, and Indro (2002), the third essay of this thesis adopts the GARCH-M framework with two major remedies to the model to test the noise trading effects in the international context. First, in addition to the regressors used by Lee, Jiang, and Indro (2002), I add the lagged values of the dividend yield, DY_{t-1}, the annual measure of inflation, PI_{t-2}, the change in the 1-month T-bill rate, DI_{t-1}, and the 12-month change in the industrial production index, DIP_{t-2}, to the mean equation because Pesaran and Timmermann (1994) find that these variables can predict monthly stock returns on the S&P 500 portfolio and Dow Jones portfolio, respectively. Second, I use the lagged value of the change in investor sentiment rather than its contemporaneous value in the mean equation in order to examine the lead-lag relationship between investor sentiment and stock returns[16].

Specifically, for each country *i*, I estimate the sentiment-volatility-return relation using the following GARCH-M model.

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 \log h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 Sent_{t-1}$$
$$+ \alpha_5 DY_{t-1} + \alpha_6 PI_{t-2} + \alpha_7 DI_{t-1} + \alpha_8 DIP_{t-2} + \varepsilon_{it},$$
$$\varepsilon_{it} \sim N(0,\ h_{it}) \qquad (3.7)$$

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{it-1}^- + \beta_3 h_{it-1} + \beta_4 R_{ft}$$
$$+ \beta_5 (\Delta S_{t-1})^2 D_{t-1} + \beta_6 (\Delta S_{t-1})^2 (1 - D_{t-1}) \qquad (3.8)$$

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[16] While most studies have provided empirical evidence that investor sentiment can predict stock returns at the monthly frequency, Wang, Keswani, and Taylor (2006) show that their sentiment measures are Granger-caused by returns at either the daily or the weekly frequency.

where R_{it} is the monthly return on a market index, R_{ft} is the risk-free rate, $Sent_{t-1}$ is a measure of noise trader risk, proxied by consumer confidence index, or investor sentiment index, or the ESI[17]. R_f and S are country-specific. The sign of the coefficient α_4 demonstrates the net *direct* effect of investor sentiment on stock returns and is determined by the relative strengths of the "price pressure" effect and the "hold more" effect. When sentiment becomes more bullish ($\Delta S_t > 0$) the "price pressure" effect predicts a negative α_4 while the "hold more" effect predicts a positive α_4.

The dummy variable I_{it-1}^{-} in Equation (3.8) acknowledges the asymmetric response in investors' formation of conditional volatility to positive and negative shocks, that is, $I_{it-1}^{-} = 1$ if $\varepsilon_{it} < 0$ and $I_{it-1}^{-} = 0$ otherwise. Glosten, Jagannathan, and Runkle (1993) find that the magnitude of the change in market volatility is greater for bad news than for good news. The coefficient β_2 captures the sensitivity of conditional volatility on negative shocks. I expect β_2 to be positive, implying that a negative shock is likely to cause volatility to rise by more than a positive shock of the same magnitude[18].

This model also recognises the possibility that individual investors may react differently to the magnitudes of the shifts in bullish and bearish sentiment through the dummy variables. In Equation (3.8), the dummy variables $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$ and $D_{t-1} = 0$ otherwise.

The coefficients β_5 and β_6 capture the impacts of the shifts in noise traders' bullish and bearish sentiment on their formation of conditional volatility, respectively. In conjunction with the coefficients β_5 and β_6, the coefficient α_1 reflects the net effect of the "create space" and the Friedman effects. For example, if β_5 is positive and statistically significant, the

[17] I use both the level of the index and the change in the index to measure $Sent_{t-1}$. Detailed discussion of the specification of the model can be found in Chapter 6.

[18] The literature gives different explanations for the asymmetric return-volatility relation. The traditional view is that of the leverage effect (see Bollerslev (2008) for a detailed discussion), while a behavioral explanation is offered by Hibbert, Daigler and Dupoyet (2008).

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indirect effect of sentiment on stock returns relies on the statistical significance of the coefficient α_1. When the "create space" effect dominates (subordinates) the Friedman effect, α_1 should be positive (negative).

CHAPTER 4 INVESTMENT SENTIMENT AS CONDITIONING INFORMATION

4.1 Introduction

The literature has documented plenty of empirical evidence that investor sentiment is related to stock returns. Methodologically, researchers of this area normally regress stock returns on a variety of investor sentiment measures to examine whether investor sentiment can predict or explain stock returns. In this chapter, I propose that investor sentiment can act as an information variable in dynamic asset pricing models when exploring the sentiment-return relation.

The CAPM of Sharpe (1964) and Lintner (1965) theorises that systematic risk is measured by the exposure to the market portfolio and the market risk is the only determinant of returns on individual stocks. Empirical studies, however, document that the CAPM cannot explain the returns on stocks with certain firm-characteristics or price histories such as the effects of firm size (Banz, 1981), value (e.g., Chan, Hamao, and Lakonishok, 1991) and momentum (Jegadeesh and Titman, 1993). These cross-sectional and time series patterns in stock returns that are not predicted by the CAPM are named financial market anomalies.

The evidence on financial market anomalies intrigues the interests of finance researchers to reexamine the well-established asset pricing paradigm. Some researchers look for the dimensions of risk other than the market risk. For example, Fama and French (1993) add size and value factors to the single-factor CAPM to form a new three-factor model, and Pastor and Stambaugh (2003) construct a liquidity factor based on the sensitivity of stock returns to liquidity measures. Other researchers pursue solution by relaxing the static nature of the factor loadings of asset pricing models. Harvey (1989) shows that factor loadings of the CAPM and multifactor models change over time. Gibbons and Ferson (1985) and Ferson, Kandel, and Stambaugh (1987) argue that conditional models appropriately capture the dynamics of factor loadings and thus outperform unconditional models in explaining stock returns. Recognising numerous empirical studies have shown that investor sentiment can influence stock prices[19], in this chapter, I assess whether the pricing ability of the asset pricing models with investor sentiment as conditioning information improves.

Researchers of behavioural finance argue that investor sentiment and trading activities of noise traders affects stock returns (Shleifer and Summers, 1990; DSSW, 1990; Campbell and Kyle, 1993; and Kelly, 1997). Fisher and Statman (2000) find that the sentiments of both small and large investors are reliable contrarian indicators for future S&P500 index returns and that high consumer confidence is generally followed by low returns. Brown and Cliff (2004) document a relationship between institutional investors' sentiments and the returns on large size stocks. Charoenrook (2005) shows that changes in consumer sentiment are positively related to contemporaneously excess market returns. Baker and Wurgler (2006) find that investor sentiment affects the cross-section of stock returns and that the impacts are most profound on the stocks whose valuations are highly subjective and difficult to arbitrage.

Investor sentiment also affects trading volume and is related to the profits to the momentum strategies. Chan, Hameed, and Tong (2000) document that increases in trading volume strengthen momentum returns. Baker and Stein (2004) argue that high market participation by irrational traders, which reflects a risk related to investor sentiment, increases trading volume. Liu (2006) finds that high investor sentiment induces high market turnover. In a similar vein, Glushkov (2006) shows that an increase in the proportion of irrationally sentimental traders on a stock increases the correlation of the stock with the common sentiment factors, and hence, leads to a higher sentiment beta.

Traditionally, researchers use two types of conditioning variables when considering time-varying betas in their empirical studies of asset pricing. Some researchers consider

[19] Baker and Wurgler (2007) state "Now, the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects."

macroeconomic variables such as the term premium, default spread, or consumption-wealth ratio as conditioning variables (e.g., Shanken, 1990; Ferson and Harvey, 1991; Braun, Nelson and Sunier, 1995; Ferson and Schadt, 1996; Jagannathan and Wang, 1996; and Lettau and Ludvigson, 2001). Other researchers scale factor loadings by firm-specific characteristics such as D/P, B/M, or market capitalization of equity (SIZE) (e.g., Cochrane, 1996; Lewellen, 1999; Gomes, Kogan, and Zhang, 2003; and Avramov and Chordia, 2006). To my best knowledge, no researchers adopt investor sentiment as a conditioning variable in examining its explanatory power for financial market anomalies. Investor sentiment is eligible for acting as conditioning information in asset pricing models because it reflects investors' expectations about the current state and future prospects of financial markets or business-cycle conditions (Schrimpf, Schroder, and Stehle, 2007).

In specifying the dynamic asset pricing models, I extend the conditional asset pricing framework of Avramov and Chordia (2006) by allowing factor loadings to vary with investor sentiment measures in addition to default spread and firm-specific characteristics – size and book-to-market ratio. The investor sentiment measures in my empirical study include three different survey-based investor sentiment indices: the Conference Board Consumer Confidence Index (CCI), the Investors Intelligence sentiment index (II), and The University of Michigan Consumer Sentiment Index (MS). To extract the common variation component of these three indicators, I further construct a composite sentiment measure (COMP) by using Principal Component Analysis.

The purpose of this study is twofold. First, this study investigates whether conditional models completely explain conditional expected returns and also tests whether conditional alphas are unrelated to the conditioning instruments as in Bauer, Cosemans, and Schotman (2010). Second, using the two-pass regression framework of Avramov and Chordia (2006), this article assesses the relative performance of various specifications of conditional asset pricing models in respect of how well these models capture the size, value, liquidity, and momentum effects. In the first-pass time-series regressions, I regress monthly individual stock returns on the risk factors of asset pricing models in which factor loadings may vary with conditioning variables. In the second-pass, I run cross-sectional regressions of the estimated risk-adjusted returns – the sums of the pricing error and the residual from the first-pass regressions – on firm characteristics of size, book-to-market ratio and variables representing the liquidity and momentum effects. The null hypothesis of exact pricing is that the conditional pricing models specified in the first-pass regressions successfully capture the anomalies, and thus, the size, value, liquidity, and momentum effects do not explain the cross-section of risk-adjusted stock returns in the second-pass regressions[20].

The primary contributions of this study to the literature are summarised as follows.

First, this study shows that incorporating investor sentiment as conditioning information enhances the overall performance of the asset pricing models in depicting stock prices. In the conditional framework, the size effect becomes less important in the conditional CAPM and is no longer significant in all the other models examined. Furthermore, the conditional models often capture the value, liquidity and momentum effects on individual stock returns, suggesting that the conditional model specifications specified in my work more appropriately capture the dynamics of factor loadings. This contribution becomes more evident when comparing my findings with those of Avramov and Chordia (2006) who do not consider investor sentiment in their conditional specifications and find that the conditional models fail to capture the impacts of the liquidity and momentum effects. In line with Hansen and Richard (1987), Ghysels (1998) and Bauer, Cosemans, and Schotman (2010), my results show that the conditional pricing models outperform unconditional models in terms of

[20] The corrections of Shanken (1992) and Jagannathan and Wang (1998) are reported in the empirical results to account for the bias in the Fama-MacBeth (1973) standard errors. Based on the tables, my empirical results, qualitatively, are not affected by such corrections.

explaining conditional alphas, capturing the financial market anomalies and the magnitude of $\bar{R}^2$.

Second, previous studies have treated investor sentiment as an explanatory variable to explore its time-series or cross-sectional relationship with stock returns. My use of investor sentiment as conditioning information in asset pricing models provides an alternative approach, which sheds light on the impacts of investor sentiment upon the dynamics of risk factors sensitivities.

Finally, the framework proposed in this study provides a platform for comparing various proxies for investor sentiment in terms of improving the performance of asset pricing models in explaining stock returns. The results indicate that, in the conditional versions of the CAPM and multifactor models, the Conference Board Consumer Confidence Index and the composite sentiment index often yield better model performance than the other sentiment measures examined.

This chapter is organised as follows. The next section provides additional information about the data used in this chapter but not discussed Chapter 3. Section 4.3 details the various specifications of the asset pricing models considered in this chapter. Section 4.4 examines whether conditional models completely explain conditional expected returns. Section 4.5 investigates the performance of the dynamic asset pricing models that contain investor sentiment as a conditioning variable in capturing the financial market anomalies Section 4.6 concludes.

4.2 Data

4.2.1 Proxies for Investor Sentiment

The first issue that researchers who investigates the sentiment-return relation need to address is the choice of an appropriate proxy for investor sentiment. Reviewing previous empirical studies shows that no consensus on the investor sentiment measure has been reached. To circumvent this problem, in this chapter, I use three survey sentiment indices, CCI, II and MS as well as the composite sentiment index extracted from these three indices to proxy for investor sentiment in my framework. I use these three investor sentiment indices because of their longer history starting from the 1960s, compared to those compiled by the American Association of Individual Investors or UBS/Gallup. Also, the length of the periods of these sentiment indices properly matches the stock returns and risk factors considered in my study.

The II Index is considered as a direct sentiment measure of the stock market investors because it reflects the opinions of the market professionals about the future movements of stock prices. In contrast, both the MS and CCI concern consumers' expectations about the overall prospects of the economy rather than the stock market per se. Nevertheless, previous studies use these two indices as proxies for investor sentiment and show that these indices predict stock returns (e.g., Fisher and Statman, 2002; Lee, Jiang and Indro, 2002; Brown and Cliff, 2004 and 2005; Lemmon and Portniagunia, 2006; and Liu, 2006). Fisher and Statman (2002) further demonstrate that consumer confidence moves stock prices.

Earlier parts of the MS and CCI indices were not released at the monthly frequency. The MS was released every quarter prior to January 1978 and the CCI was released every two months prior to January 1977. For these non-monthly data, I use the most recently available observations for the current month to align the time-series frequency of the sentiment indices with monthly stock returns (see also, Lemmon and Portniaguina, 2006). For example, the MS index published in February is used for the following March and April until the new index observation became available in May. For II, I obtain the monthly index values from the averages of the weekly data available in the same month.

Due to different formulae used to compile the sentiment indices, I use the coefficient of variation to measure the dispersion of each sentiment time-series data. The result shows that CCI and II have similar coefficients of variation of 23.45% and 22.81%, respectively. The coefficient of variation of MS is 13.97% which is relatively lower compared with those of CCI and II, indicating that the time-series of MS is more stable than CCI and II. The correlation coefficient between the two consumer confidence measures, MS and CCI, is 0.76 and statistically significant, reflecting their common nature of representing the opinions of general households. MS and II are significantly correlated with a coefficient of 0.27. The correlation coefficient between CCI and II is as low as 0.04 and insignificant.

Apparently, these three survey-based investor sentiment indicators may capture different aspects of the expectations or perceptions of certain groups of people about the economy or stock markets. An individual index may not completely reflect the common views of investors and is likely to have its own idiosyncratic nature. One of the solutions to this problem is to construct a composite sentiment index using Principal Component Analysis so that the common component contained in the three sentiment indices can be extracted. The selected first principal component from Principal Component Analysis gives a composite index,

$$COMP_t = 0.521MS_t + 0.493CCI_t + 0.912II_t \tag{4.1}$$

where each of the index components has been standardized. The $COMP_t$ represents the composite sentiment index which captures high common variation in the components of the three survey indices because it explains 60.53% of the total (standardized) sample variance. The composite sentiment index extracts essential information from the three sentiment indices and may represent a useful investor sentiment measure (see also, Brown and Cliff, 2004; and Baker and Wurgler, 2006).

4.2.2 Trading Data

The stock trading data used for this chapter includes the common stocks of the firms listed on NYSE and AMEX for the period from July 1964 through December 2005. To be considered in the analysis, the firms must meet the selection criteria specified in Section 3.2.1. The total number of common stocks in my sample is 3,918.

The following lists the detailed definitions of the monthly variables considered in my analysis[21].

MS: the level of University of Michigan Consumer Sentiment Index.,

CCI: the level of the Conference Board Consumer Confidence Index,

II: the percentage of newsletters classified as optimism by Investors Intelligence,

SIZE: the natural logarithm of the market capitalization of a firm measured in billions of dollars,

B/M: the natural logarithm of the book-to-market ratio of a firm,

TURNOVER: the ratio of trading volume to the number of shares outstanding of a firm,

RET2-3 (%): the cumulative return over the past second through the past third months,

RET4-6 (%): the cumulative return over the past fourth through the past sixth months,

RET7-12 (%): the cumulative return over the past seventh through the past twelfth months, and

z: default spread, the return difference between Baa and Aaa rated bonds.

In addition to investor sentiment, both the firm characteristics – size and book-to-market ratio and market-wide macroeconomic variable – default spread are also considered in the information set in the conditional asset pricing models under examination because the literature shows they predict stock returns. Default spread is negatively correlated with MS and CCI with both correlation coefficients of around -0.5, but is weakly and insignificantly

[21] Chapter 5 uses the same variables except the consumer confidence indices discussed here.

correlated with II with a coefficient of -0.02. Default spread also exhibits a higher coefficient of variation of 39.62% than those of the sentiment indices.

4.2.3 Descriptive Statistics

Table 4.1 summarizes the time-series averages of the cross-sectional means and standard deviations of the firm characteristics as well as the Fama-MacBeth coefficients from the regressions of the excess stock returns on the firm characteristics. Consistent with Brennan, Chordia, and Subrahmanyam (1998), Chordia, Subrahmanyam, and Anshuman (2001), and Avramov and Chordia (2006), small firms and those with high B/M ratios earn higher excess returns. The negative coefficient on turnover shows that stocks with lower liquidity have higher excess returns, consistent with Amihud and Mendelson (1986). Also, short-term prior returns are positively related to excess returns. Finally, the average $\bar{R}^2$ of 5.76 for all stocks in my sample period is close to the result in Avramov and Chordia (2006).

4.3 Specifications of Factor Loadings in Asset Pricing Models

Using the conditional asset pricing models that are discussed in Section 3.3.2, I propose a variety of specifications for each of the models. These specifications are formed based on the variables that enter into the information set in the asset pricing model examined in the first-pass regression of the framework. In particular, the specifications are

Specification A: function of $(SIZE + B/M)$ and S (i.e., $\beta_{j2} = \beta_{j4} = \beta_{j7} = \beta_{j10} = 0$)

Specification B: function of $(SIZE + B/M)$ and z (i.e., $\beta_{j3} = \beta_{j4} = \beta_{j6} = \beta_{j9} = 0$)

Specification C: function of z *and* S (i.e., $\beta_{j5} = \beta_{j6} = \beta_{j7} = \beta_{j8} = \beta_{j9} = \beta_{j10} = 0$)

Specification D: function of $(SIZE + B/M)$ (i.e., $\beta_{j2} = \beta_{j3} = \beta_{j4} = \beta_{j6} = \beta_{j7} = \beta_{j9} = \beta_{j10} = 0$)

Specification E: function of S (i.e., $\beta_{j2} = \beta_{j4} = \beta_{j5} = \beta_{j6} = \beta_{j7} = \beta_{j8} = \beta_{j9} = \beta_{j10} = 0$)

Specification F: function of z (i.e., $\beta_{j3} = \beta_{j4} = \beta_{j5} = \beta_{j6} = \beta_{j7} = \beta_{j8} = \beta_{j9} = \beta_{j10} = 0$)

Specification G: function of all variables $z, S, SIZE$ *and* B/M (i.e., all $\beta s \neq 0$)

As discussed in Chapter 3, Equation (3.3) demonstrates the factor loading on the corresponding risk factor of each asset pricing model as a function of all conditioning variables considered in the analysis, i.e., Specification G. Specification A represents the form of the conditional version of the asset pricing model that considers the firm-specific characteristics and investor sentiment in the information set, which is equivalent to say that β_{j2}, β_{j4}, β_{j7}, and β_{j10} in Equation (3.3) are all zeros. The rest of the other specifications can be formed and understood in the same way. Hence, the unconditional version of the asset pricing model with constant factor loadings simply represents a special case when all β_s in Equation (3.3) are all zeros.

4.4 Do Conditional Models Explain Conditional Expected Returns?

Prior studies document that conditional asset pricing models outperform the unconditional models in explaining stock returns. For example, Ghysels (1998) claims that a conditional model outperforms an unconditional model if the dynamics of beta are properly specified. In this section, I examine whether conditional models completely explain conditional expected returns. I specify the conditional alpha as a linear function of a set of conditioning instruments as in Shanken (1990) and Bauer, Cosemans, and Schotman (2010),

$$\alpha_{jt} = \alpha_{j0} + \alpha_{j1} W_{jt} \tag{4.2}$$

where α_{j0} is a scalar, α_{j1} a vector of parameters and W_{jt} a vector of conditioning variables considered in the paper for the conditional alpha. Specifically, I first perform an F-test for the hypothesis that the conditional alpha in the first-pass time-series regression is zero, i.e., whether α_{j0} and α_{j1} in Equation (4.2) are all equal to zero.

Using the composite sentiment index as the proxy for investor sentiment, Panel A of Table 4.2 reports the Bonferroni adjusted p values[22] for a joint test across firms and the proportions of firms having p-values lower than 0.05. The hypothesis of a zero conditional alpha is rejected at the 5% level for 22.1% of firms in the unconditional CAPM and between

[22] The Bonferroni p value is a conservative test which places an upper bound on the p value of a joint test. It equals N times the smallest of the N individual p values, where N is the number of firms.

18.4% and 21.7% of firms in the conditional versions of the CAPM. There are similar patterns in the FF-based models, i.e., the FF, FFP, FFW, and FFPW models. For each asset pricing model, specification G which allows factor loadings to vary with all the conditioning variables outperforms all the other conditional specifications in explaining conditional expected returns. The results indicate that the conditional models perform better than the unconditional ones in explaining conditional expected returns. In each asset pricing model, the Bonferroni adjusted *p* value for a joint test across firms is less than 0.05 in all specifications of beta.

I next test the weaker hypothesis that the conditional alpha is unrelated to the instrumentals ($\alpha_{j1} = 0$), i.e., that the alpha is constant in the asset pricing model. The results in Panel B of Table 4.2 show that the weaker hypothesis is rejected at the 5% level for 24.7% of firms in the unconditional CAPM and between 20.5% and 24.1% of firms in the conditional versions of the CAPM. Generally in the FF-based models, the proportion of firms to which the weaker hypothesis is rejected at the 5% level in conditional beta specifications is lower than that in the unconditional beta case. Nevertheless, the Bonferroni adjusted *p* value for a joint test across firms is close to zero in most of the beta specifications of models.

Overall, my findings show that conditional asset pricing models outperform the unconditional counterparts in explaining the dynamics of conditional expected returns, consistent with Bauer, Cosemans, and Schotman (2010). When betas are allowed to vary with investor sentiment, default spread and firm characteristics, the ability of the instruments to predict mispricing is much reduced in all the asset pricing models.

4.5 Performance of the Asset Pricing Models in Explaining Anomalies

4.5.1 Capital Asset Pricing Model (CAPM)

Next, I examine the extent to which the unconditional and conditional versions of the CAPM explain the financial market anomalies. Table 4.3 presents the Fama-MacBeth coefficient estimates from running the OLS cross-sectional regressions of monthly risk-adjusted returns of individual stocks on the anomaly variables. The first column lists the unconditional model and conditional models with various beta specifications. For the conditional models that investor sentiment enters into the time-varying beta specification, I report the results from using each of the four proxies for investor sentiment. The last four columns present, for each beta specification, the average and confidence intervals for the cross-sectional $\bar{R}^2$.

For the unconditional CAPM, the first row of Table 4.3 shows that all the coefficient estimates on the anomaly variables are all highly significant[23] and that firms with small market value, high B/M, low turnover, and high past returns earn higher risk-adjusted returns. Clearly, the CAPM with a constant beta fails to capture any of the anomalies. In the conditional versions of the CAPM, the *t*-statistic for SIZE is reduced in Specification C where the beta is allowed to vary with investor sentiment (using either CCI or COMP as the proxy) and default spread. In Specification G which uses CCI and all the other instruments in the conditional beta specification, the *t*-statistics for SIZE after using the corrections of Shanken (1992) and Jagannathan and Wang (1998) are reduced to -1.82 and -1.90, respectively. Moreover, all the conditional models have lower $\bar{R}^2$ s than that of the unconditional CAPM. Overall, the impact of firm size on the cross-section of risk-adjusted returns becomes less important when either CCI or COMP enters into the conditional beta specifications of the CAPM as in Specifications C and G.

Lewellen, Nagel, and Shanken (2008) argue that the point estimate of cross-sectional R^2 can be biased and suggest reporting confidence intervals for the $\bar{R}^2$ in order to provide more transparent information. I thus report, for each model, a confidence interval for $\bar{R}^2$. For

[23] The analysis here only reports the corrected *t*-statistics of corrections of Shanken (1992) and Jagannathan and Wang (1998) here since the differences between the unadjusted and the corrected *t*-statistics are very minor and do not affect the inferences and conclusions. Campbell, Lo, and MacKinlay (1997, p.216)) provide detailed discussion about the Shanken's adjustment. In the later sections, I include unadjusted *t*-statistics for the FF model for the purpose of illustration, but only report the corrected *t*-statistics for all the FF based models, i.e., the FFP, FFW, and FFPW models, for brevity.

example, in Table 4.3 the 5th percentile of the $\bar{R}^2$ in the unconditional CAPM is 4.39% and the 95th percentile is 5.30%. Lewellen et al. (2008) also propose the uses of GLS cross-sectional regressions for asset-pricing tests and the GLS R^2 to gauge model performance. Table 4.4 shows the results from using GLS regressions. Compared with the OLS results in Table 4.3, the magnitudes of the adjusted *t*-statistics for SIZE are dramatically decreased in all models and the size effect is no longer significant, although all the other anomaly variables remain significant. Noticeably, the model $\bar{R}^2$ increases to around 30% in the GLS regressions because the GLS uses transformed variables, and hence, reduces the noise caused by the variability of the observations.

4.5.2 Fama-French Three-Factor Model (FF)

Table 4.5 presents the results of the FF model. Compared with the unconditional CAPM, the unconditional FF model has a reduced (Shanken) adjusted *t*-statistic of -1.87 on SIZE as well as a lower $\bar{R}^2$ of 2.79%. Thus, the impact of firm size on the cross-section of risk-adjusted returns decreases when *SMB* and *HML* are included as additional risk factors. The conditional FF models outperform the unconditional FF model and all versions of the CAPM in capturing the impacts of firm attributes on stock returns. All the conditional FF models can capture the size effect. Moreover, both variables SIZE and B/M are no longer significant in the beta specifications A, B, and G that use, respectively, investor sentiment, default spread and both macroeconomic variables in addition to the firm-specific characteristics as conditioning variables. In contrast, the beta specifications D, E, and F that use either only the firm-specific characteristics or a macroeconomic variable as conditioning information are only able to capture the effect of SIZE, but not the B/M effect.

Strikingly, in the beta specification C which allows factor loadings to vary with both COMP and default spread, the impact of the short-term momentum variable RET2-3 on the cross-section of risk-adjusted returns becomes insignificant. In contrast, Avramov and

Chordia (2006) do not consider investor sentiment as conditioning information and find that the conditional FF model fails to capture the momentum effect. My results suggest that investor sentiment plays an important role for capturing the momentum effect.

I also find that the overall explanatory power of anomaly variables on risk-adjusted returns is reduced when replacing default spread by investor sentiment as conditioning information. Comparing the $\overline{R}^2$s of the conditional FF models, the beta specification E which incorporates investor sentiment as conditioning information has a lower $\overline{R}^2$ than that of the beta specification F which uses default spread. Similarly, the beta specification A which incorporates investor sentiment and firm characteristics as conditioning variables has a slightly lower $\overline{R}^2$ than that of the beta specification B which uses default spread and firm characteristics as conditioning information. These suggest that investor sentiment may be a better instrument than default spread in the pricing models for conveying conditioning information because investor sentiment directly measures investors' expectations about the conditions on stock markets and the economy.

I repeat the cross-sectional tests by using GLS regressions. The GLS results are qualitatively similar to those based on OLS regressions. Again, the beta specifications A, B, and G can capture both the SIZE and B/M effects, the beta specification C can capture both SIZE and RET2-3, but the other models can capture SIZE only. The *t*-statistics of the captured anomaly variables from using GLS are much lower than those based on OLS estimations. For example, in the beta specification B the *t*-statistics for SIZE and B/M change from -1.27 and 1.00, respectively, in the OLS regressions to 0.03 and 0.50 when GLS regressions are applied. These results indicate that using GLS estimations enhances the precision of coefficient estimates, but does not change the inferences and conclusions for the tests of the conditional FF models.

4.5.3 The FF Model plus Pastor-Stambaugh Liquidity Factor (FFP)

Pastor and Stambaugh (2003) document that high liquidity-beta stocks earn higher average returns than low liquidity-beta stocks. I examine whether the PS liquidity-augmented FF models capture the anomalies which the conditional CAPM and FF models fail to capture. Results of Table 4.6 show that the inclusion of the liquidity factor improves model performance. In the unconditional FFP model the size effect is no longer significant. The beta specification C of the FFP model fully captures the impacts of both RET2-3 and SIZE regardless of which measure of investor sentiment being used. In addition, the beta specification F which scales factor loadings by default spread alone also captures the impact of RET2-3. These findings show that return momentum is related to liquidity risk. Adding the liquidity factor to the FF models, however, does not significantly reduce the impact of TURNOVER on stock returns. The adjusted *t*-statistic for TURNOVER in the FFP model remains significant in all the beta specifications.

Similar to the results of the conditional FF models, the $\bar{R}^2$ of the beta specification E using either one of the four sentiment proxies is lower than that of the beta specification F; and the $\bar{R}^2$ of the beta specification A using either one of the four sentiment proxies is lower than that of the beta specification B. These results show that the conditional versions of the FFP model that use investor sentiment as conditioning information are better than those use default spread for explaining expected returns in the first-pass time-series regressions. Consequently, in the second-pass cross-sectional regressions the overall impact of firm attributes on risk-adjusted returns is reduced.

Using GLS regressions, I find striking results for the beta specification G that all of the (transformed) anomaly variables, namely, SIZE, B/M, TURNOVER, RET2-3, and RET4-6 are no longer significant. RET7-12 is also insignificant when using either CCI or COMP. In addition, in the beta specification D the B/M variable becomes insignificant. The results of the other conditional versions of the FFP model are qualitatively similar to those based on the OLS regressions in terms of capturing the impacts of anomalies.

4.5.4 The FF Model plus Momentum Factor (FFW)

Table 4.7 reports the results of the FFW model that adds the *WML* risk factor to the FF model. With constant betas, the unconditional FFW model does not capture any of the anomalies. Using MS, CCI or II as the proxy for investor sentiment, the beta specification G of the conditional FFW model can successfully capture the impact of TURNOVER on individual stock returns. In addition, the beta specification G captures RET2-3 when either MS or II is used to proxy for investor sentiment. Specification G also captures RET4-6 when II is used to proxy for sentiment. The results of the other conditional versions of the FFW model are qualitatively similar to those of the FFP model.

Comparing with the results of the conditional versions of the FF model, the conditional FFW models further capture the effects of TURVOVER, RET2-3, and RET4-6 in addition to the effect of SIZE. These results suggest that adding investor sentiment to the conditioning information set and adding the momentum factor to the FF model enhance the power of the asset pricing model. In the unreported results of the GLS regressions, the beta specification E which uses either CCI or COMP as conditioning information further captures RET2-3 in addition to SIZE. The results of all the other models are qualitatively unchanged from using GLS regressions.

4.5.5 The FF Model plus Liquidity and Momentum Factors (FFPW)

Finally, I ask whether adding both the liquidity and momentum factors to the FF model further enhances model performance. Table 4.8 presents the results of the FFPW model. The overall results are qualitatively similar to those of the FFP models. Contrary to expectations, the explanatory power of the beta specification G of the FFPW model is virtually reduced compared with the results of the FFW model. In particular, the beta specification G of the

FFPW model now loses its power to capture the impacts of B/M, TURNOVER, RET2-3, and RET4-6 on stock returns. All these variables become significant again when both the momentum and the Pastor-Stambaugh liquidity factors are added to the FF model. Interestingly, when using GLS cross-sectional regressions, none of the anomaly variables in the beta specification G is significant.

Overall among the conditional specifications of the liquidity and/or momentum factor augmented FF models, the beta specification C which allows factor loadings to vary with both investor sentiment and default spread always captures the short-term momentum – RET2-3 – regardless of which of the proxies for investor sentiment being used. The beta specification G that contains most comprehensive instrumental variables does not necessarily capture more anomalies than those with fewer instruments. The only exception occurs in the momentum-factor augmented FF model (FFW) in which the beta specification G is able to capture most of the anomalies.

4.6 Conclusion

Following Avramov and Chordia (2006), this chapter tests the pricing ability of investor sentiment by considering a two-pass regression framework. The first-pass regression represents the conditional asset pricing model where factor loadings are time varying with investor sentiment, default spread and firm-level size and book-to-market ratio. The second-pass regression links the cross-sectional risk-adjusted stock returns to the financial market anomalies under consideration. Several proxies are used to measure investor sentiment, including survey-based sentiment indicators such as consumer confidence indices and Investors Intelligence sentiment index. Furthermore, using the Principal Component Analysis, I develop a composite sentiment index which extracts the common variation component of these three survey indices (MS, CCI, and II).

With the proxies for investor sentiment, this chapter first tests whether conditional asset pricing models that further incorporate investor sentiment as conditioning information explain conditional alphas. The result shows that the conditional models outperform the unconditional ones in explaining the dynamics of expected stock returns.

This chapter then tests whether incorporating investor sentiment as conditioning information in pricing models helps capture the impacts of firm size, B/M, the liquidity and momentum effects on the cross-section of risk-adjusted stock returns. The result indicates that the conditional model specifications outperform the unconditional beta models in terms of capturing these anomalies. Furthermore, the conditional models often capture the value, liquidity and momentum effects. The conditional FF models that further allow factor loadings to vary with investor sentiment can often capture the impacts of the firm size and B/M effects on stock returns. The conditional liquidity-augmented FF models, which incorporate investor sentiment and default spread as conditioning information, also capture the impact of the momentum effect. In the conditional momentum-augmented FF models the impacts of both the liquidity and momentum effects on stock returns generally decline and become insignificant in many cases. Overall, the evidence of this chapter suggests that investor sentiment, as an information variable in the conditional versions of the asset pricing models, helps to capture the financial market anomalies that traditional models fail to explain. The finding that investor sentiment can act as an information variable enhance our understanding of the role that investor sentiment may play in asset pricing.

Table 4.1: Summary statistics (3,918 firms: 07/1964 - 12/2005)

	Mean	Std. Dev.	Coefficient (%)	*t*-statistics
EXCESS RETURN (%)	0.84	5.47		
SIZE ($ billions)	1.97	2.10	-0.12	-2.73
B/M	0.89	0.35	0.26	4.69
TURNOVER	0.05	0.03	-0.09	-1.63
RET2-3	2.61	8.38	0.65	2.23
RET4-6	3.93	10.58	0.82	3.13
RET7-12	7.94	15.44	0.96	6.15
$\overline{R}^2$ (%)	5.76			

This table presents the time-series averages of the cross-sectional means and standard deviations for 3918 NYSE-AMEX stocks over 498 months from July 1964 through December 2005. The column labeled with "Coefficient" represents the time-series averages of the slop coefficients from the cross-sectional OLS regressions of excess return on the firm characteristics. The *t*-values for the slop coefficients of the characteristics are in the last column. $\overline{R}^2$ denotes the adjusted R squared. SIZE represents the market capitalization in billions of dollars. B/M is the book-to-market ratio of equity. TURNOVER is the monthly trading volume of shares divided by shares outstanding. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively. A common stock must meet the following criteria in order to be included in the analysis: (i) the returns of the stock must be available in the current month, t, and over the past 36 months in the CRSP, (ii) stock prices and shares outstanding for calculating the size of a firm and the month t – 2 trading volume for calculating turnover must be available, (iii) the B/M as of December of the previous calendar year has to be available from the COMPUSTAT dataset, (iv) the B/M must be positive, and (v) the B/M values greater than the 0.995 fractile or less than the 0.005 fractile are set to be the 0.995 and 0.005 fractile values, respectively.

Table 4.2: Tests of the time-varying alphas in the first-pass time-series regressions

Panel A: Test Zero Conditional Alpha

MODEL	CAPM		FF		FFP		FFU		FFPU	
	Bonferroni	% < 0.05	Bonferroni	% < 0.05	Bonferroni	% < 0.0	Bonferroni	% < 0.05	Bonferroni	% < 0.05
UNCOND	0.001	22.11	0.002	19.05	0.008	14.07	0.009	13.39	0.006	13.49
A	0.000	19.28	0.002	14.91	0.002	14.23	0.000	12.99	0.000	12.58
B	0.000	19.43	0.001	14.58	0.002	13.37	0.000	12.16	0.000	11.62
C	0.001	20.12	0.003	17.08	0.000	13.62	0.000	12.80	0.000	12.52
D	0.000	20.43	0.001	16.93	0.001	15.57	0.000	15.01	0.000	14.37
E	0.001	20.63	0.001	18.46	0.002	14.31	0.014	13.63	0.002	14.10
F	0.001	21.68	0.005	18.16	0.001	13.24	0.000	12.62	0.000	12.07
G	0.000	18.39	0.002	13.76	0.000	12.20	0.000	10.84	0.000	11.04

Panel B: Test Constant Alpha

MODEL	CAPM		FF		FFP		FFU		FFPU	
	Bonferroni	% < 0.05	Bonferroni	% < 0.05	Bonferroni	% < 0.0	Bonferroni	% < 0.05	Bonferroni	% < 0.05
UNCOND	0.000	24.74	0.001	22.01	0.003	16.02	0.004	16.08	0.002	15.92
A	0.000	21.99	0.001	16.80	0.001	15.82	0.000	14.70	0.000	14.14
B	0.000	21.12	0.000	16.29	0.001	15.22	0.000	13.25	0.000	13.05
C	0.000	22.93	0.001	19.74	0.000	15.04	0.000	14.40	0.000	14.01
D	0.000	23.31	0.000	18.08	0.001	17.08	0.000	16.51	0.000	15.90
E	0.000	23.31	0.000	20.91	0.001	15.79	0.006	15.64	0.001	15.66
F	0.000	24.13	0.002	20.28	0.000	15.02	0.000	14.63	0.000	14.57
G	0.000	20.51	0.001	14.84	0.000	12.85	0.000	11.66	0.000	11.38

This table presents the Bonferroni adjusted p values for a joint hypothesis across firms and the percentage of firms whose p-values of an F-test are below 0.05 for the hypothesis that the conditional alpha is zero (Panel A) and the hypothesis that the alpha is constant (Panel B) for the 3,918 firm in the sample. The row of "UNCOND" displays the results of the unconditional models. The rows for the beta specifications A through G show the results for the conditional models as per the specifications described in Section 4.3.

Table 4.3: Fama-MacBeth estimates with excess market return as the risk factor (CAPM)

Specification	SIZE MS	SIZE CCI	SIZE II	SIZE COMP	B/M MS	B/M CCI	B/M II	B/M COMP
UNCOND		-0.099				0.265		
		{-2.36}				{5.01}		
		[-2.47]				[5.22]		
A	-0.093	-0.087	-0.010	-0.085	0.253	0.266	0.234	0.271
	{-2.31}	{-2.07}	{-2.47}	{-2.03}	{5.02}	{5.08}	{4.70}	{5.19}
	[-2.42]	[-2.17]	[-2.58]	[-2.13]	[5.25]	[5.31]	[4.90]	[5.43]
B		-0.087				0.241		
		{-2.15}				{4.79}		
		[-2.25]				[5.01]		
C	-0.088	-0.081	-0.099	-0.079	0.257	0.271	0.256	0.276
	{-2.13}	{-1.91}	{-2.40}	{-1.86}	{4.99}	{5.04}	{5.00}	{5.19}
	[-2.23]	[-1.99]	[-2.52]	[-1.94]	[5.20]	[5.27]	[5.22]	[5.42]
D		-0.093				0.266		
		{-2.26}				{5.20}		
		[-2.37]				[5.43]		
E	-0.097	-0.088	-0.100	-0.087	0.268	0.290	0.260	0.292
	{-2.34}	{-2.04}	{-2.40}	{-2.02}	{5.12}	{5.31}	{5.02}	{5.39}
	[-2.45]	[-2.14]	[-2.51]	[--2.11]	[5.35]	[5.55]	[5.24]	[5.63]
F		-0.095				0.268		
		{-2.28}				{5.09}		
		[-2.38]				[5.31]		
G	-0.087	-0.074	-0.093	-0.076	0.221	0.238	0.215	0.240
	{-2.19}	{-1.82}	{-2.37}	{-1.85}	{4.52}	{4.70}	{4.39}	{4.77}
	[-2.29]	[-1.90]	[-2.47]	[-1.94]	[4.73]	[4.92]	[4.58]	[4.99]

Specification	TURNOVER MS	TURNOVER CCI	TURNOVER II	TURNOVER COMP	RET2-3 MS	RET2-3 CCI	RET2-3 II	RET2-3 COMP
UNCOND		-0.161				0.764		
		{-3.84}				{2.82}		
		[-4.01]				[2.92]		
A	-0.160	-0.180	-0.157	-0.184	0.925	0.878	0.953	0.846
	{-4.08}	{-4.49}	{-3.98}	{-4.62}	{3.51}	{3.40}	{3.67}	{3.27}
	[-4.26]	[-4.69]	[-4.15]	[-4.83]	[3.63]	[3.53]	[3.79]	[3.39]
B		-0.152				0.936		
		{-3.86}				{3.58}		
		[-4.02]				[3.71]		
C	-0.162	-0.183	-0.143	-0.187	0.748	0.639	0.733	0.625
	{-3.97}	{-4.38}	{-3.48}	{-4.50}	{2.75}	{2.36}	{2.74}	{2.30}
	[-4.15]	[-4.57]	[-3.64]	[-4.70]	[2.85]	[2.44]	[2.82]	[2.38]
D		-0.158				0.852		
		{-3.92}				{3.22}		
		[-4.10]				[3.33]		
E	-0.162	-0.185	-0.158	-0.189	0.784	0.684	0.785	0.673
	{-3.93}	{-4.39}	{-3.79}	{-4.51}	{2.89}	{2.53}	{2.92}	{2.47}
	[-4.10]	[-4.59]	[-3.96]	[-4.71]	[2.99]	[2.61]	[3.01]	[2.55]
F		-0.150				0.726		
		{-3.61}				{2.70}		
		[-3.77]				[2.79]		
G	-0.157	-0.178	-0.151	-0.180	0.979	0.928	0.936	0.895
	{-4.10}	{-4.57}	{-3.93}	{-4.63}	{3.77}	{3.64}	{3.64}	{3.51}
	[-4.26]	[-4.76]	[-4.08]	[-4.82]	[3.90]	[3.78]	[3.76]	[3.64]

Specification	RET4-6 MS	RET4-6 CCI	RET4-6 II	RET4-6 COMP	RET7-12 MS	RET7-12 CCI	RET7-12 II	RET7-12 COMP
UNCOND		0.850				1.024		
		{3.56}				{7.12}		
		[3.68]				[7.40]		
A	0.933	1.005	0.968	0.977	1.046	1.151	1.067	1.125
	{4.20}	{4.54}	{4.35}	{4.38}	{7.55}	{8.21}	{7.70}	{8.00}
	[4.35]	[4.71]	[4.50]	[4.54]	[7.89]	[8.59]	[8.03]	[8.36]
B		1.009				1.119		
		{4.53}				{8.10}		
		[4.69]				[8.44]		
C	0.875	0.918	0.857	0.905	1.048	1.096	1.010	1.107
	{3.80}	{4.02}	{3.69}	{3.93}	{7.41}	{7.63}	{7.08}	{7.77}
	[3.92]	[4.12]	[3.81]	[4.06]	[7.70]	[7.95]	[7.35]	[8.09]
D		0.910				1.050		
		{3.99}				{7.39}		
		[4.14]				[7.72]		
E	0.861	0.887	0.842	0.882	1.024	1.090	1.010	1.088
	{3.70}	{3.81}	{3.56}	{3.78}	{7.20}	{7.51}	{7.07}	{7.54}
	[3.81]	[3.93]	[3.68]	[3.90]	[7.48]	[7.81]	[7.34]	[7.84]
F		0.846				1.032		
		{3.60}				{7.20}		
		[3.72]				[7.48]		
G	0.998	1.053	1.066	1.035	1.074	1.130	1.091	1.135
	{4.59}	{4.85}	{4.92}	{4.75}	{8.03}	{8.30}	{8.04}	{8.36}
	[4.76]	[5.04]	[5.08]	[4.93]	[8.37]	[8.65]	[8.35]	[8.71]

Specification	Adj. R^2(%) MS	Adj. R^2(%) CCI	Adj. R^2(%) II	Adj. R^2(%) COMP
UNCOND		4.84		
		[4.39,5.30]		
A	4.70	4.52	4.64	4.54
	[4.24,5.15]	[4.10,4.95]	[4.20,5.08]	[4.10,4.97]
B		4.67		
		[4.24,5.10]		
C	4.78	4.61	4.78	4.60
	[4.33,5.23]	[4.17,5.05]	[4.33,5.23]	[4.16,5.04]
D		4.73		
		[4.28,5.18]		
E	4.80	4.64	4.80	4.63
	[4.35,5.26]	[4.19,5.08]	[4.35,5.26]	[4.19,5.08]
F		4.81		
		[4.36,5.28]		
G	4.63	4.44	4.60	4.44
	[4.20,5.06]	[4.03,4.85]	[4.17,5.02]	[4.03,4.85]

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX individual stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess risk-adjusted return using the excess market return as the risk factor. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as defined in Section 4.2.2. UNCOND denotes the constant beta model specified in the first-pass. Specifications A – G represent the conditional versions of the asset pricing model as in Section (4.3). The conditioning variables for factor loadings are investor sentiment index, default spread, SIZE and B/M. The columns under $Adj.\ R^2$ report the time-series average and the confidence interval of the 5th and the 95th percentiles of the monthly adjusted R squared. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor's Intelligence, respectively. COMP is the composite sentiment index derived from the principal component analysis. The *t*-statistics in curly brackets use standard errors as in Shanken (1992) and the *t*-statistics in square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

Table 4.4: Fama-MacBeth GLS regression estimates with excess market return as the risk factor (GLS-CAPM)

Specification	SIZE				B/M				TURNOVER			
	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP
UNCOND		-0.057				0.251				-0.159		
		{-1.42}				{4.88}				{-3.91}		
		[-1.48]				[5.10]				[-4.09]		
A	-0.054	-0.051	-0.061	-0.048	0.239	0.255	0.222	0.260	-0.157	-0.175	-0.155	-0.182
	{-1.39}	{-1.25}	{-1.56}	{-1.18}	{4.86}	{4.97}	{4.60}	{5.08}	{-4.15}	{-4.51}	{-4.03}	{-4.71}
	[-1.46]	[-1.32]	[-1.63]	[-1.24]	[5.09]	[5.20]	[4.81]	[5.31]	[-4.34]	[-4.71]	[-4.21]	[-4.93]
B		-0.049				0.227				-0.151		
		{-1.25}				{4.61}				{-3.92}		
		[-1.30]				[4.83]				[-4.09]		
C	-0.049	-0.043	-0.060	-0.040	0.244	0.255	0.240	0.262	-0.159	-0.183	-0.138	-0.183
	{-1.23}	{-1.04}	{-1.50}	{-0.97}	{4.88}	{4.86}	{4.82}	{5.05}	{-4.01}	{-4.51}	{-3.45}	{-4.53}
	[-1.28]	[-1.09]	[-1.58]	[-1.01]	[5.10]	[5.87]	[5.04]	[5.28]	[-4.18]	[-4.71]	[-3.60]	[-4.73]
D		-0.053				0.253				-0.157		
		{-1.33}				{5.07}				{-3.99}		
		[-1.40]				[5.30]				[-4.18]		
E	-0.054	-0.049	-0.059	-0.047	0.257	0.273	0.247	0.280	-0.161	-0.184	-0.159	-0.188
	{-1.34}	{-1.17}	{-1.47}	{-1.12}	{5.04}	{5.16}	{4.91}	{5.30}	{-4.01}	{4.48}	{-3.94}	{-4.59}
	[-1.40]	[-1.22]	[-1.53]	[-1.17]	[5.26]	[5.39]	[5.13]	[5.54]	[-4.19]	[-4.69]	[-4.12]	[-4.81]
F		-0.053				0.256				-0.151		
		(-1.31)				(5.00)				(-3.74)		
		{-1.31}				{5.00}				{-3.74}		
		[-1.37]				[5.22]				[-3.91]		
G	-0.050	-0.040	-0.056	-0.041	0.212	0.226	0.205	0.225	-0.152	-0.174	-0.146	-0.177
	{-1.31}	{-1.01}	{-1.48}	{-1.03}	{4.43}	{4.57}	{4.30}	{4.59}	{-4.06}	{-4.57}	{-3.91}	{-4.67}
	[-1.37]	[-1.06]	[-1.55]	[-1.08]	[4.63]	[4.79]	[4.49]	[4.80]	[-4.22]	[-4.76]	[-4.06]	[-4.86]

Specification	RET2-3				RET4-6				RET7-12				Adj. R^2(%)			
	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP
UNCOND		0.716				0.874				1.055				32.02		
		{2.69}				{3.71}				{7.37}				[30.36,33.68]		
		[2.78]				[3.83]				[7.66]						
A	0.902	0.846	0.905	0.806	0.926	1.006	0.975	0.974	1.058	1.173	1.087	1.145	30.83	31.17	30.57	31.02
	{3.49}	{3.33}	{3.54}	{3.16}	{4.19}	{4.55}	{4.43}	{4.41}	{7.70}	{8.42}	{7.93}	{8.16}	[29.15,32.51]	[29.41,32.93]	[28.92,32.23]	[29.28,32.75]
	[3.61]	[3.45]	[3.66]	[3.27]	[4.35]	[4.73]	[4.58]	[4.58]	[8.05]	[8.81]	[8.28]	[8.54]				
B		0.902				1.019				1.128				31.99		
		{3.51}				{4.62}				{8.19}				[30.30,33.67]		
		[3.64]				[4.79]				[8.55]						
C	0.729	0.616	0.701	0.623	0.886	0.936	0.867	0.911	1.070	1.117	1.036	1.125	31.56	31.55	31.60	30.77
	{2.73}	{2.31}	{2.68}	{2.33}	{3.89}	{4.13}	{3.78}	{3.99}	{7.63}	{7.85}	{7.30}	{7.97}	[29.87,33.24]	[29.84,33.25]	[29.89,33.32]	[29.09,32.44]
	[2.83]	[2.40]	[2.76]	[2.41]	[4.02]	[4.28]	[3.90]	[4.13]	[7.95]	[8.18]	[7.59]	[8.30]				
D		0.818				0.932				1.067				32.00		
		{3.14}				{4.14}				{7.61}				[30.30,33.71]		
		[3.26]				[4.30]				[7.96]						
E	0.763	0.645	0.749	0.634	0.881	0.92	0.864	0.911	1.053	1.118	1.043	1.119	31.32	31.49	31.88	31.53
	{2.86}	{2.42}	{2.83}	{2.36}	{3.83}	{4.00}	{3.70}	{3.96}	{7.48}	{7.77}	{7.32}	{7.85}	[29.66,32.99]	[29.80,33.17]	[30.20,33.55]	[29.78,33.28]
	[2.96]	[2.50]	[2.93]	[2.44]	[3.95]	[4.14]	[3.82]	[4.09]	[7.77]	[8.09]	[7.61]	[8.17]				
F		0.699				0.873				1.055						
		(2.65)				(3.77)				(7.43)				31.41		
		{2.64}				{3.77}				{7.42}				[29.79,33.03]		
		[2.74]				[3.89]				[7.72]						
G	0.939	0.862	0.901	0.856	0.996	1.066	1.055	1.029	1.076	1.150	1.104	1.151	31.12	30.01	30.45	30.05
	{3.69}	{3.45}	{3.56}	{3.40}	{4.62}	{4.95}	{4.93}	{4.76}	{8.10}	8.49}	{8.19}	{8.52}	[29.44,32.79]	[28.42,31.61]	[28.84,32.06]	[28.37,31.72]
	[3.82]	[3.58]	[3.68]	[3.53]	[4.79]	[5.16]	[5.10]	[4.95]	[8.46]	[8.87]	[8.51]	[8.89]				

This table presents the averages of the coefficient estimates from the second-pass GLS cross-sectional regressions for the NYSE-AMEX individual stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess risk-adjusted return using the excess market return as the risk factor. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as defined in 4.2.2. UNCOND denotes the constant beta model specified in the first-pass. Specifications A – G represent the conditional versions of the asset pricing model as in Section (4.3). The conditioning variables for factor loadings are investor sentiment index, default spread, SIZE and B/M. The columns under $Adj.\ R^2$ report the time-series average and the confidence interval of the 5th and the 95th percentiles of the monthly adjusted R squared. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor's Intelligence, respectively. COMP is the composite sentiment index derived from the principal component analysis. The *t*-statistics in curly brackets use standard errors as in Shanken (1992) and the *t*-statistics in square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

Table 4.5:Fama-MacBeth estimates with Fama-French three factors as the risk factors (FF)

Specification	SIZE				B/M				TURNOVER			
	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP
UNCOND		-0.046				0.166				-0.161		
		(-1.91)				(4.04)				(-4.31)		
		{-1.87}				{3.96}				{-4.23}		
		[-1.94]				[4.11]				[-4.39]		
A	-0.029	-0.019	-0.026	-0.025	0.034	0.034	0.060	0.040	-0.154	-0.170	-0.158	-0.163
	(-1.43)	(-0.92)	(-1.29)	(-1.22)	(1.07)	(1.06)	(1.81)	(1.23)	(-4.84)	(-5.13)	(-5.01)	(-4.94)
	{-1.40}	{-0.90}	{-1.26}	{-1.19}	{1.05}	{1.04}	{1.77}	{1.21}	{-4.76}	{-5.03}	{-4.91}	{-4.85}
	[-1.46]	[-0.94]	[-1.31]	[-1.24]	[1.09]	[1.08]	[1.83]	[1.25]	[-4.91]	[-5.20]	[-5.08]	[-5.01]
B		-0.026				0.032				-0.153		
		(-1.27)				(1.00)				(-4.81)		
		{-1.25}				{0.98}				{-4.72}		
		[-1.29]				[1.01]				[-4.87]		
C	-0.040	-0.026	-0.041	-0.035	0.105	0.105	0.107	0.111	-0.151	-0.160	-0.152	-0.167
	(-1.79)	(-1.17)	(-1.84)	(-1.56)	(2.94)	(2.82)	(2.85)	(3.02)	(-4.30)	(-4.50)	(-4.37)	(-4.69)
	{-1.75}	{-1.14}	{-1.80}	{-1.53}	{2.87}	{2.76}	{2.79}	{2.96}	{-4.21}	{-4.40}	{-4.27}	{-4.59}
	[1.82]	[-1.19]	[-1.88]	[-1.59]	[2.99]	[2.87]	[2.90]	[3.07]	[-4.37]	[-4.58]	[-4.45]	[-4.77]
D		-0.030				0.083				-0.156		
		(-1.37)				(2.43)				(-4.58)		
		{-1.34}				{2.38}				{-4.49}		
		[-1.39]				[2.47]				[-4.65]		
E	-0.044	-0.037	-0.047	-0.041	0.144	0.147	0.148	0.156	-0.159	-0.171	-0.161	-0.178
	(-1.89)	(-1.55)	(-2.03)	(-1.73)	(3.71)	(3.66)	(3.72)	(3.91)	(-4.35)	(-4.58)	(-4.49)	(-4.78)
	{-1.85}	{-1.52}	{-1.99}	{-1.70}	{3.63}	{3.58}	{3.64}	{3.82}	{-4.26}	{-4.48}	{-4.39}	{-4.67}
	[-1.92]	[-1.58]	[-2.07]	[-1.77]	[3.77]	[3.73]	[3.79]	[3.97]	[-4.42]	[-4.66]	[-4.57]	[-4.86]
F		-0.040				0.135				-0.154		
		(-1.70)				(3.44)				(-4.19)		
		{-1.66}				{3.36}				{-4.10}		
		[-1.73]				[3.50]				[-4.26]		
G	-0.022	-0.007	-0.014	-0.016	0.010	0.015	0.012	0.018	-0.148	-0.157	-0.154	-0.154
	(-1.17)	(-0.37)	(-0.76)	(-0.88)	(0.35)	(0.49)	(0.39)	(0.59)	(-5.07)	(-5.21)	(-5.32)	(-5.16)
	{-1.15}	{-0.36}	{-0.75}	{-0.86}	{0.34}	{0.48}	{0.38}	{0.58}	{-4.98}	{-5.11}	{-5.22}	{-5.06}
	[-1.19]	[-0.37]	[-0.78]	[-0.89]	[0.35]	[0.49]	[0.40]	[0.60]	[-5.12]	[-5.26]	[-5.38]	[-5.22]

Specification	RET2-3				RET4-6				RET7-12				Adj. R^2(%)			
	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP
UNCOND		0.726				0.846				0.954				2.79		
		(2.91)				(3.93)				(7.10)				[2.54,3.03]		
		{2.85}				{3.85}				{6.96}						
		[2.95]				[3.99]				[7.29]						
A	0.812	0.773	0.992	0.774	0.991	0.986	1.116	0.982	1.028	1.080	1.031	1.073	2.45	2.36	2.39	2.35
	(3.46)	(3.32)	(4.38)	(3.36)	(5.44)	(5.49)	(6.34)	(5.43)	(8.97)	(9.39)	(8.65)	(9.34)	[2.26,2.64]	[2.17,2.55]	[2.20,2.59]	[2.16,2.54]
	{3.40}	{3.26}	{4.29}	{3.30}	{5.34}	{5.38}	{6.21}	{5.33}	{8.81}	{9.21}	{8.47}	{9.16}				
	[3.48]	[3.36]	[4.41]	[3.38]	[5.51]	[5.58]	[6.41]	[5.50]	[9.24]	[9.66]	[8.86]	[9.61]				
B		0.781				1.009				1.025				2.46		
		(3.36)				(5.51)				(8.78)				[2.26,2.66]		
		{3.30}				{5.40}				{8.61}						
		[3.39]				[5.58]				[9.01]						
C	0.522	0.482	0.583	0.432	0.781	0.801	0.893	0.792	0.902	0.918	0.899	0.937	2.65	2.58	2.66	2.56
	(2.09)	(1.92)	(2.36)	(1.73)	(3.87)	(4.01)	(4.53)	(3.96)	(7.28)	(7.21)	(6.97)	(7.50)	[2.42,2.87]	[2.36,2.81]	[2.44,2.89]	[2.33,2.78]
	{2.05}	{1.88}	{2.31}	{1.69}	{3.79}	{3.93}	{4.42}	{3.88}	{7.13}	{7.05}	{6.81}	{7.34}				
	[2.12]	[1.95]	[2.39]	[1.75]	[3.93]	[4.07]	[4.59]	[4.01]	[7.48]	[7.41]	[7.17]	[7.71]				
D		0.856				1.003				1.046				2.48		
		(3.65)				(5.26)				(8.39)				[2.27,2.68]		
		{3.58}				{5.16}				{8.22}						
		[3.69]				[2.34]				[8.61]						
E	0.688	0.595	0.757	0.586	0.847	0.847	0.880	0.834	0.918	0.952	0.951	0.954	2.70	2.60	2.70	2.58
	(2.78)	(2.40)	(3.09)	(2.37)	(4.13)	(4.18)	(4.26)	(4.11)	(7.14)	(7.22)	(7.19)	(7.30)	[2.46,2.94]	[2.37,2.83]	[2.46,2.93]	[2.35,2.81]
	{2.73}	{2.34}	{3.02}	{2.32}	{4.04}	{4.09}	{4.17}	{4.02}	{7.00}	{7.06}	{7.03}	{7.14}				
	[2.82]	[2.44]	[3.13]	[2.40]	[4.19]	[4.26]	[4.33]	[4.18]	[7.34]	[7.43]	[7.38]	[7.51]				
F		0.542				0.802				0.907				2.74		
		(2.18)				(3.85)				(6.87)				[2.50,2.97]		
		{2.13}				{3.77}				{6.72}						
		[2.21]				[3.91]				[7.05]						
G	0.806	0.770	0.882	0.765	0.988	0.974	1.100	1.013	0.961	0.985	0.954	1.008	2.43	2.33	2.41	2.34
	(3.44)	(3.36)	(3.85)	(3.33)	(5.63)	(5.71)	(6.57)	(5.83)	(9.14)	(9.26)	(8.63)	(9.57)	[2.24,2.61]	[2.14,2.51]	[2.22,2.60]	[2.15,2.53]
	{3.37}	{3.29}	{3.78}	{3.27}	{5.53}	{5.60}	{6.44}	{5.72}	{8.97}	{9.08}	{8.46}	{9.39}				
	[3.43]	[3.36]	[3.86]	[3.34]	[5.68]	[5.76]	[6.62]	[5.89]	[9.36]	[9.50]	[8.85]	[9.81]				

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX individual stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess risk-adjusted return using the excess market return, SMB, and HML as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as defined in Section 4.2.2. UNCOND denotes the constant beta model specified in the first-pass. Specifications A – G represent the conditional versions of the asset pricing model as in Section (4.3). The conditioning variables for factor loadings are investor sentiment index, default spread, SIZE and B/M. The columns under $Adj.\ R^2$ report the average and the confidence interval of the 5th and the 95th percentiles of the monthly adjusted R squared. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor's Intelligence, respectively. COMP is the composite sentiment index derived from the principal component analysis. The *t*-statistics in curly brackets use standard errors as in Shanken (1992) and the *t*-statistics in square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

Table 4.6: Fama-MacBeth estimates with Fama-French three factors plus Pastor-Stambaugh liquidity as the risk factors (FFP)

Specification	SIZE				B/M				TURNOVER				RET2-3				RET4-6				RET7-12				Adj. R^2(%)			
	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP
UNCOND	-0.039				0.171				-0.154				0.643				0.859				0.972				2.71			
	{-1.57}				{3.92}				{-4.08}				{2.46}				{3.86}				{6.98}				[2.46,297]			
	[-1.63]				[4.05]				[-4.21]				[2.53]				[3.99]				[7.32]				2.33	2.33	2.27	2.30
A	-0.021	-0.006	-0.013	-0.013	0.012	0.019	0.059	0.018	-0.129	-0.136	-0.132	-0.131	0.748	0.768	0.823	0.755	1.082	1.071	1.121	1.066	1.005	1.031	1.006	1.025	[2.14,2.53]	[2.14,2.51]	[2.08,2.47]	[2.12,2.49]
	{-1.05}	{-0.31}	{-0.67}	{-0.67}	{0.35}	{0.58}	{1.77}	{0.54}	{-4.21}	{-4.37}	{-4.39}	{-4.24}	{3.18}	{3.30}	{3.60}	{3.25}	{6.00}	{5.98}	{6.38}	{6.01}	{8.84}	{8.90}	{8.59}	{8.91}				
	[-1.08]	[-0.32]	[-0.69]	[-0.69]	[0.36]	[0.60]	[1.82]	[0.56]	[-4.32]	[-4.49]	[-4.52]	[-4.35]	[3.24]	[3.38]	[3.69]	[3.32]	[6.16]	[6.19]	[6.58]	[6.17]	[9.20]	[9.30]	[9.00]	[9.26]				
B	-0.012				0.026				-0.126				0.725				1.054				0.994				2.34			
	{-0.57}				{0.82}				{-4.15}				{3.07}				{5.76}				{8.83}				[2.14,2.54]			
	[-0.59]				[0.84]				[-4.26]				[3.14]				[5.93]				[9.20]							
C	-0.032	-0.021	-0.027	-0.029	0.105	0.097	0.107	0.109	-0.137	-0.129	-0.138	-0.136	0.434	0.440	0.462	0.368	0.738	0.824	0.856	0.764	0.864	0.860	0.902	0.859	2.61	2.61	2.59	2.57
	{-1.40}	{-0.92}	{-1.19}	{-1.28}	{2.85}	{2.56}	{2.78}	{2.90}	{-3.94}	{-3.76}	{-4.00}	{-3.94}	{1.66}	{1.69}	{1.80}	{1.42}	{3.60}	{4.14}	{4.28}	{3.84}	{6.92}	{6.69}	{6.97}	{6.85}	[2.36,2.85]	[2.37,2.85]	[2.35,2.82]	[2.33,2.81]
	[-1.45]	[-0.95]	[-1.24]	[-1.33]	[2.95]	[2.65]	[2.88]	[3.01]	[-4.09]	[-3.90]	[-4.15]	[-4.09]	[1.71]	[1.75]	[1.85]	[1.46]	[3.72]	[4.31]	[4.44]	[3.98]	[7.29]	[7.06]	[7.32]	[7.22]				
D	-0.024				0.074				-0.136				0.722				1.048				1.042				2.37			
	{-1.08}				{2.11}				{-4.05}				{2.99}				{5.44}				{8.24}				[2.16,2.58]			
	[-1.12]				[2.18]				[-4.17]				[3.06]				[5.62]				[8.64]							
E	-0.036	-0.032	-0.036	-0.033	0.146	0.139	0.158	0.150	-0.153	-0.146	-0.152	-0.154	0.599	0.603	0.710	0.589	0.799	0.855	0.885	0.816	0.904	0.918	0.965	0.911	2.62	2.58	2.61	2.55
	{-1.49}	{-1.32}	{-1.51}	{-1.38}	{3.58}	{3.35}	{3.74}	{3.66}	{-4.15}	{-3.99}	{-4.26}	{-4.23}	{2.34}	{2.36}	{2.80}	{2.32}	{3.80}	{4.23}	{4.20}	{4.03}	{6.77}	{6.74}	{7.09}	{6.78}	[2.37,2.87]	[2.34,2.81]	[2.37,2.85]	[2.32,2.78]
	[-1.55]	[-1.37]	[-1.56]	[-1.43]	[3.72]	[3.48]	[3.87]	[3.80]	[-4.31]	[-4.15]	[-4.41]	[-4.39]	[2.42]	[2.46]	[2.88]	[2.40]	[3.95]	[4.41]	[4.34]	[4.20]	[7.16]	[7.12]	[7.44]	[7.19]				
F	-0.037				0.135				-0.142				0.457				0.798				0.893				2.67			
	{-1.47}				{3.30}				{-3.84}				{1.75}				{3.74}				{6.64}				[2.42,2.92]			
	[-1.52]				[3.42]				[-3.97]				[1.81]				[3.87]				[6.96]							
G	0.055	0.022	0.092	-0.027	-0.213	-0.494	0.172	0.018	-0.167	-0.133	-0.192	-0.362	1.437	0.908	0.760	0.635	1.568	1.118	1.097	0.862	1.340	0.687	1.065	0.494	1.61	1.66	1.64	1.82
	{1.87}	{1.13}	{4.63}	{-1.23}	{-5.13}	{-6.32}	{4.65}	{0.45}	{-3.70}	{-3.97}	{-5.93}	{-8.55}	{4.33}	{2.73}	{3.01}	{1.97}	{5.75}	{4.24}	{5.73}	{3.10}	{7.30}	{4.18}	{8.82}	{2.59}	[1.45,1.78]	[1.50,1.82]	[1.48,1.79]	[1.54,2.10]
	[1.86]	[1.12]	[4.75]	[-1.06]	[-5.00]	[-5.98]	[4.72]	[0.37]	[-3.65]	[-3.88]	[-6.06]	[-8.09]	[4.01]	[2.36]	[2.91]	[1.43]	[5.22]	[3.49]	[5.56]	[1.76]	[6.99]	[3.63]	[8.91]	[1.80]				

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX individual stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess risk-adjusted return using the excess market return, SMB, HML and the Pastor-Stambaugh liquidity factor as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as defined in Section 4.2.2. UNCOND denotes the constant beta model specified in the first-pass. Specifications A – G represent the conditional versions of the asset pricing model as in Section (4.3). The conditioning variables for factor loadings are investor sentiment index, default spread, SIZE and B/M. The columns under $Adj.\ R^2$ report the average and the confidence interval of the 5th and the 95th percentiles of the monthly adjusted R squared. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor's Intelligence, respectively. COMP is the composite sentiment index derived from the principal component analysis. The t-statistics in curly brackets use standard errors as in Shanken (1992) and the t-statistics in square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

Table 4.7: Fama-MacBeth estimates with Fama-French three factors plus WML as the risk factors (FFW)

Specification	SIZE				B/M				TURNOVER				RET2-3				RET4-6				RET7-12				Adj. R^2(%)			
	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP
UNCOND		-0.046				0.182				-0.125				0.680				0.833				0.927				2.73		
		{-1.90}				{4.34}				{-3.30}				{2.73}				{3.99}				{6.93}				[2.49,2.96]		
		[-1.99]				[4.54]				[-3.45]				[2.85]				[4.16]				[7.29]						
A	-0.017	-0.004	-0.012	-0.012	0.061	0.063	0.051	0.073	-0.131	-0.145	-0.125	-0.139	0.676	0.642	0.934	0.666	0.862	0.872	1.074	0.917	0.948	0.963	0.944	0.976	2.26	2.15	2.25	2.14
	{-0.88}	{-0.20}	{-0.59}	{-0.59}	{1.93}	{1.99}	{1.59}	{2.28}	{-4.31}	{-4.54}	{-4.09}	{-4.41}	{2.93}	{2.80}	{4.17}	{2.95}	{5.13}	{5.23}	{6.54}	{5.49}	{8.91}	{9.27}	{8.28}	{9.43}	[2.08,2.44]	[1.99,2.31]	[2.07,2.43]	[1.97,2.30]
	[-0.92]	[-0.21]	[-0.62]	[-0.61]	[2.01]	[2.08]	[1.66]	[2.38]	[-4.49]	[-4.74]	[-4.27]	[-4.60]	[3.05]	[2.91]	[4.35]	[3.07]	[5.39]	[5.48]	[6.85]	[5.75]	[9.45]	[9.82]	[8.76]	[9.97]				
B		-0.004				0.041				-0.132				0.689				0.861				0.943				2.31		
		{-0.17}				{1.30}				{-4.29}				{2.99}				{5.04}				{8.51}				[2.13,2.50]		
		[-0.18]				[1.36]				[-4.47]				[3.12]				[5.27]				[8.98]						
C	-0.031	-0.017	-0.028	-0.025	0.151	0.154	0.133	0.166	-0.119	-0.128	-0.121	-0.133	0.333	0.363	0.456	0.301	0.621	0.706	0.830	0.673	0.795	0.835	0.819	0.840	2.48	2.44	2.57	2.40
	{-1.37}	{-0.75}	{-1.27}	{-1.09}	{4.20}	{4.16}	{3.55}	{4.51}	{-3.41}	{-3.62}	{-3.48}	{-3.74}	{1.35}	{1.46}	{1.85}	{1.22}	{3.30}	{3.75}	{4.37}	{3.59}	{6.89}	{6.85}	{6.53}	{7.12}	[2.27,2.68]	[2.24,2.64]	[2.36,2.79]	[2.20,2.60]
	[-1.44]	[-0.79]	[-1.34]	[-1.14]	[4.39]	[4.36]	[3.72]	[4.73]	[-3.56]	[-3.80]	[-3.65]	[-3.92]	[1.41]	[1.52]	[1.93]	[1.27]	[3.43]	[3.91]	[4.57]	[3.74]	[7.26]	[7.23]	[6.90]	[7.52]				
D		-0.023				0.084				-0.133				0.796				0.947				1.010				2.36		
		{-1.03}				{2.48}				{-3.92}				{3.42}				{5.24}				{8.36}				[2.17,2.55]		
		[-1.08]				[2.60]				[-4.10]				[3.56]				[5.48]				[8.83]						
E	-0.046	-0.034	-0.041	-0.040	0.181	0.183	0.170	0.195	-0.124	-0.134	-0.127	-0.140	0.579	0.485	0.736	0.496	0.764	0.785	0.870	0.785	0.866	0.897	0.911	0.904	2.57	2.46	2.64	2.46
	{-1.97}	{-1.44}	{-1.74}	{-1.68}	{4.54}	{4.51}	{4.19}	{4.79}	{-3.38}	{-3.57}	{-3.48}	{-3.74}	{2.37}	{1.98}	{3.00}	{2.02}	{3.93}	{4.07}	{4.39}	{4.07}	{7.05}	{7.07}	{6.99}	{7.24}	[2.36,2.79]	[2.25,2.66]	[2.42,2.86]	[2.25,2.66]
	[-2.07]	[-1.52]	[-1.82]	[-1.77]	[4.76]	[4.73]	[4.39]	[5.02]	[-3.54]	[-3.74]	[-3.65]	[-3.92]	[2.47]	[2.08]	[3.14]	[2.12]	[4.11]	[4.28]	[4.60]	[4.27]	[7.45]	[7.49]	[7.38]	[7.67]				
F		-0.034				0.164				-0.123				0.458				0.733				0.865				2.64		
		{-1.42}				{4.13}				{-3.31}				{1.85}				{3.64}				{6.68}				[2.42,2.87]		
		[-1.50]				[4.33]				[-3.46]				[1.93]				[3.80]				[7.03]						
G	0.049	0.034	0.112	0.065	0.105	0.241	0.076	-0.064	-0.051	0.040	0.052	-0.012	0.422	0.910	0.168	0.574	0.670	1.125	0.544	0.914	0.794	1.082	0.834	1.076	1.69	1.55	1.51	1.49
	{2.55}	{1.68}	{4.30}	{2.96}	{3.28}	{3.66}	{2.30}	{-1.83}	{-1.69}	{0.76}	{1.01}	{-3.11}	{1.70}	{3.14}	{0.46}	{2.04}	{3.77}	{5.35}	{1.87}	{4.36}	{7.39}	{8.86}	{5.36}	{9.27}	[1.52,1.86]	[1.41,1.69]	[1.36,1.67]	[1.35,1.62]
	[2.70]	[1.72]	[4.36]	[3.07]	[3.44]	[3.64]	[2.23]	[-1.87]	[-1.78]	[0.75]	[1.00]	[-3.18]	[1.74]	[2.89]	[0.38]	[2.00]	[3.91]	[4.95]	[1.61]	[4.28]	[7.90]	[8.91]	[5.09]	[9.47]				

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX individual stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess risk-adjusted return using the excess market return, SMB, HML and WML as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as defined in Section 4.2.2. UNCOND denotes the constant beta model specified in the first-pass. Specifications A – G represent the conditional versions of the asset pricing model as in Section (4.3). The conditioning variables for factor loadings are investor sentiment index, default spread, SIZE and B/M. The columns under $Adj.\ R^2$ report the average and the confidence interval of the 5th and the 95th percentiles of the monthly adjusted R squared. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor's Intelligence, respectively. COMP is the composite sentiment index derived from the principal component analysis. The *t*-statistics in curly brackets use standard errors as in Shanken (1992) and the *t*-statistics in square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

Table 4.8: Fama-MacBeth estimates with Fama-French three factors plus (PS Liquidity + WML) as the risk factors (FFPW)

Specification	SIZE				B/M				TURNOVER				RET2-3				RET4-6				RET7-12				Adj. R^2(%)			
	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP	MS	CCI	II	COMP
UNCOND		-0.045				0.184				-0.129				0.589				0.838				0.938				2.63		
		{-1.80}				{4.25}				{-3.44}				{2.32}				{3.93}				{6.91}				[2.39,2.86]		
		[-1.88]				[4.42]				[-3.57]				[2.40]				[4.09]				[7.28]						
A	-0.015	0.004	-0.003	-0.007	0.046	0.054	0.057	0.058	-0.122	-0.118	-0.126	-0.122	0.663	0.642	0.869	0.740	0.941	0.879	1.059	0.991	0.941	0.910	0.953	0.985	2.08	2.06	2.05	2.08
	{-0.79}	{0.18}	{-0.17}	{-0.36}	{1.49}	{1.71}	{1.79}	{1.83}	{-4.19}	{-3.93}	{-4.33}	{-4.17}	{3.00}	{2.80}	{3.90}	{3.33}	{5.64}	{5.17}	{6.33}	{6.00}	{9.26}	{8.52}	{8.72}	{9.58}	[1.91,2.25]	[1.90,2.22]	[1.88,2.22]	[1.92,2.24]
	[-0.82]	[0.19]	[-0.18]	[-0.38]	[1.55]	[1.79]	[1.87]	[1.91]	[-4.34]	[-4.10]	[-4.51]	[-4.33]	[3.10]	[2.89]	[4.04]	[3.45]	[5.86]	[5.38]	[6.60]	[6.24]	[9.74]	[8.98]	[9.24]	[10.06]				
B		-0.005				0.008				-0.112				0.699				0.918				0.933				2.12		
		{-0.25}				{0.24}				{-3.79}				{3.14}				{5.38}				{8.91}				[1.95,2.30]		
		[-0.26]				[0.25]				[-3.93]				[3.25]				[5.58]				[9.33]						
C	-0.032	-0.022	-0.021	-0.031	0.150	0.130	0.122	0.150	-0.118	-0.114	-0.119	-0.119	0.337	0.395	0.416	0.315	0.613	0.712	0.806	0.638	0.795	0.803	0.872	0.802	2.43	2.43	2.45	2.39
	{-1.42}	{-0.98}	{-0.97}	{-1.38}	{4.16}	{3.59}	{3.25}	{4.14}	{-3.43}	{-3.37}	{-3.54}	{-3.48}	{1.36}	{1.59}	{1.69}	{1.27}	{3.20}	{3.79}	{4.26}	{3.41}	{6.97}	{6.64}	{7.14}	{6.89}	[2.22,2.64]	[2.23,2.64]	[2.23,2.66]	[2.19,2.59]
	[-1.48]	[-1.02]	[1.01]	[-1.44]	[4.33]	[3.74]	[3.38]	[4.31]	[-3.58]	[-3.52]	[-3.70]	[-3.63]	[1.41]	[1.64]	[1.75]	[1.31]	[3.33]	[3.93]	[4.43]	[3.54]	[7.35]	[6.99]	[7.54]	[7.29]				
D		-0.025				0.073				-0.116				0.702				0.989				1.017				2.22		
		{-1.12}				{2.16}				{-3.52}				{3.04}				{5.45}				{8.57}				[2.05,2.43]		
		[1.17]				[2.24]				[-3.66]				[3.14]				[5.67]				[9.04]						
E	-0.042	-0.034	-0.036	-0.037	0.177	0.167	0.171	0.181	-0.126	-0.121	-0.131	-0.128	0.490	0.478	0.676	0.480	0.743	0.790	0.868	0.768	0.859	0.874	0.926	0.874	2.48	2.44	2.52	2.42
	{-1.76}	{-1.43}	{-1.54}	{-1.56}	{4.37}	{4.12}	{4.08}	{4.47}	{-3.48}	{-3.37}	{-3.68}	{-3.56}	{1.99}	{1.94}	{2.73}	{1.95}	{3.74}	{4.06}	{4.35}	{3.97}	{6.94}	{6.79}	{7.07}	{6.94}	[2.26,2.71]	[2.24,2.65]	[2.30,2.74]	[2.21,2.62]
	[-1.84]	[-1.50]	[-1.61]	[-1.63]	[4.56]	[4.31]	[4.26]	[4.67]	[-3.63]	[-3.53]	[-3.84]	[-3.72]	[2.06]	[2.03]	[2.83]	[2.03]	[3.90]	[4.27]	[4.55]	[4.17]	[7.35]	[7.21]	[7.46]	[7.39]				
F		-0.034				0.163				-0.123				0.415				0.745				0.884				2.56		
		{-1.36}				{4.02}				{-3.37}				{1.65}				{3.63}				{6.87}				[2.33,2.79]		
		[-1.42]				[4.21]				[-3.51]				[1.72]				[3.78]				[7.23]						
G	-0.061	0.030	0.072	-0.008	0.082	-0.096	0.140	0.176	0.040	-0.138	-0.168	-0.464	0.689	0.569	0.862	0.779	0.978	0.772	1.100	0.878	0.991	0.605	0.977	0.474	1.61	1.55	1.56	1.54
	{-2.97}	{1.70}	{3.83}	{-0.29}	{2.02}	{-2.74}	{3.96}	{4.56}	{1.21}	{-4.65}	{-4.95}	{-9.52}	{2.68}	{2.16}	{3.71}	{2.30}	{4.56}	{3.73}	{6.10}	{3.06}	{7.09}	{4.74}	{8.24}	{2.50}	[1.46,1.77]	[1.41,1.68]	[1.41,1.70]	[1.26,1.81]
	[-2.98]	[1.72]	[3.92]	[-0.25]	[2.00]	[-2.68]	[3.98]	[3.59]	[1.21]	[-4.69]	[-5.02]	[-8.90]	[2.52]	[1.77]	[3.41]	[1.48]	[4.20]	[2.86]	[5.62]	[1.44]	[6.95]	[4.28]	[8.12]	[1.52]				

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX individual stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess risk-adjusted return using the excess market return, SMB, HML, the Pastor-Stambaugh liquidity factor and WML as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as defined in Section 4.2.2. UNCOND denotes the constant beta model specified in the first-pass. Specifications A – G represent the conditional versions of the asset pricing model as in Section (4.3). The conditioning variables for factor loadings are investor sentiment index, default spread, SIZE and B/M. The columns under $Adj.\ R^2$ report the average and the confidence interval of the 5th and the 95th percentiles of the monthly adjusted R squared. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor's Intelligence, respectively. COMP is the composite sentiment index derived from the principal component analysis. The t-statistics in curly brackets use standard errors as in Shanken (1992) and the t-statistics in square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

CHAPTER 5 INVESTOR SENTIMENT AS A RISK FACTOR

5.1 Introduction

The previous chapter investigates the role of investor sentiment as conditional information in explaining the cross-section of individual stock returns. I assess the performance of the asset pricing models that incorporate investor sentiment as one of the information variables and find such models help to capture the impacts of the size, value, and momentum effects.

This chapter studies the role of investor sentiment as a risk factor. In the first part of the study, I test whether the investor sentiment factor exerts explanatory power in the cross-section of stock returns. For this purpose, I measure the sensitivity of individual stocks to the shift in the market-wide sentiment as measured by widely recognized sentiment index, and then construct a sentiment factor, SMN (sensitive minus non-sensitive). This is because although one can observe sentiment directly from a reported sentiment index or other proxies, such observations do not provide a measure of the sensitiveness at the level of individual stocks. The study presents evidence that this sentiment factor has significant explanatory power in the cross-section of individual stock returns. In the second part of the study, I investigate whether the sentiment-augmented models help explain asset pricing anomalies. The evidence shows that the asset pricing models that include this sentiment factor often capture the size, value, and momentum effects.

The analysis starts with the estimation of the sensitivity of the excess returns on individual stocks to the changes in the market-based investor sentiment index. Prior studies that explore the relation between investor sentiment and stock returns use sentiment measures based on either survey indices or market data. This chapter considers both the raw sentiment index and the index that is orthogonalized to macroeconomic variables by Baker and Wurlgler (2006). The study also uses the survey-based sentiment index – the Investors Intelligence sentiment index which reflects the perceptions of investment newsletter writers about the stock market. Brown and Cliff (2005) use Investors Intelligence sentiment index and provide evidence that the market is overvalued when this index level is high.

I estimate the sentiment beta for each stock on a monthly rolling basis, and then break the sample stocks, in each month, into five sentiment beta groups based on the absolute value of the sentiment beta. The higher the absolute value of the sentiment beta, the higher the responsiveness of stock returns to the change in sentiment. The absolute value of the sentiment beta rather than its raw value us is used in order to capture the "riskiness" of sentiment a stock exhibits, i.e., the degree to which stock returns move in response to the change in investor sentiment. This classification can distinguish the stocks by the responsiveness of the stock returns to the shifts in investor sentiment.

I obtain the monthly returns on the SMN factor by subtracting the returns on the equally weighted portfolio of the lowest sentiment beta group (non-sensitive portfolio) from the returns on the equally weighted portfolio of the highest sentiment beta group (sensitive portfolio). The average return on this SMN factor is about 0.8% per month, regardless of the different sentiment indices I use to estimate the sentiment beta.

My approach of constructing the sentiment factor is in the spirit of the SMB and HML factors constructed by Fama and French (1993) and the liquidity factor of Pastor and Stambaugh (2003). In particular, SMB, HML, and the liquidity factors capture the average return differences between the stocks with high and low values of the interested firm characteristics or estimates: market capitalization, book-to-market ratio, and the sensitivity of stock returns to liquidity (the liquidity beta), respectively. Likewise, the sentiment factor SMN in our paper captures the average return difference between stocks with high and low sensitivities (the sentiment beta) to investor sentiment.

I first test whether the sentiment factor commands a risk premium using the procedure of Fama-MacBeth (1973). The results show that the risk premium of the sentiment factor is statistically significant at the magnitude of 6% annually over the sample period. This finding indicates that stocks with high sensitivities to shifts in investor sentiment earn high expected returns, suggesting that investors demand positive compensation for bearing such sensitivity.

I also present evidence that high sentiment beta stocks tend to have small market capitalisation, high book-to-market ratio, and higher turnover, collaborating with the finding of Baker and Wurgler (2006) that some stocks are more sensitive to shifts in investor sentiment than others because they are difficult-to-value and hard-to-arbitrage. Moreover, I find that high sentiment beta stocks outperform low sentiment beta stocks over various lengths of past horizons. These findings complement my results of the Fama-MacBeth test of the positive risk premium of investor sentiment, and suggest that the sentiment factor may exhibit explanatory power for the asset-pricing anomalies.

Next, I form a sentiment-augmented pricing model to investigate the explanatory power of the sentiment factor on the size, value, turnover and momentum effects. I adopt the two-pass regression framework of Avramov and Chordia (2006) in which I obtain the risk-adjusted return in the first-pass regression using conventional risk factors and the sentiment factor, and then in the second-pass, I run the regression of the risk-adjusted return on the variables of asset-pricing anomalies. If the risk factors specified in the first-pass regression capture the expected stock return, the anomalies variables in the second-pass regression should be statistically insignificant.

This study shows that the impact of size reduces significantly once the sentiment factor is present in the first-pass regression, even when the asset pricing models are of unconditional forms. In other words, the explanatory power of the sentiment risk factor for the size effect does not rely on time-varying factor loadings. The model specified in the first-pass regression with a single sentiment risk factor alone outperforms all the unconditional versions of the traditional asset pricing models I examined in terms of its explanatory power for the size effect. In addition, all the sentiment-augmented unconditional models capture the impact of size on the cross-section of risk-adjusted returns. Moreover, when allowing the factor loadings to vary with firm characteristics and the default spread, the model with a sentiment factor alone generally captures the size effect. My results from modeling the SMN risk factor represent a major breakthrough for the findings of Avramov and Chordia (2006) as they document that almost all models they examined fail to capture the size effect in their sample that includes NASDAQ stocks as in our sample.

The results indicate that the high returns on small stocks are attributable to their high sensitivities to the sentiment risk, suggesting that the size premium is directly associated with the sentiment risk factor. Numerous studies provide empirical evidence that the size premium is closely related to investor sentiment. Neal and Wheatley (1998) report that sentiment measures of closed-end fund discount and net mutual fund redemptions predict the size premium. Lee, Shleifer, and Thaler (1991) and Nagel (2005) provide evidence that individual investors who are more prone to sentiment than institutions tend to have disproportionally large holdings on small size stocks. Baker and Wurgler (2006) demonstrate that small stocks are difficult to arbitrage and hard to value, and hence are more responsive to investor sentiment than large size stocks (see also, Lee, Shleifer and Thaler (1991) and Lemmon and Portniaguina (2006)).

Motivated by the theory and empirical evidence that dynamic versions of pricing models provide better descriptions of the stock price behaviour than static models (e.g., Hansen and Richard (1987), Gomes, Kogan, and Zhang (2003), and Avramov and Chordia (2006)), as in the previous chapter, this chapter considers the time-varying asset pricing models in which the loadings of the risk factors time vary over time and across the cross-section of stocks with firm-level characteristics of size and book-to-market ratio as well as with the default spread. Remarkably, the results show that the SMN-augmented FF-based models where the factor loadings are scaled by (SIZE+B/M)def successfully capture both the size and value effects regardless of the measures of investor sentiment used to construct the SMN factor[24].

Furthermore, I find that the impact of short-term prior returns on the cross-section of stock returns can be greatly reduced when the factor loadings vary with the default spread in the models that contain the SMN and Fama-French factors.

Overall, the evidence suggests that the risk associated with investor sentiment significantly affects expected stock returns and helps explain the anomalies I examined.

The rest of this chapter is organised as follows. Section 5.2 describes the specifications of the conditional versions of the sentiment-augmented asset pricing models. Section 5.3 empirically tests whether investor sentiment is priced. Section 5.4 presents the results of the pricing ability of the sentiment factor for the anomalies. Section 5.5 concludes.

5.2 Conditional Sentiment-Augmented Asset Pricing Models

The analysis of the explanatory power of investor sentiment for stock returns starts with a single-factor model that contains only the sentiment factor, SMN as described in Chapter 3. The sentiment factor then is added to the models with the traditional risk factors in the first-pass regression to test whether the impacts of the asset-pricing anomalies on the risk-adjusted stock returns in the second-pass regression are eliminated. The pricing models assessed include: (i) the sentiment model – the SMN model (with SMN as the only factor), (ii) the SCAPM model (the sentiment-augmented CAPM), (iii) the SFF model (the sentiment-augmented Fama-French (1993) three-factor model), (iv) the SFFP model (the sentiment-augmented Fama-French model plus the Pastor-Stambaugh (2003) liquidity factor, (v) the SFFW model (the sentiment-augmented Fama-French model plus the momentum factor, and the (vi) the SFFPW model (the sentiment-augmented Fama-French model plus both the liquidity factor and the momentum factor).

[24] This explanatory power is present except for those that include the momentum factor.

I first examine the unconditional version of each of the sentiment-augmented models. I then allow the factor loadings in the models to vary with firm-specific market capitalization and the book-to-market ratio as well as the default spread. To illustrate the specification of the time-varying factor loadings, I use the most parsimonious asset pricing – the SMN model – as an example. The specification of the conditional sentiment beta of security j, β_j, is

$$\begin{aligned}\beta_{jt-1} = \beta_{j1} + \beta_{j2} z_{t-1} + (\beta_{j3} + \beta_{j4} z_{t-1}) SIZE_{jt-1} \\ +(\beta_{j5} + \beta_{j6} z_{t-1}) B/M_{jt-1}\end{aligned} \tag{5.1}$$

where all the variables are defined exactly the same as described before. The specifications of the conditional betas depend on the conditioning variables considered. For example, an unconditional model emerges when all βs are restricted to be zero except for β_1. One can arrive at three conditional specifications by considering the beta to be a function of different conditioning variables:

Specification A: function of (SIZE + B/M) (i.e., $\beta_{j2} = \beta_{j4} = \beta_{j6} = 0$)

Specification B: function of *def* (i.e., $\beta_{j3} = \beta_{j4} = \beta_{j5} = \beta_{j6} = 0$)

Specification C: function of (SIZE + B/M)*def* (i.e., all $\beta s \neq 0$)

The most comprehensive version, specification C, forms a conditional SMN model in the first-pass time-series regression as

$$\begin{aligned}r_{jt} = \alpha_j + \beta_{j1} SMN_t + \beta_{j2} z_{t-1} SMN_t + \beta_{j3} SIZE_{jt-1} SMN_t \\ +\beta_{j4} z_{t-1} SIZE_{jt-1} SMN_t + \beta_{j5} B/M_{jt-1} SMN_t + \beta_{j6} z_{t-1} B/M_{jt-1} SMN_t + u_{jt}\end{aligned} \tag{5.2}$$

Again, I run the time-series regression of Equation (5.2) over the entire sample period, and obtain the estimated risk-adjusted return on stock j at time t by summing the intercept and the residual. I then run the cross-sectional regression of the estimated risk-adjusted returns on the variables of asset-pricing anomalies.

The same sample selection criteria as described in Chapter 3 must be met. In addition, a firm's monthly returns in the current month, *t*, and over the past 60 months must be available[25]. After the screening process, the total amount of different stocks is 8,526 over the period of 1968 through 2005.

Table 5.1 reports the descriptive statistics of firm characteristics and the Fama-MacBeth coefficients from regressing the excess returns on firm characteristics over the sample period of this chapter. The mean excess return of all stocks in our sample is 0.88% per month. The average firm market capitalization is $1.22 billion. The average monthly turnover is 6.27%. Table 5.1 also shows that the firm-level characteristics are associated with cross-sectional differences in average returns. Smaller firms and firms with lower turnover have higher excess returns. Also, firms with higher book-to-market ratio and firms with better past performance tend to yield higher excess returns.

5.3 Is Investor Sentiment Priced?

5.3.1 Investor Sentiment Beta and Firm Characteristics

The construction of the investor sentiment factor, SMN, is based on the sentiment beta in Equation (3.6). For each month during the sample period, each stock is grouped into 5 quintiles based on the absolute value of its sentiment beta. An examination of the firm-specific characteristics of each sentiment-beta portfolio could provide some insight into whether SMN has potential explanatory power in explaining the financial market anomalies under consideration.

Figures 1, 2 and 3, with different investor sentiment proxies, graphically demonstrate the firm-specific characteristics across the sentiment-beta groups. Several interesting patterns are observed from the bar charts.

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[25] As described in Section 3.3.3, apart from the requirement of 36 monthly observations availability for the first-pass regression, another 24 observations are required to calculate the sentiment beta for each firm.

First, it appears that the monthly average stock returns are positively correlated with the sentiment beta. This suggests that investors require higher risk premium to take additional risk caused by the unpredictable shifts in investor sentiment. The monthly return difference between the highest sentiment-beta group and the lowest sentiment-beta group is around 0.85% and statistically significant at the 1% level.

Second, the sentiment beta increases monotonically and sharply as firm size decreases. This suggests that small firms tend to be more responsive to the shifts in investor sentiment, consistent with the findings of Baker and Wurgler (2006) who argue that this is because small firms are difficult-to-value and hard-to-arbitrage.

Third, high sentiment beta stocks tend to have larger B/M, higher turnover, and superior past returns of various horizons. These patterns suggest that the returns of value stocks, liquid stocks, and past winners are more sensitive to the beliefs of investors.

Overall, this evidence indicates that the investor sentiment as a risk factor is important in determining the returns of stocks with different firm-specific characteristics.

5.3.2 Do Investors Require Investor Sentiment Risk Premium?

Now I statistically test whether the investor sentiment factor, SMN, commands a premium using the cross-sectional regression approach of Fama and MacBeth (1973) [26]. In the first stage, I estimate the SMN betas for each firm by running time-series regressions on a rolling basis of contemporaneous excess returns on SMN using estimation windows of 13, 25, and 37 months, respectively. In the second stage, I run a cross-sectional regression each month of excess stock returns on the SMN beta estimates β_{jt}^{SMN} as

$$R_{jt} - R_{Ft} = \lambda_0 + \lambda_1\beta_{jt}^{SMN} + \lambda_2\beta_{jt} + \lambda_3\beta_{jt}^{SMB} + \lambda_4\beta_{jt}^{HML} + \mu_{jt} \tag{5.3}$$

[26] This method has been widely used in the literature. For example, Jagannathan and Wang (1996) test the conditional CAPM and Petkova (2006) test the intertemporal CAPM. Pastor and Stambaugh (2003) also use this approach to test liquidity risk.

The purpose is to test whether the coefficient estimate of λ_1 on the SMN factor beta is statistically significant. The results show that that λ_1 is significantly different from zero, indicating that the SMN factor commands a reward. A positive sign of this coefficient estimate suggests that the sentiment factor has a positive risk premium, in other words, investors require higher expected returns as a compensation for bearing the sentiment risk.

Tables 5.2–5.4 report the estimates of the Fama-MacBeth tests using different sentiment proxies. The results show that the estimated coefficient λ_1 is positive and statistically significant at the 5% level regardless of the length of the window for estimating the SMN beta and the raw sentiment index used to construct the SMN. The λ_1 estimate is about 0.5% with significant *t*-statistics[27]. This finding supports the prediction of the noise trader model of De Long, Shleifer, Summers, and Waldmann (1990) and the finding of Brown and Cliff (2005) that stock prices could be influenced by investor sentiment. My finding also provides supportive evidence the work of Baker and Wurgler (2006) that investor sentiment not only exhibits time-series but also cross-sectional effects on stock returns.

5.4 Sentiment-Augmented Models and Anomalies

The previous section provides empirical evidence that the constructed investor sentiment, SMN, is a priced factor. It would be then appropriate to consider its explanatory power for the anomalies when standing alone or working with other traditional risk factors. I assess the extent to which the unconditional and conditional versions of the pricing models, without or with the SMN factor, explain the anomalies.

The models specified in the time-series regression are deemed to have better pricing ability than others if the significance of the coefficient estimates in the cross-sectional regressions of risk-adjusted returns on size, book-to-market, turnover, and prior returns drops considerably.

[27] Interestingly, SMB and HML completely lose their pricing ability when SMN is present.

The financial market anomalies under consideration are deemed to be captured if the corresponding coefficient estimates become statistically insignificant.

5.4.1 Unconditional Sentiment-Augmented Asset Pricing Models

I first examine the pricing abilities of the unconditional SMN model and the unconditional version of the traditional asset pricing models. I then add the SMN factor to each of the unconditional pricing models to test whether the sentiment-augmented models improve the models' performance in explaining the anomalies. Table 5.5 reports the Fama-MacBeth coefficient estimates from running cross-sectional regressions of monthly risk-adjusted returns of individual stocks on the anomaly variables. The first column under each model presents the results for the traditional sentiment-free model and the second column reports the results for the sentiment-augmented model.

Panel A presents the results for the tests where the SMN factor is constructed based on ΔBW. I start by testing to what extent the SMN factor *alone* explains the pricing anomalies and report the results in the first column of Table 5.5. Strikingly, using the SMN as the single factor the *t*-statistic for SIZE is as low as 1.41. In contrast, all standard asset pricing models without the SMN factor show statistically significant coefficients on all the anomaly variables, indicating that they fail to capture these anomalies. More importantly, adding SMN to the standard asset pricing models makes a remarkable difference in terms of capturing the size effect. I find that the significance of the coefficient estimate for SIZE is greatly reduced and is no longer significant when SMN is present in a model. The efficacy of the sentiment-augmented model in explaining the size effect is more pronounced in the SFF and SFFP models. For example, the *t*-statistic for SIZE under the unconditional CAPM is -1.88 but it notably drops to -1.33 in absolute terms under the sentiment-augmented CAPM (i.e., SCAPM). The *t*-statistic for SIZE under the standard FF (FFP) is -2.00 (-1.93). When SMN is added to the standard FF (FFP), the *t*-statistic for SIZE drops considerably to 0.94 (0.99) in absolute terms, indicating that the impact of firm size on the risk-adjusted return has been removed with the SFF and SFFP models.

Panels B and C report the results when SMN is constructed based on ΔBWort and ΔII, respectively. Again, the results show that the SMN factor *alone* and the SMN-augmented models successfully explain the size effect. The impact of SIZE on the cross-section of individual stock returns becomes statistically insignificant for all asset pricing models once SMN is added to the models. For example, the *t*-statistics for SIZE under the sentiment-augmented CAPM are -1.66 for ΔBWort and 1.40 for ΔII, respectively. Overall, the results show that the size effect is largely captured by the sentiment factor, suggesting that the size effect is closely related to investor sentiment. The ability of the sentiment-augmented asset pricing models in explaining the size effect is consistent and robust with respect to these measures of investor sentiment.

The evidence that SMN helps to capture the impact of size on individual stock returns reported in Table 5.5 is robust regardless of the raw sentiment index used to construct the investor sentiment factor. As noted earlier, different investor sentiment proxies may capture different aspects of investor beliefs about the stock market. The addition of the investor sentiment factor to the traditional risk factors in the constant beta framework shows significant improvement in explaining the size effect.

In each of the FF-based models, after adding SMN to the traditional risk factors, I find that the reduction in the absolute value of the *t*-statistic for SIZE in Panel C is greater than that in Panels A and B, suggesting that ΔII brings stronger improvement in capturing SIZE than the sentiment indices developed by Baker and Wurgler (2006) when working with the Fama-French three factors.

Overall, the finding of this section shows that the constructed investor sentiment factor exhibits pricing ability to capture the size effect on stock returns and this ability does not require the factor loadings to be time-varying. Despite SMN exhibits explanatory power for the size effect, unfortunately, the unconditional models examined here show no ability to capture other anomalies like the size and momentum effects. In the following sections, I continue to test whether time-varying models with SMN can help to explain the other anomalies in addition to the size effect.

5.4.2 Conditional Single Sentiment Risk Factor Model

In this section, I assess the performance of the most parsimonious version of the dynamic asset pricing model where only one factor – SMN – is present in the first-pass regression. The variables used to scale beta are the firm-specific size and book-to-market ratio and default spread. Table 5.6 reports the results of the coefficient estimates for the anomalies variables.

The results here are highly consistent across different investor sentiment measures when the factor loading is conditional on the default spread: the firm size no longer has impact on the cross-section of the stock returns. In particular, using the SMN derived from ΔBW, Table 5.6 shows that the single-factor SMN model conditional on the default spread successfully removes the impact of size with a *t*-statistic on SIZE of 0.98. The same results that statically insignificant coefficient on SIZE are also present for ΔBWort and ΔII. The *t*-statistic on SIZE in the conditional SMN model (conditional on the default spread) is always smaller than the corresponding unconditional SMN model when different sentiment measures are used [28], suggesting that dynamic version of the SMN model exhibit superior performance in reducing the size effect in this case.

Depending on the conditional variables used in the dynamic model, the ability to capture the size effect varies across the investor sentiment measures. All of the dynamic specifications of the single-factor SMN model based on ΔBW can always capture the size effect. The *t*-statistics

[28] For example, the *t*-statistic on SIZE is 0.98(1.35, and 130) in the dynamic SMN model while it is 1.41 (1.71, and 1.68) in the static model for the case of SMN based on ΔBW (ΔBWort, ΔII).

for SIZE are 1.85, 0.98, and 1.31 for Specifications A, B, and C, respectively, which are all dramatically smaller than the critical value.

In the ΔBWort case, SIZE becomes insignificant whenever the default spread appears in the information set. The *t*-statistics in the second and third columns under ΔBWort in Table 5.6 are 1.35 and 1.87, respectively, suggesting that the time-varying SMN model can capture the size effect in Specifications B and C which both in common contain the default spread in the information sets.

On the contrary, the SMN based on ΔII can successfully explain the size effect in a dynamic single-factor SMN framework only when this model is conditional on the default spread. This indicates that for the ΔII-based SMN the dynamic version of the single-factor SMN model is not necessarily superior to its static counterpart. The results of the different pricing ability of the conditional versions of the sentiment-augmented model for different investor sentiment measures highlight the importance of selecting appropriate conditioning variables and investor sentiment measures in empirical analysis.

Table 5.6 shows that using different scaling variables in the first-pass regression leads to different levels of *t*-statistics for SIZE, and hence different degrees of improvement in the ability of capturing the size effect. Specifically, the results indicate that the *t*-statistic for SIZE when SMN is scaled by the default spread is always the lowest compared with those when SMN is scaled by the firm-specific size and book-to-market ratio or all three conditioning variables. For example, under the ΔBW scenario, the *t*-statistic for SIZE when SMN is scaled by the default spread is as low as 0.98, while the *t*-statistics are higher when SMN is scaled by other conditioning variables. Under the ΔII scenario, only the conditional model that is scaled by the default spread can successfully capture for SIZE.

Another interesting finding is that the $\overline{R}^2$ under the conditional SMN model is always lower than the one under the unconditional SMN model for the ΔBW and ΔII scenarios, showing that the impact of the anomalies variables on risk-adjusted returns are alleviated under the conditional SMN-alone model for these two investor sentiment measures. For example, in the first column of panel A in Table 5.5, the $\overline{R}^2$ under the unconditional model is 3.25%, while in Table 5.6, the corresponding $\overline{R}^2$ under the conditional SMN model can be further reduced to as low as 3.21%. In addition, the results indicate that a model with more conditioning variables does not necessarily exhibit superior explanatory power for the anomalies and does not guarantee better overall pricing performance. Overall, the SIZE variable, in general, ceases to exert its cross-sectional impact on risk-adjusted returns when the model in the first-pass regression incorporates the SMN factor alone.

5.4.3 Conditional Sentiment-Augmented Capital Asset Pricing Model (Conditional SCAPM)

I now consider the pricing ability of a two-factor model that consists of SMN and excess market return. Table 5.7 reports that, similar to the results in Table 5.5 for the unconditional SMN-augmented CAPM, the conditional versions exhibit the ability to explain the size effect. Allowing betas to vary over time, however, does not help explain other asset pricing anomalies such as the value or momentum effects.

Table 5.7 shows that the SMN derived from ΔBW exhibits superior explanatory power than the one obtained from ΔBWor and ΔII, respectively. In particular, the ΔBW-based sentiment factor can always capture the size effect regardless of the conditioning information considered while the SMN factors derived from the other two raw sentiment indices can capture the size effect only when the factor loadings are scaled by the default spread. The superior pricing ability of ΔBW for the size effect also reflects in the value of the *t*-statistic. For example, when the factor loadings are scaled by the default spread, the *t*-statistic for SIZE under ΔBW is as low as 0.99, as opposed to 2.48 under ΔBWort and 1.04 under ΔII, respectively, suggesting that ΔBW has a greater explanatory power than the other two investor sentiment measures in explaining the impact of firm size on the risk-adjusted returns.

The improvement in reduction of the size effect on stock returns by allowing the factor loadings to be time-varying depends on the condition variables used in the pricing model. When the factor loadings are scaled by the default spread, the *t*-statistics for SIZE in the conditional SCAPM are all significantly lower than those in the unconditional SCAPM regardless of the investor sentiment measures. For example, the *t*-statistic for SIZE in the unconditional SCAPM in Table 5.5 is 1.33 and is dramatically reduced to as low as 0.99 in Table 5.7 when the factor loadings are scaled by the default spread. Similar patterns are also observed when using the other two investor sentiment measures. However, the conditional versions of the SCAPM that under ΔBWort and ΔII do not always capture the size effect as the unconditional SCAPM. The conditional SCAPM loses its ground in explaining the size effect when the firm-specific characteristics size and book-to-market ratio are present in the information set.

Comparing the results in Table 5.6 (the conditional SMN-alone model) and Table 5.7 (conditional SCAPM) shows that the pricing ability of the SMN factor for SIZE reduces after controlling for the excess market return. In particular, when SMN is formed based on the ΔBW and ΔBWort, the *t*-statistics for SIZE in the SMN-alone model are always lower than those in the SCAPM model where the excess market return is present in addition to SMN in the model. Furthermore, when betas are scaled by (SIZE+B/M)def, the single-factor SMN model shows ability the capture the size effect with a *t*-statistic of 1.87 for SIZE while the two-factor model (SCAPM) fails to capture the size effect with a *t*-statistic of 2.39 for SIZE. When SMN is based on ΔBW or ΔBWort, the *t*-statistics for SIZE are always lower in all conditional versions of the SMN-alone model than those in the conditional SCAPM models, suggesting that the ability of SMN to capture the size effect does not necessarily improve when the excess market return is used as a controlled variable in the conditional model. This result indicates that the size effect appears more closely associated with the investor sentiment factor than the market factor. Adding the excess market return to the SMN-alone model adversely affects the ability of the model in explaining the size effect.

5.4.4 Conditional Sentiment-Augmented Fama-French Model (Conditional SFF Model)

The models, both unconditional and conditional version, I have examined so far show that the presence of SMN in the asset pricing model helps to explain the size effect. However, the models assessed in the previous sections show no pricing ability to capture the financial market anomalies other than the size effect. In this section, I examine whether the conditional versions of the Fama-French three-factor model augmented with the investor sentiment factor (conditional SFF model) can capture the other anomalies.

Table 5.8 presents the estimates of coefficients on the anomaly variables when in the first–pass regression the risk-adjusted return is estimated based on the conditional SMN-augmented Fama-French model. Similar to the models examined in the previous sections, in all cases the size variable does not exert any significant impact on the cross-section of risk-adjusted returns.

Strikingly, apart from capturing the size effect as in previous models, the conditional SFF models can successfully capture the value and momentum effects. In terms of capturing the value effect the third row under each SMN factor in Table 5.8 shows that when the factors are scaled by (SIZE+B/M)def, the coefficient on book-to-market ratio is no longer significant in every case. The *t*-statistic on B/M can be reduced as low as 1.21 as reported in the third column under ΔBW. When using the Baker and Wurgler's investor sentiment indices to construct the corresponding investor sentiment factors and betas are scaled by the default spread, the short-term momentum (RET2-3) loses its power in explaining the cross-section of stock returns.

This finding fills the gap left by Avramov and Chorida (2006) whose conditional models can successfully capture the size and value effects but fail to completely eliminate the momentum effect. The authors state "*However, it does suggest that the payoffs to a momentum strategy vary with the business cycle……We argue that it may be premature to discard rational asset pricing model. It is possible that there exists a yet undiscovered risk factor related to the business cycle that may capture the impact of momentum on the cross-section of individual stock returns*" (*p*.1034) . The literature provides empirical evidence that investor sentiment is closely related to the business cycle. My finding that the conditional versions of the sentiment-augmented FF model exhibit ability to capture the momentum effect shows that the risk factor constructed based on investor sentiment could be the *undiscovered risk factor related to the business cycle* suspected by Avramov and Chordia (2006). It is worth noting that the ability of capturing the momentum effect in the conditional SFF models does not require returns to be risk-adjusted by liquidity and momentum factors.

Finally, in addition to successfully capturing the size, value, and momentum effects, the superior pricing ability of the conditional versions of the SFF models also manifests in the corresponding lower values of $\overline{R}^2$, compared to those in the models examined earlier.

5.4.5 Conditional Sentiment-Augmented Fama-French-Liquidity Factor Model (Conditional SFFP Model)

Despite the conditional SFF models show ability to capture the size, value, and momentum effects, all of the examined sentiment-augmented models so far, both unconditional and conditional, are unable to capture the liquidity effect on the risk-adjusted stock returns. In this section, I examine whether adding the Pastor-Stambaugh (2003) liquidity factor to the conditional SMN-augmented FF model helps eliminate the liquidity effect[29].

Table 5.9 presents the results. I find that adding the liquidity factor to the sentiment-augmented FF model does not help capture the impact of turnover on the cross-section of

[29] Pastor and Stambaugh (2003) find that the stocks with high sensitivities to liquidity, on average, earn significantly higher returns than those with low sensitivities to liquidity. I thank Lubos Pastor for providing data of this factor.

individual stock returns. Overall, the results presented here are very similar to those in Table 5.8. The only improvement noted is that the values of the *t*-statistics for B/M (the value effect) in the conditional SFFP models are all smaller than those in the conditional SFF models. For example, under the third column of ΔBW the *t*-statistic for B/M is significantly reduced to a low level of 0.49 in Table 5.9 from 1.21 in Table 5.8.

Overall, once the conditional forms of the SMN-augmented FF model has been considered, the Pastor-Stambaugh liquidity factor does not seem to provide incremental explanatory power to the cross-section of stock returns.

5.4.6 Conditional Sentiment-Augmented Fama-French-Momentum Factor Model (Conditional SFFW Model)

I now ask whether adding a momentum factor to the SMN-augmented FF models helps capture the examined anomalies. Following Avramov and Chordia (2006), I use the momentum factor obtained from Ken French's website that reflects the momentum strategy of buying winners and selling losers as depicted by Jegadeesh and Titman (1993).

After adding the momentum factor to the conditional SFF models, Table 5.10 shows not only the Baker and Wurlger's sentiment measures show ability to capture the momentum effect but also the Investors Intelligence investor sentiment can considerably reduce the impact of the short-term prior returns of a stock on its returns when betas are scaled by the default spread. However, the conditional SFFW models now have limited ability to capture the size effect and have no power to capture the value effect at all. For example, when betas are scaled by (SIZE+B/M)def (i.e., Specification C) none of the investor sentiment factors constructed can capture the size effect. Also, the coefficient estimates on B/M are always statistically significant regardless of the investor sentiment measures and the time-varying specifications for the SFFW models.

5.4.7 Conditional Sentiment-Augmented Fama-French-Liquidity-Momentum Model (Conditional SFFPW Model)

The results of SFFP and SFFW models indicate that adding either a liquidity factor or a momentum factor seem not necessarily enhance the pricing ability of the conditional versions of the sentiment-augmented Fama-French models. In this section, I I ask whether adding both the liquidity and momentum factors in the sentiment-augmented Fama-French model would result in any improvement in the explanatory power for the asset-pricing anomalies.

Table 5.11 presents the results. The results of the conditional SFFPW models reported in Table 5.11 do not indicate any superior performance in capturing the financial market anomalies, compared to results of the more parsimonious conditional SFF models. The only anomaly that all investor sentiment measures can capture in the conditional SFFPW models is the momentum factor. Only under some conditional beta specifications can the SFFPW models capture the size effect using Baker and Wurgler's sentiment indices. SMN based on ΔBW can capture both the size and value effects only when betas are time-varying with (SIZE+B/M)def. In the conditional SFFPW models ΔBW and ΔII all lose their ability to capture the value effect which can always be successfully eliminated in the conditional SFF models when betas are scaled by (SIZE+B/M)def.

Overall, these findings clearly indicate that the sentiment-augmented models that contain the most risk factors do not necessarily enhance the pricing ability for anomalies of the conditional versions of the asset pricing models. Adding a liquidity factor or a momentum factor to the sentiment-augmented Fama-French models does not increase the number of anomalies captured.

5.4.8 Discussion

Two distinctive findings are present from the sentiment-augmented conditional models examined here as opposed to those documented in the sentiment-free framework proposed by Avarmove and Chorida (2006). First, when conditioning on the default spread, all of the discussed models containing the sentiment factor can often capture the size effect. In contrast, in Avarmov and Chordia (2006) the size effect can be largely eliminated only under particular model specification[30]. Second, the evidence in Tables 5.10-5.11 suggests that the models in which investor sentiment factor and Fama-French factors are present at the same time and betas are scaled by the default spread exhibit explanatory power for the short-term momentum effect (RET2-3) which Fama and French (1996) and Avarmov and Chordia (2006) fail to explain using their models.

5.5 Conclusion

This chapter explores the role of investor sentiment as a risk factor in asset pricing. It constructs a investor sentiment factor using the sentiment indices compiled by Baker and Wurgler (2006) and Investors Intelligence, respectively. The analysis shows that the returns of the stocks with certain firm characteristics tend to be more responsive to the shifts in investor sentiment, suggesting that investor sentiment may help to explain the differential in individual stock returns.

The constructed investor sentiment factor, SMN, has an average monthly return of 0.08%, and commands a positive and statistically significant risk premium of 6% annually. Extending the framework of Avramov and Chordia (2006), this chapter investigates the performance of the asset pricing models with the sentiment risk factor by assessing their ability to capture the anomalies. The results show that the sentiment-augmented models frequently capture the size,

[30] See Panel A of Tables 4, 5, and 8 for the results which the Fama-French three factors and the liquidity factor are conditional on (SIZE+B/M)def for the sample firms listed on the NYSE, AMEX, and NASDAQ.

value, and momentum effects, particularly when both the SMN and Fama-French factors are present in the conditional asset pricing models.

The study shows that the sentiment factor exhibits significant power in explaining the impact of firm size on the cross-section of individual stock returns. The firm size is no longer significant when the sentiment factor is present in the unconditional asset pricing models. The models incorporating the sentiment risk factor always capture the size effect for the NYSE, AMEX and NASDAQ stocks even when betas are constant over time. In contrast, the conditional models specified by Avramov and Chordia (2006) only explain the size effect for the NYSE and AMEX stocks but are not so successful for their sample that also includes the NASDAQ stocks.

Furthermore, this chapter shows that the momentum effect sharply reduces when the factor loadings are conditional on the default spread in the sentiment-augmented models that contain the Fama-French factors. The ability of capturing the momentum effect is irrelevant to the presence of the momentum factor in the asset pricing models. As long as the models contain the investor sentiment and Fama-French factors and betas are scaled by the default spread, the conditional models can capture the momentum effect.

In summary, this chapter points a new direction in studying investor sentiment in asset pricing: investor sentiment can play a role as a risk factor. Investor sentiment is priced. Combined with the traditional risk factors, the investor sentiment risk factor helps to explain the financial market anomalies.

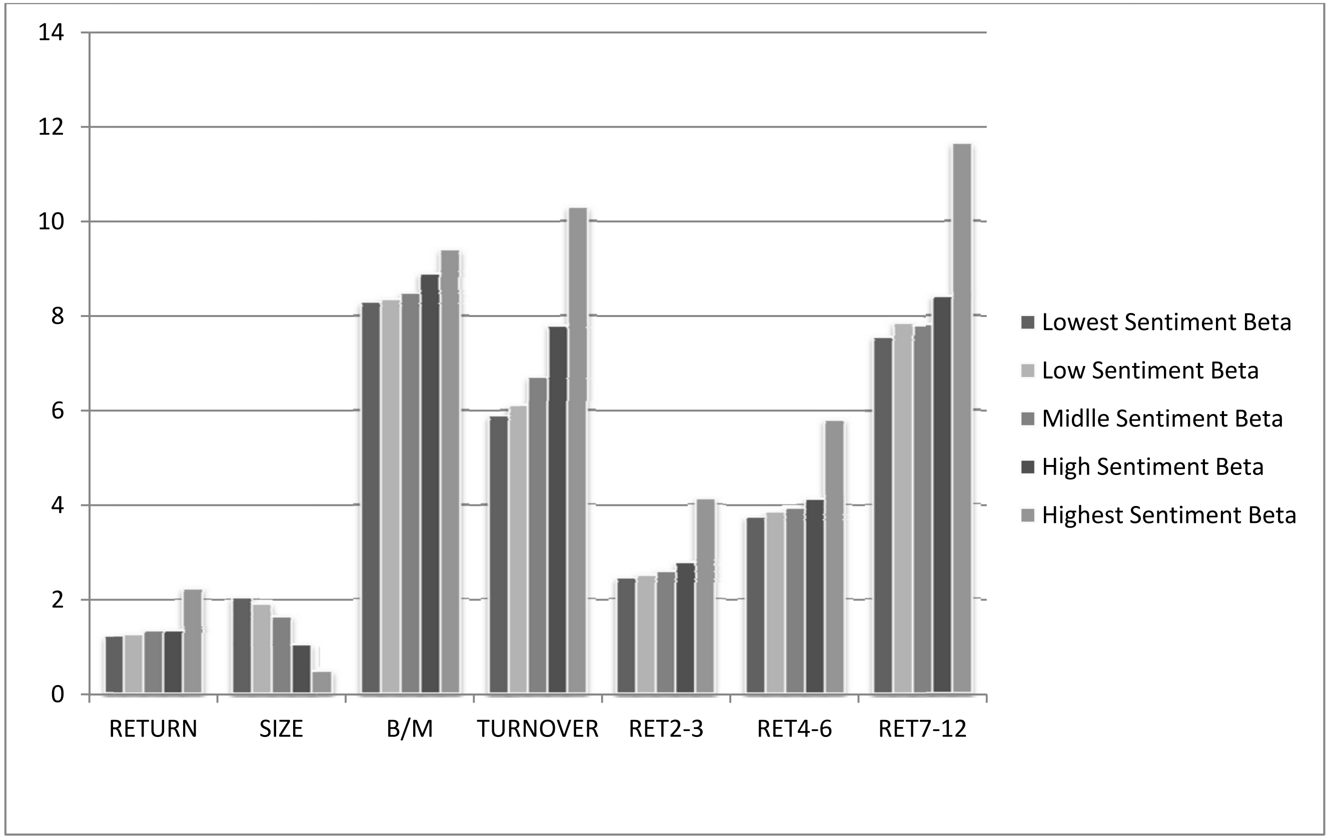

Figure 1: Firm-specific characteristics by sentiment beta based on ΔBW.

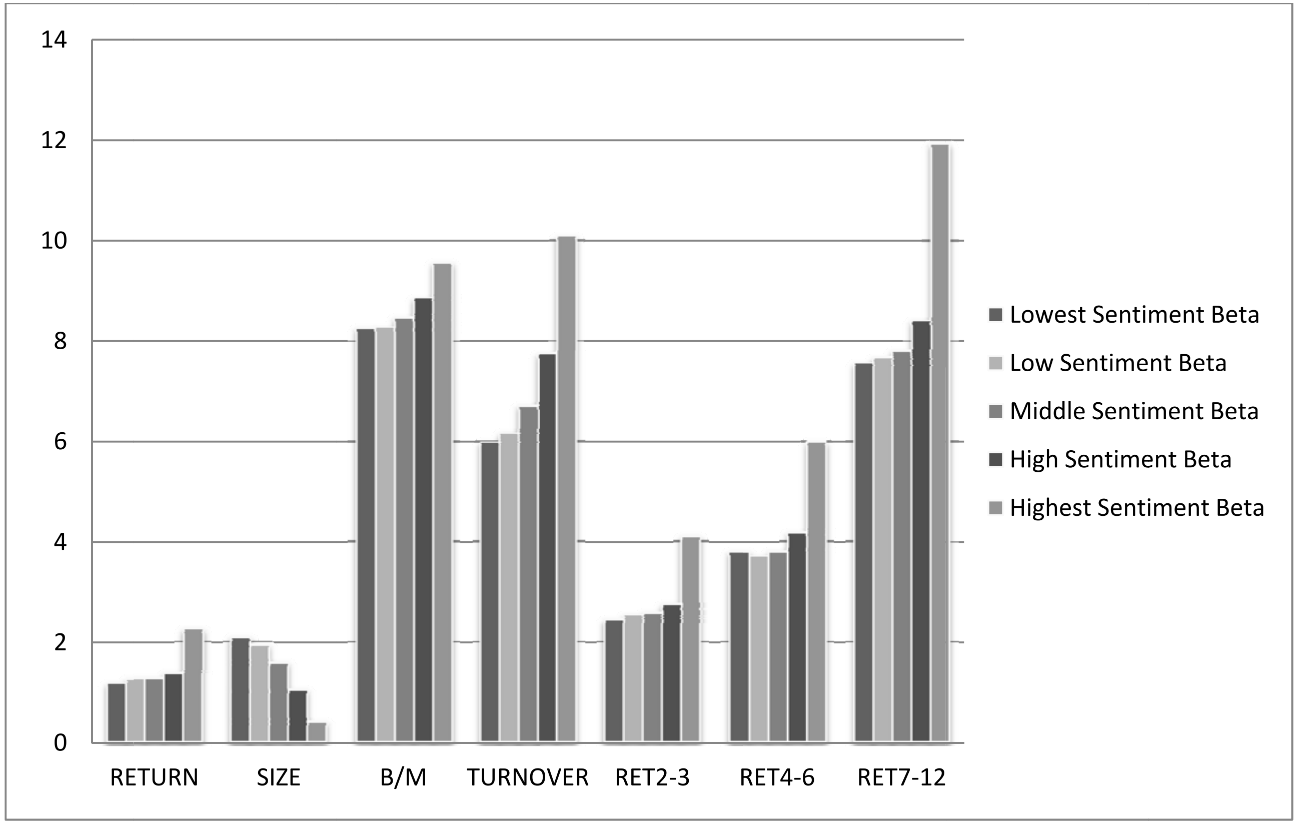

Figure 2: Firm-specific characteristics by sentiment beta based on ΔBWort.

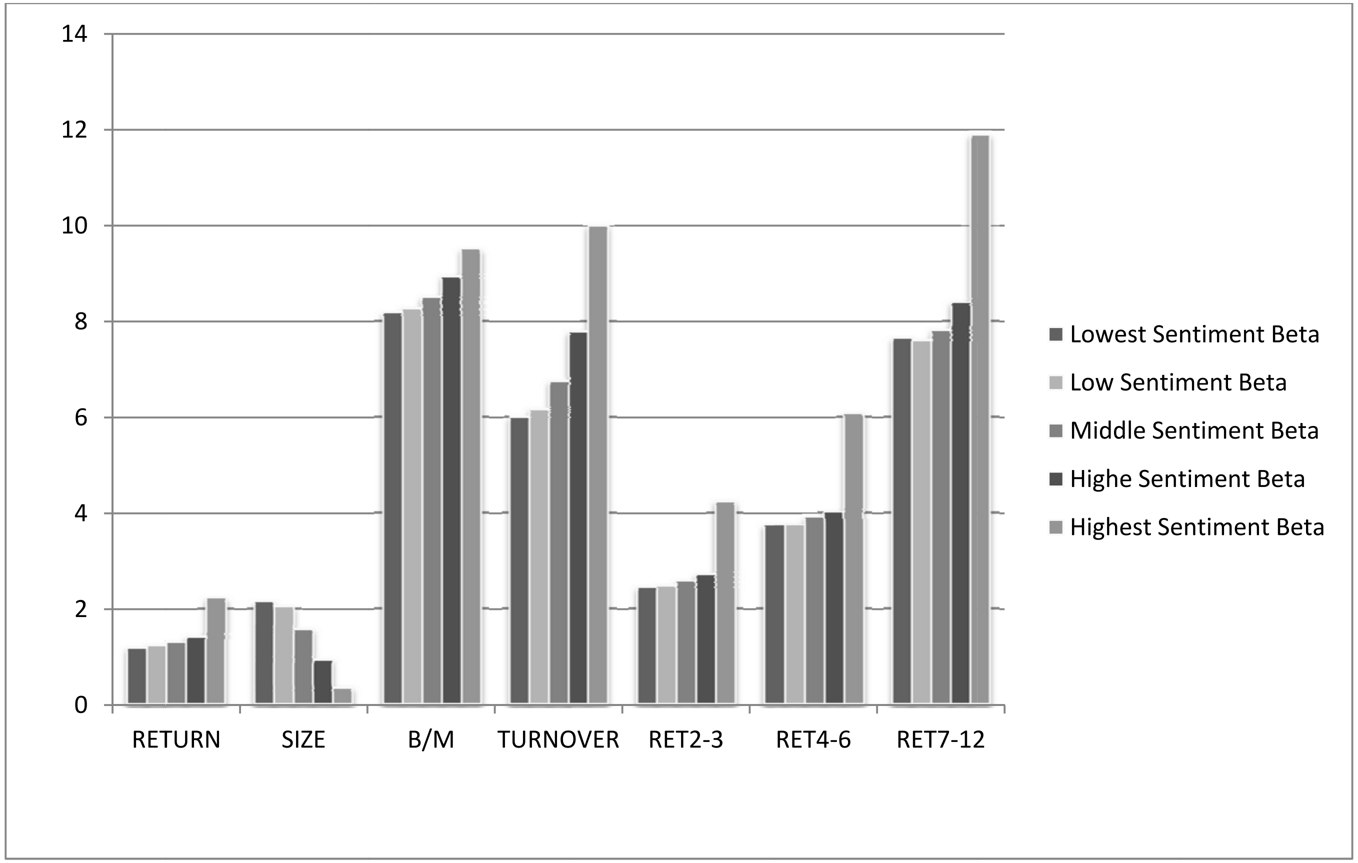

Figure 3: Firm-specific characteristics by sentiment beta based on ΔII.

Table 5.1: Summary statistics (8,526 NYSE/AMEX/NASDAQ firms (with positive B/M): 01/1968 - 12/2005)

	Mean	Median	Std	Reg. Coefficient (%)	t -value
EXCESS RETS (%)	0.88	1.06	5.67		
SIZE ($ billions)	1.22	0.70	1.09	-0.11	-2.10
B/M	0.90	0.86	0.28	0.32	4.96
TURNOVER (%)	6.27	5.19	3.82	-0.09	-1.40
RET2-3 (%)	2.69	2.92	8.67	0.64	2.31
RET4-6 (%)	4.00	3.70	10.98	0.82	3.50
RET7-12 (%)	8.01	7.33	15.71	0.86	6.15
$\overline{R}^2$ (%)	5.05				

This table presents the time-series averages of the cross-sectional means and standard deviations for 8,526 NYSE-AMEX-NASDAQ stocks from January 1968 through December 2005. The column labeled with "Coefficient" represents the time-series averages of the slop coefficients from the cross-sectional OLS regressions of excess return on the firm characteristics. The t-values for the slop coefficients of the characteristics are in the last column. $\overline{R}^2$ denotes the adjusted R squared. SIZE represents the market capitalization in billions of dollars. B/M is the book-to-market ratio of equity. TURNOVER is the monthly trading volume of shares divided by shares outstanding. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively. A common stock must meet the following criteria in order to be included in the analysis: (i) the returns of the stock must be available in the current month, t, and over the past 36 months in the CRSP, (ii) stock prices and shares outstanding for calculating the size of a firm and the month t – 2 trading volume for calculating turnover must be available, (iii) the B/M as of December of the previous calendar year has to be available from the COMPUSTAT dataset, (iv) the B/M must be positive, and (v) the B/M values greater than the 0.995 fractile or less than the 0.005 fractile are set to be the 0.995 and 0.005 fractile values, respectively

Table 5.2: Cross-sectional regressions of excess returns on SMN beta using ΔBW as sentiment measure and Fama-French three factors

	Intercept	β^{S}	β	β^{SMB}	β^{HML}	$\overline{R}^2$ (%)
	0.002**	0.005**	0.004**	0.002	- 0.001	
13	[2.15]	[2.36]	[1.94]	[1.51]	[- 0.57]	35.1%
	(0.03)	(0.02)	(0.05)	(0.13)	(0.57)	
	0.003***	0.005**	0.004*	0.002	- 0.001	
25	[3.59]	[2.08]	[1.74]	[1.30]	[- 0.13]	22.3%
	(<.001)	(0.04)	(0.08)	(0.20)	(0.89)	
	0.004***	0.005**	0.003	0.002	0.001	
37	[4.08]	[2.08]	[1.28]	[1.12]	[0.23]	16.8%
	(<.001)	(0.04)	(0.20)	(0.26)	(0.81)	

This table presents the estimated coefficients of the cross-sectional regression of firm-specific excess returns on the estimated betas for the SMN factor and the Fama-French three factors using the Fama-MacBeth (1973) approach. Specifically, I run the following regression.

$$R_{jt} - R_{Ft} = \lambda_0 + \lambda_1\beta_{jt}^{SMN} + \lambda_2\beta_{jt} + \lambda_3\beta_{jt}^{SMB} + \lambda_4\beta_{jt}^{HML} + \mu_{jt}$$

The regression model is estimated using 13-, 25-, and 37-month rolling window, respectively. ΔBW is the change in the composite investor sentiment index constructed by Baker and Wurgler (2006). The *t*-statistics are reported in square brackets and the *p*-values in parentheses. ***, **, * indicate significant at the level of 1%, 5%, and 10%, respectively.

Table 5.3: Cross-sectional regressions of excess returns on SMN beta using ΔBWort as sentiment measure and Fama-French three factors

	Intercept	β^{s}	β	β^{SMB}	β^{HML}	$\overline{R}^2$ (%)
	0.002*	0.005***	0.004**	0.002	- 0.001	
13	[1.99]	[2.46]	[1.97]	[1.47]	[- 0.61]	34.9%
	(0.05)	(0.01)	(0.05)	(0.14)	(0.54)	
	0.003***	0.006**	0.004*	0.002	- 0.001	
25	[3.28]	[2.31]	[1.78]	[1.30]	[- 0.07]	22.3%
	(<.001)	(0.02)	(0.08)	(0.19)	(0.94)	
	0.004	0.005**	0.003	0.002	0.001	
37	[3.90]	[2.08]	[1.36]	[1.14]	[0.23]	16.9%
	(<.001)	(0.04)	(0.18)	(0.26)	(0.82)	

This table presents the estimated coefficients of the cross-sectional regression of firm-specific excess returns on the estimated betas for the SMN factor and the Fama-French three factors using the Fama-MacBeth (1973) approach. Specifically, I run the following regression.

$$R_{jt} - R_{Ft} = \lambda_0 + \lambda_1\beta_{jt}^{SMN} + \lambda_2\beta_{jt} + \lambda_3\beta_{jt}^{SMB} + \lambda_4\beta_{jt}^{HML} + \mu_{jt}$$

The regression model is estimated using 13-, 25-, and 37-month rolling window, respectively. ΔBWort is the change in the composite investor sentiment index constructed by Baker and Wurgler (2006). The *t*-statistics are reported in square brackets and the *p*-values in parentheses. ***, **, * indicate significant at the level of 1%, 5%, and 10%, respectively.

Table 5.4: Cross-sectional regressions of excess returns on SMN beta using ΔII as sentiment measure and Fama-French three factors

	Intercept	β^{s}	β	β^{SMB}	β^{HML}	$\overline{R}^{2}$ (%)
	0.002**	0.005**	0.004*	0.002	- 0.001	
13	[1.97]	[2.09]	[1.92]	[1.59]	[- 0.52]	34.9%
	(0.05)	(0.04)	(0.06)	(0.11)	(0.61)	
	0.003***	0.005**	0.004*	0.002	0.001	
25	[3.39]	[1.93]	[1.69]	[1.37]	[0.01]	22.1%
	(<.001)	(0.05)	(0.09)	(0.17)	(0.99)	
	0.004***	0.005**	0.003	0.002	0.001	
37	[3.87]	[1.88]	[1.30]	[1.27]	[0.33]	16.8%
	(<.001)	(0.06)	(0.19)	(0.21)	(0.74)	

This table presents the estimated coefficients of the cross-sectional regression of firm-specific excess returns on the estimated betas for the SMN factor and the Fama-French three factors using the Fama-MacBeth (1973) approach. Specifically, I run the following regression.

$$R_{jt} - R_{Ft} = \lambda_0 + \lambda_1\beta_{jt}^{SMN} + \lambda_2\beta_{jt} + \lambda_3\beta_{jt}^{SMB} + \lambda_4\beta_{jt}^{HML} + \mu_{jt}$$

The regression model is estimated using 13-, 25-, and 37-month rolling window, respectively. ΔII is the change in the Investors' Intelligence investor sentiment index. The *t*-statistics are reported in square brackets and the *p*-values in parentheses. ***, **, * indicate significant at the level of 1%, 5%, and 10%, respectively.

Table 5.5: Fama-MacBeth regression estimate for unconditional models

Coefficients	SMN	CAPM		FF		FFP		FFW		FFPW	
		CAPM	SCAPM	FF	SFF	FFP	SFFP	FFW	SFFW	FFPW	SFFPW
Panel A: SMN based on ΔBW											
Intercept	0.255	0.416	0.145	0.135	-0.012	0.133	-0.012	0.253	0.106	0.249	0.104
	(1.26)	(3.15)	(1.47)	(2.06)	(-0.22)	(2.06)	(-0.23)	(4.23)	(2.08)	(4.23)	(2.07)
SIZE ($ billions)	0.049	-0.093	0.044	-0.069	0.026	-0.065	0.027	-0.072	0.049	-0.068	0.051
	(1.41)	(-1.88)	(1.33)	(-2.00)	(0.94)	(-1.93)	(0.99)	(-2.12)	(1.84)	(-2.03)	(1.91)
B/M	0.373	0.329	0.375	0.190	0.245	0.189	0.243	0.197	0.252	0.197	0.279
	(6.36)	(5.48)	(6.55)	(4.42)	(5.61)	(4.46)	(5.63)	(4.61)	(6.65)	(4.65)	(6.65)
TURNOVER (%)	-0.216	-0.159	-0.227)	-0.120	-0.170	-0.123	-0.173	-0.083	-0.145	-0.086	-0.147
	(-4.53)	(-3.33)	(-6.16)	(-3.21)	(-5.08)	(-3.31)	(-5.22)	(-2.24)	(-4.30)	(-2.35)	(-4.43)
RET2-3 (%)	0.677	0.737	0.759	0.549	0.565	0.529	0.551	0.541	0.582	0.520	0.568
	(2.96)	(2.95)	(3.51)	(2.38)	(2.68)	(2.28)	(2.60)	(2.47)	(2.83)	(2.36)	(2.75)
RET4-6 (%)	0.939	0.819	0.921	0.719	0.818	0.699	0.799	0.711	0.827	0.692	0.808
	(4.88)	(4.02)	(5.01)	(3.90)	(4.67)	(3.76)	(4.50)	(4.10)	(4.94)	(3.95)	(4.75)
RET7-12 (%)	0.890	0.928	0.889	0.761	0.763	0.771	0.775	0.736	0.753	0.747	0.765
	(7.36)	(7.40)	(7.61)	(6.49)	(6.75)	(6.60)	(6.86)	(6.60)	(6.91)	(6.72)	(7.02)
Adj. R^2 (%)	3.25	4.04	2.77	2.29	1.97	2.29	1.98	2.24	1.92	2.24	1.93
Panel B: SMN based on ΔBWort											
Intercept	0.214	0.416	0.131	0.135	-0.004	0.133	-0.003	0.253	0.119	0.249	0.118
	(1.09)	(3.15)	(1.32)	(2.06)	(-0.07)	(2.06)	(-0.06)	(4.23)	(2.32)	(4.23)	(2.32)
SIZE ($ billions)	0.057	-0.093	0.052	-0.069	0.030	-0.065	0.030	-0.072	0.043	-0.068	0.043
	(1.71)	(-1.88)	(1.66)	(-2.00)	(1.13)	(-1.93)	(1.15)	(-2.12)	(1.62)	(-2.03)	(1.66)
B/M	0.377	0.329	0.381	0.190	0.251	0.189	0.248	0.197	0.276	0.197	0.2722
	(6.51)	(5.48)	(6.75)	(4.42)	(5.85)	(4.46)	(5.83)	(4.61)	(6.59)	(4.65)	(6.57)
TURNOVER (%)	-0.225	-0.159	-0.230	-0.120	-0.170	-0.123	-0.171	-0.083	-0.140	-0.086	-0.141
	(-4.66)	(-3.33)	(-6.15)	(-3.21)	(-5.02)	(-3.31)	(-5.11)	(-2.24)	(-4.14)	(-2.35)	(-4.23)
RET2-3 (%)	0.622	0.737	0.710	0.549	0.508	0.529	0.492	0.541	0.524	0.520	0.508
	(2.65)	(2.95)	(3.18)	(2.38)	(2.65)	(2.28)	(2.26)	(2.47)	(2.49)	(2.36)	(2.40)
RET4-6 (%)	0.959	0.819	0.949	0.719	0.836	0.699	0.819	0.711	0.839	0.692	0.822
	(4.93)	(4.02)	(5.09)	(3.90)	(4.73)	(3.76)	(4.58)	(4.10)	(4.99)	(3.95)	(4.81)
RET7-12 (%)	0.909	0.928	0.898	0.761	0.769	0.771	0.780	0.736	0.756	0.747	0.767
	(7.39)	(7.40)	(7.49)	(6.49)	(6.64)	(6.60)	(6.75)	(6.60)	(6.80)	(6.72)	(6.90)
Adj. R^2 (%)	3.24	4.04	2.76	2.29	1.97	2.29	1.98	2.24	1.92	2.24	1.93
Panel C: SMN based on ΔII											
Intercept	0.224	0.416	0.127	0.135	0.005	0.133	0.004	0.253	0.116	0.249	0.114
	(1.11)	(3.15)	(1.34)	(2.06)	(0.10)	(2.06)	(0.08)	(4.23)	(2.44)	(4.23)	(2.42)
SIZE ($ billions)	0.058	-0.093	0.046	-0.069	0.002	-0.065	0.019	-0.072	0.049	-0.068	0.049
	(1.68)	(-1.88)	(1.40)	(-2.00)	(0.65)	(-1.93)	(0.68)	(-2.12)	(1.77)	(-2.03)	(1.81)
B/M	0.367	0.329	0.365	0.190	0.238	0.189	0.235	0.197	0.227	0.197	0.274
	(6.25)	(5.48)	(6.35)	(4.42)	(5.52)	(4.46)	(5.52)	(4.61)	(6.57)	(4.65)	(6.55)
TURNOVER (%)	-0.208	-0.159	-0.216	-0.120	-0.161	-0.123	-0.162	-0.083	-0.142	-0.086	-0.143
	(4.25)	(-3.33)	(5.82)	(-3.21)	(-4.78)	(-3.31)	(-4.88)	(-2.24)	(-4.22)	(-2.35)	(-4.32)
RET2-3 (%)	0.824	0.737	0.884	0.549	0.657	0.529	0.630	0.541	0.677	0.520	0.650
	(363)	(2.95)	(4.14)	(2.38)	(3.11)	(2.28)	(2.96)	(2.47)	(3.29)	(2.36)	(3.14)
RET4-6 (%)	0.946	0.819	0.926	0.719	0.792	0.699	0.776	0.711	0.797	0.692	0.781
	(4.99)	(4.02)	(5.14)	(3.90)	(4.57)	(3.76)	(4.42)	(4.10)	(4.79)	(3.95)	(4.62)
RET7-12 (%)	0.890	0.928	0.906	0.761	0.781	0.771	0.790	0.736	0.768	0.747	0.778
	(7.32)	(7.40)	(7.64)	(6.49)	(6.82)	(6.60)	(6.89)	(6.60)	(6.94)	(6.72)	(7.02)
Adj. R^2 (%)	3.21	4.04	2.69	2.29	1.96	2.29	1.97	2.24	1.90	2.24	1.91

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1968-2005. The dependent variable is the excess risk-adjusted return using the SMN factor, excess market return, SMB, HML, the Pastor-Stambaugh liquidity factor and the momentum factor as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as described in the note for Table 4.1. The betas in the first-pass regression are constant over time. The sentiment-augmented models are constructed by adding the SMN factor to the existing pricing models, for example, SCAPM indicates that the SMN factor is used as an additional risk factor in the CAPM. ΔBW is the change in the composite investor sentiment index constructed by Baker and Wurgler (2006). ΔBWort is the one that the business cycle variation has been removed. ΔII is the change in the Investors' Intelligence investor sentiment index. The *t*-statistics are reported in parenthesis. All coefficients are multiplied by 100.

Table 5.6: Fama-MacBeth regression estimate with sentiment-based risk factor SMN (conditional SMN)

Coefficients	SMN based on ΔBW			SMN based on ΔBWort			SMN based on ΔII		
	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def
Intercept	0.209	0.251	0.271	0.142	0.190	0.191	0.117	0.204	0.154
	(1.06)	(1.25)	(1.40)	(0.75)	(0.97)	(1.03)	(0.60)	(1.03)	(0.81)
SIZE ($ billions)	0.062	0.033	0.043	0.071	0.044	0.059	0.077	0.043	0.068
	(1.85)	(0.98)	(1.31)	(2.22)	(1.35)	(1.87)	(2.37)	(1.30)	(2.16)
B/M	0.320	0.645	0.270	0.331	0.356	0.291	0.331	0.351	0.295
	(5.76)	(5.98)	(5.03)	(5.95)	(6.25)	(5.37)	(6.00)	(6.07)	(5.49)
TURNOVER (%)	-0.215	-0.208	-0.197	-0.224	-0.221	-0.213	-0.217	-0.206	-0.208
	(-4.64)	(-4.40)	(-4.31)	(-4.82)	(-4.63)	(-4.66)	(-4.54)	(-4.25)	(-4.50)
RET2-3 (%)	0.837	0.640	0.862	0.735	0.566	0.755	1.027	0.818	1.043
	(3.85)	(2.83)	(3.88)	(3.31)	(2.41)	(3.33)	(4.60)	(3.57)	(4.52)
RET4-6 (%)	1.088	0.952	1.133	1.146	0.979	1.188	1.120	0.948	1.149
	(6.10)	(5.03)	(6.52)	(6.34)	(5.06)	(6.55)	(6.30)	(5.04)	(6.50)
RET7-12 (%)	0.965	0.880	0.976	1.100	0.905	1.000	0.974	0.902	1.010
	(8.07)	(7.40)	(8.34)	(8.20)	(7.44)	(8.28)	(8.17)	(7.46)	(8.71)
Adj. R^2 (%)	3.21	3.21	3.23	3.23	3.24	3.29	3.16	3.18	3.20

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1968-2005. The dependent variable is the excess risk-adjusted return using the SMN factor as the risk factor. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as described in the note for Table 4.1. The betas in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (def). ΔBW is the change in the composite investor sentiment index constructed by Baker and Wurgler (2006). ΔBWort is the one that the business cycle variation has been removed. ΔII is the change in the Investors' Intelligence investor sentiment index. The *t*-statistics are reported in parenthesis. All coefficients are multiplied by 100.

Table 5.7: Fama-MacBeth regression estimate with excess market return and sentiment-based risk factor SMN as the risk factors (conditional SCAPM)

Coefficients	SMN based on ΔBW			SMN based on ΔBWort			SMN based on ΔII		
	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def
Intercept	0.096	0.149	0.135	0.067	0.125	0.090	0.055	0.140	0.078
	(1.05)	(1.54)	(1.52)	(0.73)	(1.29)	(1.02)	(0.63)	(1.51)	(0.94)
SIZE ($ billions)	0.063	0.032	0.048	0.077	0.045	0.068	0.073	0.033	0.063
	(1.93)	(0.99)	(1.59)	(2.55)	(1.48)	(2.39)	(2.24)	(1.04)	(2.15)
B/M	0.309	0.349	0.248	0.317	0.362	0.262	0.311	0.348	0.264
	(5.87)	(6.28)	(4.96)	(6.03)	(6.57)	(5.22)	(5.92)	(6.25)	(5.30)
TURNOVER (%)	-0.222	-0.214	-0.198	-0.226	-0.222	-0.205	-0.217	-0.208	-0.201
	(-6.45)	(-5.94)	(-5.98)	(-6.49)	(-6.03)	(-6.08)	(-6.22)	(-5.75)	(-6.05)
RET2-3 (%)	0.874	0.707	1.071	0.875	0.653	1.00	1.111	0.863	1.231
	(4.77)	(3.30)	(5.15)	(4.18)	(2.94)	(4.74)	(5.35)	(4.00)	(5.74)
RET4-6 (%)	1.056	0.932	1.054	1.136	0.975	1.146	1.100	0.920	1.070
	(5.98)	(5.03)	(5.93)	(6.30)	(5.16)	(6.21)	(6.34)	(5.10)	(5.10)
RET7-12 (%)	0.981	0.888	0.977	0.996	0.900	0.992	0.994	0.910	1.008
	(8.74)	(7.68)	(9.03)	(8.53)	(7.52)	(8.63)	(8.85)	(7.74)	(9.36)
Adj. R^2 (%)	2.68	2.75	2.73	2.66	2.75	2.73	2.60	2.66	2.65

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1968-2005. The dependent variable is the excess risk-adjusted return using the SMN factor and excess market return as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as described in the note for Table 4.1. The betas in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (def). ΔBW is the change in the composite investor sentiment index constructed by Baker and Wurgler (2006). ΔBWort is the one that the business cycle variation has been removed. ΔII is the change in the Investors' Intelligence investor sentiment index. The *t*-statistics are reported in parenthesis. All coefficients are multiplied by 100.

Table 5.8:Fama-MacBeth regression estimate with Fama-French three factors and sentiment-based risk factor SMN as the risk factors (conditional SFF)

Coefficients	SMN based on ΔBW			SMN based on ΔBWort			SMN based on ΔII		
	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def
Intercept	0.032	-0.024	0.043	0.030	-0.017	0.031	0.048	-0.006	0.041
	(0.76)	(-0.50)	(1.03)	(0.70)	(-0.35)	(0.72)	(1.22)	(-0.13)	(1.11)
SIZE ($ billions)	0.028	0.026	0.028	0.035	0.033	0.040	0.027	0.023	0.035
	(0.97)	(0.99)	(1.08)	(1.29)	(1.26)	(1.64)	(0.86)	(0.83)	(1.26)
B/M	0.095	0.201	0.037	0.102	0.211	0.052	0.105	0.203	0.052
	(2.66)	(5.03)	(1.21)	(2.90)	(5.34)	(1.69)	(2.92)	(5.17)	(1.72)
TURNOVER (%)	-0.156	-0.163	-0.128	-0.160	-0.164	-0.135	-0.149	-0.155	-0.126
	(-5.21)	(-5.01)	(-4.73)	(-5.38)	(-4.98)	(-4.97)	(-4.94)	(-4.81)	(-4.60)
RET2-3 (%)	0.888	0.361	0.843	0.810	0.300	0.816	0.959	0.448	0.889
	(4.32)	(1.73)	(4.04)	(3.89)	(1.40)	(3.88)	(4.50)	(2.10)	(4.03)
RET4-6 (%)	1.039	0.802	1.002	1.096	0.826	1.075	1.039	0.768	0.992
	(6.36)	(4.63)	(6.39)	(6.59)	(4.71)	(6.58)	(6.38)	(4.51)	(6.24)
RET7-12 (%)	0.886	0.717	0.841	0.885	0.725	0.848	0.907	0.742	0.887
	(8.40)	(6.47)	(8.65)	(8.19)	(6.42)	(8.48)	(8.63)	(6.70)	(9.40)
Adj. R^2 (%)	1.80	1.94	1.87	1.81	1.93	1.89	1.81	1.93	1.92

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1968-2005. The dependent variable is the excess risk-adjusted return using the SMN factor and the Fama-French three factors as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as described in the note for Table 4.1. The betas in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (def). ΔBW is the change in the composite investor sentiment index constructed by Baker and Wurgler (2006). ΔBWort is the one that the business cycle variation has been removed. ΔII is the change in the Investors' Intelligence investor sentiment index. The *t*-statistics are reported in parenthesis. All coefficients are multiplied by 100.

Table 5.9:Fama-MacBeth regression estimate with Fama-French three factors, Pastor-Stambaugh liquidity, and sentiment-based risk factor SMN as the risk factors (conditional SFFP)

Coefficients	SMN based on ΔBW			SMN based on ΔBWort			SMN based on ΔII		
	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def
Intercept	0.026	-0.023	0.035	0.025	0.016	0.026	0.037	-0.007	0.028
	(0.63)	(-0.49)	(0.86)	(0.60)	(-0.33)	(0.63)	(0.96)	(-0.16)	(0.76)
SIZE ($ billions)	0.030	0.030	0.029	0.036	0.035	0.039	0.032	0.026	0.040
	(1.07)	(1.12)	(1.16)	(1.38)	(1.37)	(1.69)	(1.06)	(0.97)	(1.53)
B/M	0.089	0.194	0.014	0.093	0.204	0.031	0.098	0.197	0.041
	(2.58)	(4.91)	(0.49)	(2.72)	(5.22)	(1.08)	(2.87)	(5.06)	(1.42)
TURNOVER (%)	-0.147	-0.162	-0.114	-0.152	-0.161	-0.120	-0.141	-0.154	-0.111
	(-5.03)	(-5.10)	(-4.42)	(-5.22)	(-5.01)	(-4.62)	(-4.76)	(-4.87)	(-4.27)
RET2-3 (%)	0.896	0.389	0.866	0.799	0.325	0.811	0.931	0.452	0.902
	(4.42)	(1.84)	(4.29)	(3.90)	(1.50)	(3.97)	(4.40)	(2.10)	(4.19)
RET4-6 (%)	1.017	0.765	0.949	1.087	0.793	1.045	1.022	0.736	0.982
	(6.01)	(4.41)	(6.01)	(6.34)	(4.55)	(6.40)	(6.06)	(4.32)	(6.08)
RET7-12 (%)	0.899	0.706	0.812	0.894	0.710	0.813	0.922	0.727	0.893
	(8.59)	(6.38)	(8.53)	(8.33)	(6.31)	(8.33)	(8.85)	(6.55)	(9.58)
Adj. R^2 (%)	1.83	1.96	1.87	1.83	1.95	1.89	1.84	1.95	1.94

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1968-2005. The dependent variable is the excess risk-adjusted return using the SMN factor, the Fama-French three factors, and the Pastor-Stambaugh liquidity factor as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as described in the note for Table 4.1. The betas in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (def). ΔBW is the change in the composite investor sentiment index constructed by Baker and Wurgler (2006). ΔBWort is the one that the business cycle variation has been removed. ΔII is the change in the Investors' Intelligence investor sentiment index. The *t*-statistics are reported in parenthesis. All coefficients are multiplied by 100.

Table 5.10:Fama-MacBeth regression estimate with Fama-French three factors, momentum factor, and sentiment-based risk factor SMN as the risk factors (conditional SFFW)

Coefficients	SMN based on ΔBW			SMN based on ΔBWort			SMN based on ΔII		
	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def
Intercept	0.111	0.097	0.111	0.120	0.107	0.103	0.122	0.106	0.104
	(2.63)	(2.13)	(2.80)	(2.85)	(2.36)	(2.53)	(3.14)	(2.48)	(2.95)
SIZE ($ billions)	0.058	0.051	0.064	0.052	0.047	0.067	0.059	0.053	0.068
	(2.00)	(1.94)	(2.49)	(1.88)	(1.84)	(2.67)	(1.87)	(1.97)	(2.47)
B/M	0.140	0.242	0.085	0.141	0.242	0.096	0.139	0.244	0.080
	(4.13)	(6.26)	(2.96)	(4.23)	(6.31)	(3.32)	(4.13)	(6.38)	(2.75)
TURNOVER (%)	-0.133	-0.133	-0.111	-0.136	-0.131	-0.119	-0.131	-0.133	-0.102
	(-4.58)	(-4.13)	(-4.36)	(-4.69)	(-4.07)	(-4.66)	(-4.47)	(-4.15)	(-3.96)
RET2-3 (%)	0.959	0.348	0.906	0.864	0.300	0.876	1.008	0.399	0.805
	(4.80)	(1.73)	(4.61)	(4.26)	(1.45)	(4.35)	(4.92)	(1.94)	(3.91)
RET4-6 (%)	1.045	0.768	0.994	1.082	0.791	1.065	1.041	0.718	0.916
	(6.74)	(4.65)	(6.70)	(6.99)	(4.76)	(6.99)	(6.74)	(4.38)	(6.09)
RET7-12 (%)	0.885	0.069	0.824	0.878	0.699	0.819	0.901	0.698	0.788
	(8.91)	(6.54)	(9.12)	(8.63)	(6.52)	(8.88)	(9.14)	(6.65)	(9.04)
Adj. R^2 (%)	1.73	1.87	1.76	1.73	1.87	1.79	1.73	1.86	1.74

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1968-2005. The dependent variable is the excess risk-adjusted return using the SMN factor, the Fama-French three factors, and the momentum factor as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as described in the note for Table 4.1. The betas in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (def). ΔBW is the change in the composite investor sentiment index constructed by Baker and Wurgler (2006). ΔBWort is the one that the business cycle variation has been removed. ΔII is the change in the Investors' Intelligence investor sentiment index. The *t*-statistics are reported in parenthesis. All coefficients are multiplied by 100.

Table 5.11: Fama-MacBeth regression estimate with Fama-French three factors, Pastor-Stambaugh liquidity, momentum factor and sentiment-based risk factor SMN as the risk factors (conditional SFFPW)

Coefficients	SMN based on ΔBW			SMN based on ΔBWort			SMN based on ΔII		
	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def	Size+B/M	def	(Size+B/M) def
Intercept	0.105	0.095	0.155	0.117	0.106	0.025	0.116	0.102	0.045
	(2.56)	(2.11)	(3.98)	(2.84)	(2.35)	(0.60)	(3.02)	(2.41)	(1.26)
SIZE ($ billions)	0.059	0.054	0.032	0.053	0.050	0.106	0.052	0.057	0.087
	(2.10)	(2.07)	(1.24)	(1.95)	(1.95)	(3.73)	(2.03)	(2.13)	(3.31)
B/M	0.134	0.233	0.009	0.131	0.233	0.096	0.133	0.236	0.092
	(4.05)	(6.10)	(0.31)	(4.06)	(6.14)	(3.05)	(4.03)	(6.23)	(3.13)
TURNOVER (%)	-0.125	-0.133	-0.065	-0.127	-0.131	-0.096	-0.122	-0.131	-0.054
	(-4.41)	(-4.23)	(-2.54)	(-4.51)	(-4.13)	(-3.16)	(-4.24)	(-4.18)	(-2.06)
RET2-3 (%)	0.939	0.377	0.060	0.830	0.321	0.830	0.958	0.409	0.873
	(4.81)	(1.85)	(2.70)	(4.19)	(1.52)	(3.89)	(4.74)	(1.97)	(4.30)
RET4-6 (%)	1.015	0.723	0.697	1.069	0.753	0.976	1.014	0.680	0.966
	(6.31)	(4.34)	(4.22)	(6.61)	(4.49)	(5.83)	(6.35)	(4.11)	(6.21)
RET7-12 (%)	0.897	0.689	0.600	0.886	0.694	0.688	0.915	0.691	0.869
	(9.06)	(6.53)	(6.01)	(8.72)	(6.50)	(6.65)	(9.30)	(6.58)	(9.80)
Adj. R^2 (%)	1.75	1.90	1.45	1.75	1.90	1.46	1.77	1.88	1.62

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1968-2005. The dependent variable is the excess risk-adjusted return using the SMN factor, the Fama-French three factors, the Pastor-Stambaugh liquidity factor, and the momentum factor as the risk factors. The explanatory variables are SIZE, B/M, TURNOVER, RET2-3, RET4-6, and RET7-12 as described in the note for Table 4.1. The betas in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (def). ΔBW is the change in the composite investor sentiment index constructed by Baker and Wurgler (2006). ΔBWort is the one that the business cycle variation has been removed. ΔII is the change in the Investors' Intelligence investor sentiment index. The *t*-statistics are reported in parenthesis. All coefficients are multiplied by 100.

CHAPTER 6 INVESTOR SENTIMENT, FUNDAMENTAL VALUES, AND STOCK MARKET PERFORMANCE

6.1 Introduction

Chapters 4 and 5 examine the roles of investor sentiment as a conditioning variable and a risk factor in various asset pricing models, respectively. The findings show that investor sentiment exhibits explanatory power in capturing the financial market anomalies such as the size, value, and momentum effects at the firm level. In this chapter, I investigate, at the market level, whether investor sentiment affects stock market volatility. Also, I examine whether the current monthly investor sentiment measure predicts the market returns for the subsequent month, and whether the market returns are also indirectly influenced by invest sentiment through the risk caused by investor sentiment in the form of volatility. Unlike Chapters 4 and 5 that completely focus on the U.S. market, this chapter extends the analysis to the non-U.S. markets.

Traditional financial theories assume that investors are rational and, hence, stock prices should react only to any information related to fundamentals. However, believers who hold the view that market is efficient face a great challenge by the publication of Shiller's (1981) and Leroy and Porter's (1981) volatility tests. Their findings show that stock prices are too volatile to be justified by changes in future dividends. In his seminal work, Black (1986) claims that some investors in the market who trade on 'noise' as if it were profitable information that is associated with fundamentals can affect stock price behaviour. Investors of this kind are called 'noise traders'. De Long, Shleifer, Summers, and Waldmann (1990) develop a theoretical model that shows noise traders who have erroneous beliefs can drive stock prices away from fundamental values and increase volatility. Numerous empirical studies, as discussed in Chapter 3, have provided supportive evidence that investor sentiment or noise trading indeed plays a critical role in determining stock price behaviour. Hence, the question now is not whether investor sentiment affects stock prices or not but to what extent can investor sentiment impact stock market.

The analysis of this chapter contributes to the extant literature by examining the extent to which the impact of investor sentiment on stock market volatility and returns. Specifically, the work contributes to the current knowledge of the sentiment-stock market relation in a number of aspects. First, unlike previous research which mainly focuses on the influence of investor sentiment on the mean of stock returns, this essay examines the impact of investor sentiment on both the volatility of returns and stock returns at the market level. Second, most empirical studies on sentiment-stock market relation utilise the U.S. data in their tests. Apart from the U. S. stock market, this chapter also considers the impact of investor sentiment on stock price behaviour in the international markets[31]. The understanding of this issue in the international context is important, as investors nowadays tend to diversify their investment portfolios across borders. Third, for the European markets, this chapter uses both the consumer confidence indices and economic sentiment indices to proxy for investor sentiment. This analysis aims to investigate how the perception of the consumers about the economy may bring different impact on the stock market, as opposed to the belief of the public that contains both consumers and manufacturers.

Despite this chapter adopts the empirical framework of Lee, Jiang, and Indro (2002), it differs from their model in the following aspects[32]. First, unlike their GARCH-M model that completely overlooks the predictability of the macroeconomic variables for stock returns and ignores the possible fundamental information contained in the consumer confidence indices, the mean equation of the analysis in this chapter controls for the lagged values of the dividend yield, the annual measure of inflation, the change in the short-term risk-free rate, and the 12-month

[31] Very few research studies the investor sentiment impact on stock market in the international context. The recently published work of Schmeling (2009) that investigates this issue in 18 industrialized countries is one of the closest research similar to my work here in terms of the markets under consideration.

[32] The author gratefully thanks to the examiners for these comments and suggestions during the viva.

change in the industrial production index that are capable of predicting monthly stock market returns (Pesaran and Timmermann, 1994). Second, instead of using the contemporaneous investor sentiment in the mean equation like Lee, Jiang, and Indro (2002) does in their model, the analysis uses the lagged value of investor sentiment. Despite Fisher and Statman (2003) and Charoenrook (2005) show that changes in consumer confidence are positively related to contemporaneous excess stock market returns, Wang, Keswani and Taylor (2006) report evidence that their sentiment measures are caused by returns[33]. Using the lagged sentiment rather than the contemporaneous sentiment helps to clearly demonstrate the predictive power of sentiment for the aggregate market returns and avoids the ambiguity of the role that investor sentiment plays in the sentiment-return relation.

For each country under consideration, I estimate a set of GJR type of GARCH-M models that consider the lagged values of the macroeconomic variables and investor sentiment measures. Consistent with the well-documented U.S. evidence, this chapter shows that periods of high sentiment level tend to be followed by low aggregate market returns in the sample countries. The negative relationship between current consumer confidence level and subsequent excess monthly return is statistically significant not only for the U.S. market but also for France and Italy. The only exception is Japan where the current consumer confidence level boosts the excess market return of next month. In contrast, the lagged value of change in consumer confidence exhibits no predictive power for excess stock market return in most of the countries except for Japan where a positive and statistically significant relation exists.

This chapter also finds that investor sentiment is an important factor in explaining changes in conditional volatility. However, such impact is country-specific. Interestingly, apart from the

[33] Note these studies use different data frequency and investor sentiment measures. Fisher and Statman (2003) and Charoenrook (2005) use monthly consumer confidence and stock returns while Wang, Keswani, and Taylor 2006) use daily and weekly data of investor sentiment indicators compiled by American Association for Individual Investors (AAII) and Investors Intelligence (II), as well as the investor sentiment measures that are obtained based on stock transaction activity.

U.S. market, the indirect impact of consumer confidence on stock returns via conditional volatility is present in Italy only.

The predictive power of the macroeconomic variables for stock return varies across countries. In general, the lagged values of the dividend yield and the annual measure of inflation often exhibit statistically significant impacts on stock returns across the countries.

Finally, results show that the shifts in economic sentiment, available for the European countries only, move the conditional volatility but not stock return.

The rest of the chapter is organised as follows. Section 6.2 describes in detail the data and methodology adopted in this chapter[34]. Section 6.3 presents the empirical results, and Section 6.4 concludes.

6.2 Data and Methodology

6.2.1 Investor Sentiment Data

In order to investigate the link between investor sentiment and stock price behaviour of each country, following the literature, I use the country-specific consumer confidence to proxy the investor sentiment for each country[35]. For the U.S. market, I use the consumer confidence indices compiled by the University of Michigan (MS) and the Conference Board, respectively. For the European markets, I use the consumer confidence index of each country, developed by the European Commission, to represent the investor sentiment. Similarly, the corresponding consumer confidence index is used to proxy investor sentiment for Japan, Australia, and New Zealand, respectively. Despite the consumer confidence index for each country is calculated differently and by different institutions, most of the consumer confidence indices developed outside the U.S. adopt questions and score calculation procedure similar to MS, and hence, can be compared with each other for the purpose of my study in this chapter.

[34] Despite Chapter 3 has described the monthly stock market indices, investor sentiment measures, and the framework of the GARCH-M model for this chapter, more detailed information is provided in this section.

[35] Due to data availability in non-U.S. markets, consumer confidence has been widely used as a proxy for investor sentiment in the literature.

Apart from consumer confidence, I also consider another two investor sentiment proxies: the Investors Intelligence sentiment index and the Economic Sentiment Index for the U.S and European countries, respectively. Using different investor sentiment proxies helps to capture the information that is not contained in consumer confidence.

6.2.2 Stock Market Indices and Macroeconomic Variables

Stock market indices are used to represent the performance of the stock market in each country. Since these market indices are frequently reported in the headlines of mass media, like TV, newspapers or magazines, they always draw the attention of the public as well as stock market investors worldwide. The monthly stock market return indices, collected from Datastream, include S&P500 (the U.S.), FTSE100 (the U.K.), CAC40 (France), DAX30 (Germany), MIB30 (Italy), NIKKEI225 (Japan), ASX20 (Australia), and NZ50CAP (New Zealand). Due to the availability of the data needed in my analysis, the sample start dates vary across countries but all end in September 2006.

Unlike the mean equation examined by Lee, Jiang, and Indro (2002) who do not consider the impact of fundamental variables on stock market performance, I add four macroeconomic variables to my mean equation, along with the variables used in their work. In their examination of stock returns forecasting at the annually, quarterly, and monthly horizons, Pesaran and Timmermann (1994) identify that the lagged values of the dividend yield, the annual measure of inflation, the change in the 1-month T-bill rate, and the 12-month change in the industrial production index are capable of predicting excess returns at both the quarterly and monthly horizons. Following their empirical evidence, I collect these data from Global Finance Data and include these macroeconomic variables in the mean equation of the GARCH-M model for each country. Controlling for these macroeconomic variables in the mean equation that contains investor sentiment can separate the marginal explanatory power that is attributed to the pure investor sentiment component contained in the indicator of investor sentiment. The symbols and explanation of these macroeconomic variables are summarised below.

DY: Dividend yield on stock market index, computed as $\frac{Dividend_{t-1}}{Market\ Index_t}$. .

PI: The 12-month inflation rate is calculated as $\log\left(\frac{CPIAV_t}{CPIAV_{t-1}}\right)$. $CPIAV$ is annual average of Consumer Price Index[36].

DI: 1-month change in the 1-month T-bill rate, computed as $R_{ft} - R_{ft-1}$.

DIP: The 12-month rate of change in industrial production, computed as $\log\left(\frac{IPAV_t}{IPAV_{t-1}}\right)$. $IPAV$ is 12-month average of the industrial production index.

6.2.3 Model Specification

I consider three versions of the GJR type of GARCH-M model based on the presence and the form of the investor sentiment measure appearing in the mean equation and the volatility equation. In particular, I start with a model without investor sentiment but containing the macroeconomic variables, dummies for January and October, and volatility variable. This model, labelled as Model 1, can be viewed as a base model before investor sentiment is incorporated into the model. Based on Equation (3.7), Model 1 takes the following form:

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 \log h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 DY_{t-1} + \alpha_5 PI_{t-2} + \alpha_6 DI_{t-1} + \alpha_7 DIP_{t-2} + \varepsilon_{it},\ \varepsilon_{it} \sim N(0,\ h_{it}) \quad (6.1)$$

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{it-1}^- + \beta_3 h_{it-1} + \beta_4 R_{ft} \quad (6.2)$$

Model 1 can test the risk-return relation, α_1, seasonal effects, α_2 and α_3, and fundamental effects on the monthly excess return. The findings of Pesaran and Timmermann (1994) show that the yield variable has a positive effect on excess return while the effect on excess return of the inflation rate, the change in the 1-month T-bill rate, and the rate of change in industrial

[36] Due to data availability, consumer price index is used in my study rather than producer price index as in Pesaran and Timmermann (1994).

production are all negative. Furthermore, they find no evidence of January effect on the S&P 500 market index.

I then test how investor sentiment is related to volatility and excess market return using Model 2 in which the one-period lagged value of investor sentiment level, S_{t-1}, is used in place of $Sent_{t-1}$ in Equation (3.7), Model 2 takes the form as follows:

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 \log h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 S_{t-1} + \alpha_5 DY_{t-1} + \alpha_6 PI_{t-2} + \alpha_7 DI_{t-1} + \alpha_8 DIP_{t-2} + \varepsilon_{it},\ \varepsilon_{it} \sim N(0,\ h_{it}) \tag{6.3}$$

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{it-1}^{-} + \beta_3 h_{it-1} + \beta_4 R_{ft} + \beta_5 (\Delta S_{t-1})^2 D_{t-1} + \beta_6 (\Delta S_{t-1})^2 (1 - D_{t-1}) \tag{6.4}$$

As noted by Lee, Jiang, and Indro (2002), the second moment measure of noise trader risk is Var(ΔS_{t-1}). Since the mean of the change in sentiment is close to zero, the variance of the change in sentiment can be approximated by $(\Delta S_{t-1})^2$, as shown in Equation (6.4).

Using the same specification as Equation (6.4), the third model employs the lagged value of the monthly change in investor sentiment measure, ΔS_{t-1}, in the mean equation. The mean equation of Model 3 is:

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 \log h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 \Delta S_{t-1} + \alpha_5 DY_{t-1} + \alpha_6 PI_{t-2} + \alpha_7 DI_{t-1} + \alpha_8 DIP_{t-2} + \varepsilon_{it},\ \varepsilon_{it} \sim N(0,\ h_{it}) \tag{6.5}$$

In the next section, controlling for the macroeconomic variables, I present the empirical evidence on the relation between sentiment, conditional volatility, and excess market return.

6.3 Empirical Results

6.3.1 Investor Sentiment and Stock Returns

Table 6.1 summarises the descriptive statistics for the sentiment measures and stock returns. Panel A reports these results using the level of investor sentiment indicator while Panel B considers the change in investor sentiment.

According to Panel A, consumer confidence, on average, is negative for each of the European countries. The consumer confidence level and the ESI level of the U.K. register a slightly higher average score than its European counterparts. Among the European countries, Italy shows the smallest variation of outlook based on its consumer confidence; however, its producer sentiment is the most volatile. The averages of the U.S. consumer confidence indices are 91.85 for the MS and 101.23 for the CCI[37]. The scores for the Asia-Pacific countries are close to each other, centring around 100. With the exception of the ESI for Italy, the first order autocorrelations of the index levels exceed 0.9, and the second order autocorrelations range between 0.80 (consumer confidence for Australia) and 0.93 (the ESI for France). According to Panel B, the consumers of most of the countries in the sample are on average optimistic about the prospectus of the future local economy except for Germany, Italy and New Zealand where the public are on average pessimistic. Panel C shows that, on average, investors earn positive returns of about 1% per month for most of the countries during the sample periods. MIB30 shows the highest average return of 1.09%, while NIKKEI225 earns the lowest return of 0.14%.

Table 6.2 reports the correlation coefficients of the sentiment indicators. The consumer confidence indices of the U.S. exhibit positive and statistically significant correlations with all the European countries, but the correlations with the Asia-Pacific countries are weaker. The correlations between the European and the Asia-Pacific countries are generally low. Japan, for example, shows low correlations (close to zero) with all other countries, except Italy. The consumer confidence indices of Australia and New Zealand are significantly and positively correlated, and most of the correlations among European countries are positive, possibly due to economy proximity within the geographic region.

[37] The base periods for these two indicators are different.

6.3.2 Consumer Confidence, Macroeconomic Variables, and the U.S. Stock Market

Table 6.3 reports the empirical evidence of the sentiment-volatility and sentiment-return relations for the U.S. market. I start with a GARCH-M framework that excludes investor sentiment in the mean and conditional volatility equations and report the finding in the second column of Table 6.3.

In the absence of investor sentiment in the model, the coefficient estimates of Model 1 show that conditional volatility is negatively associated with the excess market return proxied by the S&P 500 index. The coefficient estimate on $\log h_{it}$ is statically significant at the 1% level. The negative risk-return relation is consistent with Fama and Schwert (1977), Campbell (1987), Pagan and Hong (1991), Breen, Glosten, and Jagannathan (1989), Turner, Startz, ande Nelson (1989), Nelson (1991), and Glosten, Jagannathan, and Runkle (1993)[38].

The direction of the impact of the lagged values of the macroeconomic variables on monthly stock return is generally in line with the findings of Pesaran and Timmermann (1994). Specifically, the yield variable, with a coefficient of 0.809, shows a positive effect on excess return and is statistically significant at the 1% level. The effect of the inflation rate and the change in the 1-month T-bill rate is negative, respectively, though statistically insignificant. Nevertheless, to the contrary of Pesaran and Timmermann's (1994) finding, the result here shows that the rate of change in industrial production on excess market return is positive. The opposite evidence might be attributed to the difference in sample periods[39].

The result for the conditional volatility equation indicates that the conditional volatility is positively serially correlated, and positively related to the risk-free rate. Investors perceive

[38] However, empirical evidence in the literature on the risk-return relation has mixed results. For example, French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992) find a positive relationship between conditional expected excess return and conditional variance, and Chan, Karolyi, and Stulz (1992), however, find no evidence of a relationship between risk and return for the U.S. market.

[39] Pesaran and Timermann's (1994) findings is based on the monthly data for the 1954-1990 period, which has only a 6-year overlap with the data used in my analysis.

positive and negative shocks asymmetrically in forming their expectations of conditional volatility.

Columns 3 – 8 in Table 6.3 report the coefficient estimates of the GARCH-M models augmented by the sentiment measures, namely, MS, CCI, and II, respectively. The results of Model 2 in which investor sentiment is measured by the level of investor sentiment indicator show current high sentiment is followed subsequently by low excess stock market return, regardless which investor sentiment index is examined. Among the investor sentiment indicators considered, there is evidence that MS exhibits a significant and negative lead-lag relationship with S&P 500 excess return. This finding is consistent with Fisher and Statman (2003) who find a negative relationship between the *level* of the investor sentiment in one month and the stock returns over the *next* month and the next 6 and 12 months. In contrast, no lead-lag relationship is found under Model 3 in which the investor sentiment is measured by the monthly change in sentiment.

The shifts in investor sentiment can influence the formation of conditional volatility. For consumer confidence (MS and CCI) the shifts investor sentiment are negatively associated with conditional volatility. Verma and Verma (2007) also document a negative relationship between noise trading and volatility. Kurov (2008) also documents that high investor sentiment has a negative impact on the transitory volatility in the futures market. In contrast, II's impact on stock volatility is positive and only marginally significant at the 10% level for the bullish sentiment measures. The risk-return relation, reflected in α_1, is insignificant at the 5% level. As a result, any change in investor sentiment fails to further impact stock return via its influence on conditional volatility.

Compared to Model 1, the macroeconomic variables that show predictability for the market performance are different when investor sentiment is included in the mean equation. Dividend yield exhibits positive predictive power for S&P 500 only in Model 3; however, according to the *p*-value, its explanatory power is weakened when investor sentiment is present in the model. The rate of change in industrial production maintains its ability to positively forecast excess market return in Model 2 but not Model 3 at the 5% level for MS and CCI while it loses explanatory power for market return for II. Statistically, inflation rate shows no ability to explain stock return in Model 1 while its explanatory power enhances dramatically in Models 2 and 3 in which a negative lead-lag relationship is observed.

6.3.3 Consumer Confidence, Macroeconomic Variables, and the European Stock Markets

I now turn to the tests of the influence of investor sentiment as well as the macroeconomic variables on the stock market performance of the European countries, namely, the U.K., France, Italy, and Germany. Table 6.4 presents the empirical results using the consumer confidence indices compiled by the European Commission as the investor sentiment measure.

The first column under each examined country in Table 6.4 reports the coefficient estimates of the GARCH-M model as specified in Model 1 in which sentiment is excluded from the mean equation. The macroeconomic variables that have impacts on stock returns in the European countries differ from the result reported in Table 6.3 for the U.S. market. First, among the European markets under examination, only the U.K. market shows the predictive power of dividend yield for stock return as in the U.S. market. The dividend yields in other European countries are all insignificant. Second, unlike the U.S. market where inflation rate is statistically insignificant in Model 1, the evidence of the European countries shows that inflation is statistically significant and negatively related to the subsequent stock returns in U.K., France, Germany, and Italy. Third, the impacts of industrial production on stock returns in the European stock markets are negative while this impact is positive in the U.S. market. The significance of industrial production is present in Germany only. Similar to the U.S. evidence, the monthly changes in 1-month T-bill rate are all statistically insignificant.

The second column under each country in Table 6.4 reports the coefficient estimates of the sentiment-augmented GARCH-M models for the European markets. The results show that when investor sentiment is measured by the level of the lagged consumer confidence high investor sentiment is followed by low excess stock returns in France and Italy. The coefficient estimates for the lagged sentiment level of these two markets are both negative and statistically significant at the 5% level. In contrast, consistent with the U. S. evidence, no evidence shows that monthly change in consumer confidence exhibits such explanatory power for the subsequent stock returns.

The impact of the shifts in investor sentiment on the conditional volatility varies across the countries. In Model 2, bullish shifts in sentiment in the current period result in statistically significant upward revisions in the volatility of future returns are observed only in France while bearish shifts in sentiment can affect volatility in other three European countries but not in France. In Model 3, in the U.K. market, the direction of shifts in sentiment can have an asymmetric impact on conditional volatility. Specifically, bullish shifts in sentiment in U.K. cause downward revisions of volatility while bearish shifts in sentiment result in upward revisions of volatility. Similar evidence is also found in Italy where bullish shifts in sentiment also reduce conditional volatility and the coefficient is statistically significant at the 1% level. France is the only country which shows a positive and statistically significant relationship between bullish shifts in sentiment and conditional volatility under Model 3 among the European countries.

The impacts of the macroeconomic variables on the excess stock market returns in the sentiment-augmented models, namely, Models 2 and 3, are qualitatively similar to the results reported for Model 1that excludes investor sentiment. Specifically, high dividend yield of the current month predicts high stock market return and the estimated coefficient on dividend coefficient remains statistically significant at the 1% level in the U.K. stock market. For the U.K. and France, as in Model 1, high inflation rate is followed by low future stock market return in both Models 2 and 3. In contrast, the negative inflation rate-stock return relation holds statistically significantly only in Model 3for Germany and in Model 2 for Italy, respectively. Germany is the only country among the European countries under consideration where the rate of change in industrial production exhibits statistically significant predictive power for market return after investor sentiment is added to the mean equation.

6.3.4 Consumer Confidence, Macroeconomic Variables, and the Asia-Pacific Stock Markets

Table 6.5 presents the empirical results for Japan, Australia, and New Zealand. Similar to the U.S. evidence, the coefficient estimate on $\log h_{it}$ is negative and statically significant at the 1% level when investor sentiment in not present in the mean equation. Interestingly, New Zealand is the only country among the examined Asia-Pacific countries where seasonal patterns are present in the stock market. The stock market in New Zealand exhibits superior performance during January and October.

In Model 1, consistent with the U.S. and European evidence, dividend yield is positive and statistically significant for Japan and Australia. A negative inflation-return relation is present for Australia and New Zealand. New Zealand is the only Asia-Pacific country under examination where the monthly change in the 1-month T-bill rate exhibits negative and statically significant explanatory power for the subsequent excess market return at the 5% level. The results for Model 1 show no evidence that industrial production predicts future market returns for these three Asia-Pacific countries. The empirical outcomes of the conditional volatility equation show that the volatility of stock returns of these countries is primarily affected by the lagged volatility. Current high volatility is associated with high volatility in the subsequent month.

The impact of investor sentiment on stock market performance is country specific. The second and third columns under each country show that the contemporaneous consumer confidence in Japan is positively related to its subsequent market performance while no evidence supports such relation in Australia and New Zealand. In Japan, high consumer confidence predicts high stock market return. In addition, in Model 2, the bullish shifts in consumer confidence cause upward revisions in the volatility of future returns, together with a statistically significant and positive risk-return relation reflected in the mean equation, bullish sentiment of the current month leads to high excess market return for the next month. Conversely, consumer confidence shows no explanatory power for either their market returns or volatilities in the stock markets of Australia and New Zealand.

For these three countries, the predictive power of dividend yield and inflation rate for stock returns in the sentiment-augmented models (Models 2 and 3) is generally similar to the evidence in Model 1. For Japan and Australia, the inclusion of invest sentiment measures does not change the direction of the impacts of dividend yield and inflation rate on returns, and the qualitative features of the corresponding coefficient estimates remain unchanged. In contrast, compared to Model 1, the coefficient estimate on the monthly change in the 1-month T-bill rate becomes marginally significant in both Models 2 and 3 for Australia, while it becomes insignificant in the sentiment-augmented models for New Zealand. Interestingly, the industrial production in New Zealand exhibits a statistically significant impact on the excess return in Model 2 but not in Model 3.

6.3.5 Economic Sentiment Indicator, Macroeconomic Variables, and the European Stock Markets

Section 6.3.3 examines the sentiment-return relation using consumer confidence to proxy investor sentiment. Despite empirical studies that examine the impact of investor sentiment on stock market performance have emerged in the past two decades, researchers adopt uniformly either consumer confidence (like MS or CCI) or investor sentiment indictor (like the Investors Intelligence Index) to gauge market sentiment due to the availability of sentiment data. The implicit rationale underlying these studies is that stock return is related to the consumption decisions of the investing public.

However, according to the production-based (or investment-based) asset pricing models (Cochrane, 1991& 1996), stock return is also correlated with the investment decisions of firms. In this section, I investigate the sentiment-return relation using the Economic Sentiment Indicator to proxy investor sentiment in the GARCH-M framework to explore to what degree the public's sentiment that reflects both the producers' and consumers' perceptions of the economy affect the stock market performance in the European countries[40]. Since the ESI score largely consists of the opinions of firms about the future economy prospects, to some degree it represents the sentiment of producers.

Using the ESI, I repeat the analysis for the European countries and present the results in Table 6.6. The empirical result shows no evidence that the ESI has a profound effect on the excess returns for the four European countries[41], even for the countries like France and Italy where consumer confidence exhibit significant capability to predict the subsequent excess stock returns. No statistically significant sentiment-return relation is present when the ESI is employed as an investor sentiment proxy. Compared to the evidence for France and Italy reported in Table 6.4, the results of Table 6.6 suggest that that stock returns in these two European countries are more sensitive to the consumption decisions of the consumers than the investment decisions of the producers.

Despite the impacts of the ESI on the excess returns for the European countries are not so impressive compared to the consumer confidence scenario, the ESI exhibits some degree of influence on the formation of the conditional volatility for the U.K. and France. Table 6.6 shows that the bullish shifts in the ESI lead to upward revisions in the conditional volatility for these

[40] I use the ESI to test the sentiment-return relation for the European countries because I have no access to similar data, if available, for the U.S. and Asia-Pacific countries.
[41] I also explore whether this observed relatively weak link between the ESI and stock returns could be attributed to the lag effect of investment decisions on stock returns. To address this issue, I repeat the analysis by lagging the sentiment variables by 3, 6, 9, 12, 18, and 24 months, respectively. The empirical evidence in general fails to support this speculation.

two countries. Furthermore, the bearish shifts in the ESI cause upward revisions of a larger magnitude for the U.K. The indirect impacts of the ESI on the stock returns are not present since the risk-return relation in these countries is statistically insignificant.

6.4 Conclusion

Using international stock market data, in this essay, I empirically test the degree to which investor sentiment affects stock market returns and volatility, and also explore how fundamental values help to forecast stock returns. In addition, this study also examines whether a sentiment measure that primarily reflects the perceptions of the producers about the prospect of economy predicts stock price behaviour at the market level. The findings of this study are summarised as follows.

First, my analysis provides evidence that contemporaneous consumer confidence exhibits predictive power for the subsequent stock market returns, but this predictability is country-specific. High consumer confidence predicts low excess stock market returns in the U.S., France and Italy while high consumer confidence is followed by high market returns in Japan. Consumer confidence shows no explanatory power for the subsequent market returns for the U.K., Germany, Australia, and New Zealand.

Second, the shifts in consumer confidence have an impact on conditional volatility of stock returns for most of the countries except for Australia and New Zealand. The shifts in bullish sentiment and in bearish sentiment cause country-specific and asymmetric impacts on the revisions of conditional volatility. However, such impacts cannot transmit to stock returns via the risk-return link.

Third, the tests show that the lagged values of the fundamental variables are related to stock market returns. This study tests the explanatory power of the four macroeconomic variables for stock returns and finds that dividend yield and inflation rate exhibit the most prevalent influence on stock returns as opposed to the monthly change in the short-term interest rate and industrial production.

Fourth, unlike consumer confidence, the Economic Sentiment Index has no predictive capability for the stock returns at all for the European stock markets. This result implies that consumption-based asset pricing model might be more appropriate than production- or investment-based asset pricing model in describing the stock price behaviour of these countries.

Overall, the outcomes of the empirical tests suggest that the US evidence should not be simply transferred to the rest of the world when investigating the influence of sentiment on stock market activities.

Table 6.1: Descriptive statistics of sentiment and stock return

	Mean	Standard deviation	Min	Max	Autocorrelation	
					ρ_1	ρ_2
Panel A: Sentiment						
MS	91.848	9.350	63.900	112.000	0.916	0.838
CCI	101.231	22.135	47.320	144.710	0.964	0.927
UK CC	-7.712	7.628	-28.100	6.900	0.928	0.876
France CC	-17.491	8.585	-34.100	3.700	0.938	0.876
Germany CC	-11.216	8.357	-27.700	6.300	0.957	0.911
Italy CC	-10.975	5.593	-21.300	2.000	0.904	0.827
Japan	98.823	2.367	94.297	102.879	0.974	0.923
Australia	101.309	2.242	95.167	105.791	0.924	0.795
New Zealand	101.975	1.405	98.863	104.118	0.943	0.844
UK ESI	102.267	12.040	68.700	132.200	0.953	0.913
France ESI	99.926	10.122	71.700	118.500	0.971	0.933
Germany ESI	98.121	9.017	78.700	118.900	0.965	0.919
Italy ESI	101.232	19.096	-107.700	121.300	0.104	0.082
Panel B: Change in sentiment						
ΔMS	-0.041	3.801	-12.200	17.300		
ΔCCI	0.015	5.949	-23.010	21.680		
UK ΔCC	0.018	2.872	-11.200	9.600		
France ΔCC	0.016	2.968	-10.600	9.900		
Germany ΔCC	-0.025	2.395	-6.300	6.400		
Italy ΔCC	-0.043	2.419	-7.600	5.900		
Japan	0.027	0.471	-1.278	0.964		
Australia	0.023	0.729	-2.032	1.755		
New Zealand	-0.013	0.373	-1.109	0.837		
UK ΔESI	-0.005	3.709	-10.400	10.200		
France ΔESI	0.506	8.128	-4.800	114.000		
Germany ΔESI	0.559	8.831	-5.000	118.900		
Italy ΔESI	0.763	10.071	-8.900	114.800		
Panel C: Index return (%)						
S&P500	0.868	4.295	-21.763	13.177		
FTSE100	1.009	4.592	-25.946	14.530		
CAC40	0.937	5.536	-17.490	13.415		
DAX30	0.972	6.243	-25.422	21.378		
MIB30	1.091	6.016	-17.553	21.391		
NIKKEI225	0.136	5.783	-16.731	16.144		
ASX20	1.012	3.761	-8.791	9.360		
NZ50CAP	0.846	3.377	-7.507	7.099		

This table presents the summary statistics for investor sentiment level, change in investor sentiment, and index return over the sample period for each country in the sample. CC is the consumer confidence index. ESI denotes the Economic Sentiment Indicator. Δ denotes the change in the investor sentiment. Panel C reports the statistics for each market index: S&P500 (the U.S.), FTSE100 (the U.K.), CAC40 (France), DAX30 (Germany), MIB30 (Italy), NIKKEI225 (Japan), ASX20 (Australia), and NZ50CAP (New Zealand).

Table 6.2: Correlation coefficients between sentiment indicators

	US(MS)	US(CCI)	UK	France	Germany	Italy	Japan	Australia	New Zealand
Panel A: Consumer Confidence									
US(MS)	1.000	0.868	0.530	0.539	0.351	0.189	-0.086	0.263	0.538
		(<.01)	(<.01)	(<.01)	(<.01)	(0.024)	(0.278)	(<.01)	(<.01)
US(CCI)	0.868	1.000	0.594	0.683	0.550	0.291	-0.007	0.171	-0.049
	(<.01)		(<.01)	(<.01)	(<.01)	(<.01)	(0.931)	(0.025)	(0.689)
UK	0.530	0.594	1.000	0.337	0.191	-0.206	-0.007	0.280	0.491
	(<.01)	(<.01)		(<.01)	(<.01)	(0.014)	(0.933)	(<.01)	(<.01)
France	0.539	0.683	0.337	1.000	0.781	0.334	0.034	0.124	-0.073
	(<.01)	(<.01)	(<.01)		(<.01)	(<.01)	(0.664)	(0.105)	(0.551)
Germany	0.351	0.550	0.191	0.781	1.000	0.541	0.020	0.017	-0.400
	(<.01)	(<.01)	(<.01)	(<.01)		(<.01)	(0.798)	(0.820)	(<.01)
Italy	0.189	0.291	-0.206	0.334	0.541	1.000	-0.409	-0.412	-0.132
	(0.024)	(<.01)	(0.014)	(<.01)	(<.01)		(<.01)	(<.01)	(0.279)
Japan	-0.086	-0.007	-0.007	0.034	0.020	-0.409	1.000	0.124	-0.062
	(0.278)	(0.931)	(0.933)	(0.664)	(0.798)	(<.01)		(0.116)	(0.615)
Australia	0.263	0.171	0.280	0.124	0.017	-0.412	0.124	1.000	0.597
	(<.01)	(0.025)	(<.01)	(0.105)	(0.820)	(<.01)	(0.116)		(<.01)
New Zealand	0.538	-0.049	0.491	-0.073	-0.400	-0.132	-0.062	0.597	1.000
	(<.01)	(0.689)	(<.01)	(0.551)	(<.01)	(0.279)	(0.615)	(<.001)	
Panel B Economic Sentiment Indicator									
UK	0.487	0.534	1.000	0.408	0.255	0.106			
	(<.01)	(<.01)		(<.01)	(<.01)	(0.211)			
France	0.485	0.659	0.408	1.000	0.633	0.216			
	(<.01)	(<.01)	(<.01)		(<.01)	(<.01)			
Germany	0.403	0.551	0.255	0.633	1.000	0.192			
	(<.01)	(<.01)	(<.01)	(<.01)		(0.022)			
Italy	0.187	0.158	0.106	0.216	0.192	1.000			

This table shows the Pearson correlation coefficients between the investor sentiment measures of the countries in the sample. Panel A reports the outcomes using the consumer confidence index of each country as an investor sentiment measure. Panel B reports the outcomes using the Economic Sentiment Indicator as an investor sentiment measure. The figures in parentheses are the significance levels of the correlation coefficients.

Table 6.3: The U.S.: investor sentiment, excess return, and conditional volatility

Coefficients	Model 1	MS		CCI		II	
		Model 2	Model 3	Model 2	Model 3	Model 2	Model 3
α_0	-0.046***	0.130**	0.026	0.033	0.025	0.030	0.064
	(<.01)	(0.05)	(0.16)	(0.40)	(0.50)	(0.41)	(0.22)
$\log(h_t)$	-0.004***	0.007	0.004*	0.0007	0.003	-0.0002	0.010
	(<.01)	(0.24)	(0.08)	(0.85)	(0.53)	(0.94)	(0.20)
Jan_t	0.010	0.009	0.003	0.015*	-0.001	0.007	0.011
	(0.32)	(0.40)	(0.78)	(0.09)	(0.87)	(0.51)	(0.26)
Oct_t	0.002	-0.010	-0.006	0.005	-0.0009	-0.003	0.003
	(0.76)	(0.30)	(0.55)	(0.52)	(0.94)	(0.72)	(0.82)
S_{t-1}		-0.001**		-0.0003		-0.0005	
		(0.03)		(0.12)		(0.21)	
ΔS_{t-1}			0.0004		0.0004		-0.001
			(0.36)		(0.37)		(0.35)
DY_{t-1}	0.809***	0.609	0.798**	0.063	0.631*	0.255	0.725*
	(<.01)	(0.18)	(0.05)	(0.84)	(0.09)	(0.52)	(0.06)
PI_{t-2}	-0.048	-0.645*	-0.483	-0.2311	-0.533*	-0.444	-0.612*
	(0.85)	(0.06)	(0.11)	(0.47)	(0.07)	(0.26)	(0.06)
DI_{t-1}	-3.231	-2.423	-3.083	-2.423	-3.076	-7.841	-2.836
	(0.51)	(0.68)	(0.60)	(0.60)	(0.60)	(0.15)	(0.62)
DIP_{t-2}	0.148**	0.277**	0.097	0.247**	0.092	0.121	0.153*
	(0.04)	(0.02)	(0.32)	(0.03)	(0.36)	(0.27)	(0.09)
β_0	-0.0001***	0.0004	0.0004	0.0001***	0.0003	-0.0001**	0.0003*
	(<.01)	(0.18)	(0.12)	(<.01)	(0.16)	(0.04)	(0.08)
ε^2_{t-1}	0.093***	0.066	0.025	0.021**	-0.110***	0.034	-0.101***
	(<.01)	(0.65)	(0.83)	(0.02)	(<.01)	(0.67)	(<.01)
$\varepsilon^2_{t-1}\,\Gamma_{t-1}$	-0.116***	0.088	0.232	-0.032***	0.486***	0.113	0.247***
	(<.01)	(0.59)	(0.18)	(0.01)	(<.01)	(0.17)	(0.01)
h_{t-1}	0.968***	0.511*	0.496***	1.000***	0.530***	0.834***	0.559***
	(<.01)	(0.06)	(0.01)	(<.01)	(<.01)	<.01)	(<.01)
$R_{f,t}$	0.030***	0.096*	0.089	-0.001	0.085**	0.032**	0.021
	(<.01)	(0.10)	(0.05)	(0.77)	(0.05)	(0.04)	(0.50)
$(\Delta S_{t-1})^2 D_{t-1}$		-0.000005	-0.00001*	-0.000004***	<.00001	0.00001*	0.00001**
		(0.19)	(0.08)	(<.01)	(0.67)	(0.10)	(0.05)
$(\Delta S_{t-1})^2 (1-D_{t-1})$		-0.00001**	-0.0001***	-0.000002***	-0.000002	<.00001	<.00001
		(0.05)	(<.01)	(<.01)	(0.44)	(0.91)	(0.35)
Ljung-Box *Q*-statistic	6.89	9.97	8085	10.61	7.18	7.67	8.794
	(0.87)	(0.62)	(0.72)	(0.56)	(0.85)	(0.81)	(0.72)
Bera-Jarque statistic	21.07***	77.89***	78.71***	21.05***	82.10***	50.39***	50.95***
	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)

This table reports the GARCH-in-mean models, described in Equation (3.7) for the S&P500 Index. MS, CCI and II are the confidence indices compiled by University of Michigan and Consumer Conference Board and the Investors' Intelligence sentiment index, respectively. Model 1 denotes the model that does not include the effect of investor sentiment. Model 2 and Model 3 represent the models that incorporate the effect of sentiment level and changes in investor sentiment (ΔS), respectively. DY_{t-1} denotes the dividend yield. PI_{t-2} denotes the inflation rate. DI_{t-1} represents the change in the 1-month T-bill rate. PI_{t-2} is the rate of change in industrial production. Dummy variables D_{t-1} and 1- D_{t-1} are used to indicate the direction of changes towards more bullish and more bearish sentiment. The Ljung-Box *Q*-statistics tests for serial correlation in standardized residuals for lags up to twelfth order autocorrelation. Normality tests are based on the Bera-Jarque statistics. *** significant at 1% level. ** significant at 5% level. * significant at 10% level.

Table 6.4: European countries: consumer confidence index, excess return, and conditional volatility

Coefficients	UK (FTSE100)			France (CAC40)			Germany (DAX30)			Italy (MIB30)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
α_0	-0.043	-0.057***	-0.043	0.003	-0.034	-0.049	-0.077	-0.027	-0.001	0.160**	0.317***	0.277***
	(0.29)	(<.01)	(0.32)	(0.94)	(0.50)	(0.38)	(0.26)	(0.67)	(0.97)	(0.04)	(<.01)	(<.01)
$\log(h_t)$	-0.001	-0.002	-0.001	0.00007	-0.005	-0.009	-0.015	-0.004	-0.004	0.021*	0.047***	0.038***
	(0.78)	(0.18)	(0.81)	(0.99)	(0.54)	(0.25)	(0.16)	(0.74)	(0.58)	(0.09)	(<.01)	(<.01)
Jan_t	-0.007	-0.005	-0.001	0.012	0.009	0.007	0.019	0.015	0.025	0.020	0.030*	0.030*
	(0.45)	(0.60)	(0.93)	(0.38)	(0.47)	(0.55)	(0.29)	(0.52)	(0.11)	(0.27)	(0.07)	(0.07)
Oct_t	-0.007	-0.005	-0.005	0.003	-0.001	-0.003	0.003	0.009	0.008	-0.011	-0.013	-0.004
	(0.51)	(0.61)	(0.61)	(0.84)	(0.95)	(0.83)	(0.86)	(0.70)	(0.69)	(0.39)	(0.38)	(0.84)
S_{t-1}		0.001			-0.001***			-0.001			-0.002***	
		(0.13)			(0.01)			(0.13)			(<.01)	
ΔS_{t-1}			-0.001			-0.001			-0.003			0.004
			(0.67)			(0.59)			(0.17)			(0.11)
DY_{t-1}	1.738***	1.862***	1.660***	0.951	0.504	0.746	1.037	0.527	0.411	0.841	0.315	-0.641
	(<.01)	(<.01)	(<.01)	(0.20)	(0.52)	(0.43)	(0.29)	(0.60)	(0.68)	(0.28)	(0.39)	(0.43)
PI_{t-2}	-0.572***	-0.474**	-0.600***	-1.209*	-1.521***	-1.093*	-1.532**	-1.004	-1.167*	-1.824**	-2.559***	-1.111
	(0.01)	(0.02)	(<.01)	(0.06)	(0.01)	(0.09)	(0.03)	(0.22)	(0.06)	(0.02)	(<.01)	(0.11)
DI_{t-1}	2.122	-5.664	-4.374	10.653	4.738	3.137	-14.457	-16.905	4.131	-4.715	14.049	14.955
	(0.80)	(0.44)	(0.50)	(0.49)	(0.73)	(0.83)	(0.69)	(0.70)	(0.90)	(0.86)	(0.58)	(0.49)
DIP_{t-2}	-0.166	-0.035	-0.016	-0.179	0.255	-0.019	-0.328**	-0.032	-0.400***	-0.142	-0.123	-0.24
	(0.23)	(0.77)	(0.88)	(0.32)	(0.28)	(0.93)	(0.05)	(0.89)	(0.01)	(0.51)	(0.58)	(0.22)
β_0	-0.0002	0.0001	0.0005***	0.0001	0.0001	0.0002	0.0002	0.003***	0.0005	-0.0004	-0.00001	0.001
	(0.25)	(0.65)	(<.01)	(0.51)	(0.61)	(0.50)	(0.20)	(<.01)	(0.24)	(0.36)	(0.68)	(0.12)
ε^2_{t-1}	0.293**	0.262*	0.30*	0.173	0.004	-0.026	0.148	0.091	0.188	-0.102*	-0.16***	-0.045
	(0.05)	(0.09)	(0.08)	(0.17)	(0.97)	(0.72)	(0.20)	(0.53)	(0.24)	(0.06)	(<.01)	(0.21)
$\varepsilon^2_{t-1}\Gamma_{t-1}$	0.238	0.239	0.12	0.080	0.340**	0.293**	0.055	0.213	0.114	0.322**	0.249***	0.215
	(0.32)	(0.32)	(0.59)	(0.47)	(0.03)	(0.03)	(0.57)	(0.23)	(0.49)	(0.05)	(<.01)	(0.19)
h_{t-1}	0.330***	0.243***	0.28**	0.669***	0.592***	0.662***	0.768***	0.412**	0.637***	0.407	0.814***	0.480**
	(0.01)	(0.01)	(0.03)	(<.01)	(<.01)	(<.01)	(<.01)	(0.02)	(<.01)	(0.16)	(<.01)	(0.05)
$R_{f,t}$	0.156***	0.087*	0.02	0.058	0.087	0.057	-0.0001	-0.176*	-0.069	0.575	0.247***	0.130
	(<.01)	(0.10)	(0.48)	(0.26)	(0.14)	(0.18)	(0.99)	(0.08)	(0.21)	(0.05)	(<.01)	(0.20)
$(\Delta S_{t-1})^2 D_{t-1}$		-0.00001	-0.00002***		0.0001*	0.0001***		-0.000003	0.00002		-0.00003	-0.0001***
		(0.28)	(<.01)		(0.06)	(0.05)		(0.94)	(0.65)		(0.35)	(0.01)
$(\Delta S_{t-1})^2 (1-D_{t-1})$		0.00001**	0.00006**		-0.00002	-0.00002		-0.00001***	0.0001		-0.00005**	<.00001
		(0.03)	(0.04)		(0.40)	(0.40)		(<.01)	(0.21)		(0.05)	(0.86)
Ljung-Box *Q*-statistic	5.29	3.25	4.71	12.34	11.31	10.97	10.32	11.32	10.51	20.27*	15.82	21.01**
	(0.95)	(0.99)	(0.97)	(0.42)	(0.50)	(0.53)	(0.59)	(0.50)	(0.57)	(0.06)	(0.20)	(0.05)
Bera-Jarque statistic	56.27***	41.80***	43.69***	2.73	2.82	0.93	7.53**	8.63***	1.52	6.77**	20.12***	7.16**
	(<.01)	(<.01)	(<.01)	(0.25)	(0.24)	(0.63)	(0.02)	(0.01)	(0.47)	(0.03)	(<.01)	(0.03)

This table reports the GARCH-in-mean models, described in Equation (3.7) for the European markets. Model 1 denotes the model that does not include the effect of investor sentiment. Model 2 and Model 3 represent the models that incorporate the effect of sentiment level and changes in investor sentiment (ΔS), respectively. DY_{t-1} denotes the dividend yield. PI_{t-2} denotes the inflation rate. DI_{t-1} represents the change in the 1-month T-bill rate. PI_{t-2} is the rate of change in industrial production. Dummy variables D_{t-1} and 1- D_{t-1} are used to indicate the direction of changes towards more bullish and more bearish sentiment. The Ljung-Box *Q*-statistics tests for serial correlation in standardized residuals for lags up to twelfth order autocorrelation. Normality tests are based on the Bera-Jarque statistics. *** significant at 1% level. ** significant at 5% level. * significant at 10% level.

Table 6.5: Asia-Pacific countries: consumer confidence index, excess return, and conditional volatility

Coefficients	Japan (NIKKEI225)			Australia (ASX2)			New Zealand (NZ5CAP)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
α_0	0.463	-0.402	0.253	-0.130***	-0.132	-0.039	0.338***	1.521	0.302*
	(0.58)	(0.19)	(0.28)	(<.01)	(0.47)	(0.45)	(<.01)	(0.76)	(0.09)
$\log(h_t)$	0.091	0.035**	0.052	-0.013***	0.009	0.006	0.021	-0.014	0.039*
	(0.53)	(0.04)	(0.19)	(<.01)	(0.29)	(0.44)	(0.12)	(0.73)	(0.09)
Jan_t	0.012	0.005	0.006	0.002	0.005	0.004	0.021***	0.044	0.004
	(0.51)	(0.76)	(0.78)	(0.88)	(0.68)	(0.73)	(0.01)	(0.86)	(0.85)
Oct_t	-0.017	-0.021	-0.014	0.001	0.0005	-0.0003	0.050***	0.610***	0.027
	(0.41)	(0.23)	(0.48)	(0.87)	(0.96)	(0.97)	(<.01)	(<.01)	(0.53)
S_{t-1}		0.005*			0.001			-0.009	
		(0.06)			(0.59)			(0.85)	
ΔS_{t-1}			0.072***			0.0004			0.004
			(<.01)			(0.93)			(0.85)
DY_{t-1}	6.337*	9.426***	4.801*	1.509**	3.069***	2.842***	-1.592	-4.641	-0.008
	(0.10)	(<.01)	(0.07)	(0.05)	(0.01)	(0.01)	(0.18)	(0.30)	(0.99)
PI_{t-2}	0.318	0.440	0.444	-0.231*	-0.507**	-0.493***	-5.437***	-16.707	-1.201
	(0.63)	(0.46)	(0.47)	(0.06)	(0.03)	(0.03)	(<.01)	(0.13)	(0.45)
DI_{t-1}	-26.089	-58.218	-64.925	-12.019	-38.086*	-34.918*	-110.601**	-23.195	-55.149
	(0.61)	(0.33)	(0.33)	(0.47)	(0.06)	(0.09)	(0.04)	(0.94)	(0.42)
DIP_{t-2}	0.090	-0.090	0.067	-0.196	-0.216	-0.184	-0.102	-3.266***	0.227
	(0.46)	(0.46)	(0.54)	(0.16)	(0.22)	(0.27)	(0.82)	(<.01)	(0.48)
β_0	0.0006	0.004***	0.003***	0.0003***	0.001	0.0007	-0.008*	0.023	-0.0001
	(0.48)	(<.01)	(<.01)	(<.001)	(0.27)	(0.25)	(0.06)	(0.78)	(0.85)
ε^2_{t-1}	0.048	0.117	0.011	0.118	0.193	0.165	0.268	-0.093	-0..335
	(0.59)	(0.13)	(0.75)	(0.12)	(0.22)	(0.28)	(0.52)	(0.94)	(0.02)
$\varepsilon^2_{t-1}\,\Gamma_{t-1}$	-0.023	-0.111	0.038	-0.236***	-0.103	-0.087	-0.806	-0.111	0.481**
	(0.74)	(0.18)	(0.70)	(<.01)	(0.55)	(0.64)	(0.12)	(0.93)	(0.04)
h_{t-1}	0.756***	-0.843***	-0.018	0.859***	0.581**	0.574**	0.621***	-0.132	0.456
	(<.01)	(<.01)	(0.90)	(<.01)	(0.02)	(0.04)	(<.01)	(0.92)	(0.21)
$R_{f,t}$	0.0811	2.669**	-0.262	-0.021	-0.079	-0.093	1.969*	2.295	0.105*
	(0.57)	(0.02)	(0.36)	(0.32)	(0.37)	(0.33)	(0.06)	(0.88)	(0.06)
$(\Delta S_{t-1})^2\,D_{t-1}$		0.004**	-.001*		-0.000002	0.00001		0.0001	-0.0004
		(0.04)	(0.08)		(0.99)	(0.95)		(0.99)	(0.43)
$(\Delta S_{t-1})^2\,(1-D_{t-1})$		0.001	0.007**		0.0004	0.0003		-0.007	0.0006
		(0.20)	(0.05)		(0.37)	(0.41)		(0.82)	(0.48)
Ljung-Box *Q*-statistic	32.38***	6.62	8.99	7.76	11.92	12.48	7.67	108.24***	26.14***
	(<.01)	(0.88)	(0.70)	(0.80)	(0.45)	(0.41)	(0.81)	(<.01)	(0.01)
Bera-Jarque statistic	6.23**	0.82	0.92	0.99	1.61	1.98	1.33	3.54	2.71
	(0.04)	(0.66)	(0.63)	(0.61)	(0.45)	(0.37)	(0.51)	(0.17)	(0.26)

This table reports the GARCH-in-mean models, described in Equation (3.7) for the Asia-Pacific markets. Model 1 denotes the model that does not include the effect of investor sentiment. Model 2 and Model 3 represent the models that incorporate the effect of sentiment level and changes in investor sentiment (ΔS), respectively. DY_{t-1} denotes the dividend yield. PI_{t-2} denotes the inflation rate. DI_{t-1} represents the change in the 1-month T-bill rate. PI_{t-2} is the rate of change in industrial production. Dummy variables D_{t-1} and $1- D_{t-1}$ are used to indicate the direction of changes towards more bullish and more bearish sentiment. The Ljung-Box *Q*-statistics tests for serial correlation in standardized residuals for lags up to twelfth order autocorrelation. Normality tests are based on the Bera-Jarque statistics. *** significant at 1% level. ** significant at 5% level. * significant at 10% level.

Table 6.6: European countries: Economic Sentiment Index, excess return, and conditional volatility

Coefficients	UK		France		Germany		Italy	
	Model 2	Model 3	Model 2	Model 3	Model 2	Model 3	Model 2	Model 3
α_0	-0.019	-0.070**	0.056	0.006	-0.034	-0.045	0.094	0.083
	(0.61)	(0.03)	(0.45)	(0.87)	(0.76)	(0.40)	(0.06)	(0.11)
$\log(h_t)$	-0.005	-0.005	-0.002	0.0004	-0.010	-0.010	0.013	0.011
	(0.03)	(0.18)	(0.74)	(0.92)	(0.35)	(0.29)	(0.08)	(0.14)
Jan_t	-0.010	-0.007	0.011	0.013	0.020	0.020	0.014	0.006
	(0.200	(0.41)	(0.39)	(0.29)	(0.28)	(0.30)	(0.49)	(0.68)
Oct_t	(-0.003	-0.004	-0.003	-0.001	0.004	0.004	-0.022**	-0.022*
	(0.66)	(0.65)	(0.85)	(0.92)	(0.83)	(0.84)	(0.03)	(0.06)
S_{t-1}	-0.005		-0.001		-0.0005		-0.0001	
	(0.11)		(0.28)		(0.95)		(0.89)	
ΔS_{t-1}		-0.001		-0.0005		0.001		-0.001
		(0.15)		(0.82)		(0.70)		(0.37)
DY_{t-1}	1.635***	1.712***	0.785	0.991	0.839	1.002	0.688	0.682
	(<.01)	(<.01)	(0.32)	(0.23)	(0.40)	(0.34)	(0.18)	(0.06)
PI_{t-2}	-0.508**	-0.464**	-1.376***	-1.342***	-1.492*	-1.505*	-1.001**	-0.957**
	(0.03)	(0.05)	(0.01)	(0.01)	(0.07)	(0.07)	(0.03)	(0.03)
DI_{t-1}	11.396	4.443	14.214	11.222	-24.231	-24.192	0.069	0.083*
	(0.15)	(0.47)	(0.29)	(0.42)	(0.49)	(0.48)	(0.15)	(0.08)
DIP_{t-2}	0.022	-0.092	0.119	-.053	-0.308	-0.289	-0.085	-0.107
	(0.89)	(0.46)	(0.64)	(0.80)	(0.15)	(0.13)	(0.46)	(0.32)
β_0	-0.005***	-0.0003**	0.0001	0.0001	0.0003	0.0002	0.0001	0.0001
	(<.01)	(0.05)	(0.70)	(0.61)	(0.24)	(0.24)	(0.51)	(0.51)
ε^2_{t-1}	0.384***	0.403***	-0.090	-0.100	0.107	0.108	-0.171***	-0.192***
	(<.01)	(0.01)	(0.42)	(0.31)	(0.26)	(0.25)	(<.01)	(<.01)
$\varepsilon^2_{t-1}\Gamma_{t-1}$	-0.024	0.100	0.344	0.351	0.090	0.087	0.532***	0.562***
	(0.87)	(0.67)	(0.02)	(0.02)	(0.34)	(0.35)	(<.01)	(0.01)
h_{t-1}	0.487***	0.308***	0.565***	0.550***	0.797***	0.798***	0.628***	0.636***
	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)
$R_{f,t}$	0.092***	0.104**	0.072	0.069	0.018	0.021	0.090	0.075
	(<.01)	(0.02)	(0.17)	(0.22)	(0.72)	(0.65)	(0.25)	(0.34)
$(\Delta S_{t-1})^2 D_{t-1}$	0.00002**	0.00002	0.0002***	0.0002***	-0.00005	-0.00005	0.00001	0.00002
	(0.02)	(0.21)	(0.01)	(<.01)	(0.37)	(0.40)	(0.56)	(0.43)
$(\Delta S_{t-1})^2 (1-D_{t-1})$	0.00003***	0.00004***	0.00005	0.0001	-0.00005	-0.00005	0.00002	0.00002
	(<.01)	(<.01)	(0.31)	(0.29)	(0.17)	(0.19)	(0.51)	(0.51)
Ljung-Box *Q*-statistic	7.73	5.67	10.55	10.59	10.05	10.72	11.61	14.39
	(0.81)	(0.93)	(0.57)	(0.56)	(0.61)	(0.55)	(0.48)	(0.28)
Bera-Jarque statistic	10.22***	13.79***	2.74	1.48	4.03	4.50	2.13	2.65
	(<.01)	(<.01)	(0.25)	(0.48)	(0.13)	(0.11)	(0.35)	(0.27)

This table reports the GARCH-in-mean models, described in Equation (3.7) for the European markets using the Economic Sentiment Indicator to proxy for investor sentiment. Model 2 and Model 3 represent the models that incorporate the effect of sentiment level and changes in investor sentiment (ΔS), respectively. DY_{t-1} denotes the dividend yield. PI_{t-2} denotes the inflation rate. DI_{t-1} represents the change in the 1-month T-bill rate. PI_{t-2} is the rate of change in industrial production. Dummy variables D_{t-1} and 1- D_{t-1} are used to indicate the direction of changes towards more bullish and more bearish sentiment. The Ljung-Box *Q*-statistics tests for serial correlation in standardized residuals for lags up to twelfth order autocorrelation. Normality tests are based on the Bera-Jarque statistics. *** significant at 1% level. ** significant at 5% level. * significant at 10% level.

CHAPTER 7 CONCLUSION

7.1 Concluding Remarks

This thesis has examined various roles of investor sentiment in stock market in an asset pricing context. Despite the existing literature provides extensive evidence that investor sentiment shows explanatory power for stock price, no studies explore the roles that investor sentiment plays in standard asset pricing models. To fill this gap, at the firm level, this thesis examines two distinctive roles that investor sentiment can potentially play in asset pricing. In the first essay, I adopt investor sentiment as a conditioning variable in the information set for various asset pricing models and assess its ability to capture the size, value, and momentum effects. In the second essay, I construct a risk factor on the basis of the sensitivity of stock returns to investor sentiment. Motivated by the noise trader risk model (DSSW, 1990) and the cross-sectional effect of investor sentiment on stock returns (Baker and Wurger, 2006), I then ask two questions. First, I ask whether the sentiment-based factor is priced so that investors would require compensation for bearing noise trader risk. Second, I ask whether the sentiment risk factor, either standing alone or working with other risk factors, helps to explain the financial market anomalies. At the market level, the third essay investigates two vital impacts of investor sentiment on stock price behaviour as described in DSSW (1990). I ask whether investor sentiment affects stock volatility and returns in international stock markets.

The most important contribution of this thesis is that it shows leaving out behavioural factors from the traditional financial theory could face the risk of failing to provide a full picture of stock price behaviour. The assumptions underlying the EMH have long been challenged by behavioural financial economists in the past decades. They argue that not all investors are fully rational when making investment decisions. Also, market is not efficient. Mispricing occurs when investors suffer systematic biases and there are limits to arbitrage due to the risk-averse nature of arbitrageurs. As a result, noise trader could have significant effects on stock market. It is natural to conjecture that including a behavioural or psychological component in asset pricing models may help to supplement the traditional finance theory in describing stock price behaviour.

This thesis consists of three interrelated essays on the roles of investor sentiment in asset pricing. The first two essays provide empirical evidence that incorporating investor sentiment into traditional asset pricing models actually helps to enhance the performance of the pricing models in describing stock returns and capturing the anomalies. The identified ability of investor sentiment in explaining the anomalies reveals that, to some extent, the causes of anomalies are closely related to noise traders' behaviour. This thesis is the first that presents a behavioural model by considering investor sentiment as a conditioning variable or a risk factor in the time-varying asset pricing models in order to directly test the relationship between investor sentiment and the anomalies. This thesis also contributes the literature by proposing the new roles that an investor sentiment indicator can play when investigating its explanatory power for stock prices. By showing that investor sentiment exhibits ability to capture the anomalies when playing different roles in the asset pricing models, this thesis also sheds some light on new methodological directions of how consumer confidence or investor sentiment indices could be used in analyzing stock price behaviour. Using investor sentiment as a conditioning variable or a risk factor in asset pricing models provides a new direction of the method that researchers can use to study investor sentiment and stock market relationships.

The third essay explores the role that investor sentiment plays in determining stock volatility and returns at the market level in an international context. Using the stock market data of eight industrialised countries, the findings of the third essay indicate that one cannot simply apply the U.S. evidence to other international markets when examining the role of investor sentiment in stock market. Investor sentiment actually plays a different role in affecting stock market volatility and returns across countries. Investor sentiment could significantly affect both stock volatility and returns in some counties while it could have very limited influence on the stock markets in other countries.

7.2 Summary of Findings

The primary focus of this thesis is twofold. First, it evaluates various roles of investor sentiment in asset pricing by testing its ability to explain cross-sectional stock returns and capture the financial market anomalies using a two-pass regression framework (Avramov and Chordia, 2006). Second, it investigates to what extent investor sentiment affects stock volatility and returns in various international stock markets using the GARCH-M models.

The empirical analysis of the thesis is presented in Chapters 4 through 6. Chapters 4 and 5 examine the roles of investor sentiment as an information variable or a risk factor in various time-varying pricing models. Chapter 4 relaxes the static nature of the factor loadings of asset pricing models by allowing them to be time-varying with the investor sentiment, default spread, and firm-specific size and book-to-market ratio. Several specifications of conditional asset pricing models are discussed based on the information variables and risk factors considered. Chapter 4 addresses two questions. First, it asks whether conditional models outperform unconditional models. Second, it assesses the pricing performance of the conditional asset pricing models in capturing the financial market anomalies, with an emphasis on the conditional models that includes investor sentiment as an information variable.

The following summarises the findings of Chapter 4. Overall, the results suggest that the conditional asset pricing models outperform the unconditional models in describing the dynamic expected stock returns. The superior performance of the conditional models is manifest in their explanatory power for the conditional alphas, the capability in capturing the financial market anomalies, and the magnitude of the adjusted R-square of the overall model. Furthermore, the results support my conjecture that when investor sentiment plays as an information variable in the examined asset pricing models these models can often capture the financial market anomalies. Specifically, first, the conditional models with the Fama-French factors time-varying with investor sentiment can often capture the size and value effects. Second, the conditional models that contain the Pastor-Stambaugh liquidity factor and the Fama-French factors can even explain the momentum effect when the factor loadings are conditional on investor sentiment and default spread. Finally, the conditional versions of the models that contain the momentum factor and the Fama-French factors reduce the impacts of liquidity and momentum on the risk-adjusted returns.

Continuing the research questions addressed in Chapter 4, Chapter 5 again explores the pricing ability of investor sentiment for individual stocks but from a different angle with respect to the role of investor sentiment. In the analysis of Chapter 5, investor sentiment plays a role as a risk factor in the same time-varying asset pricing models assessed in Chapter 4. I first construct a factor on the basis of the sensitivity of stock returns to the raw investor sentiment measure. I then employ the two-stage regression model proposed by Fama and MacBeth (1973) to test whether investors request premiums for bearing the noise trader risk. The results show that the stocks with the highest sentiment beta outperform those with the lowest sentiment beta by approximately 0.8% per month. This evidence is robust regardless of the raw investor sentiment indices used when constructing the sentiment factor. The results also indicate a statistically significant risk premium related to the noise trader risk. The estimated risk premium of the investor sentiment risk factor is close to 6% annually. This finding formally quantifies the magnitude of noise trader risk as suggested by DSSW (1990) and Shleifer and Summers (1990).

Chapter 5 also finds that stocks with small capitalisation, high book-to-market ratio, high turnover, and superior past performance tend to be more responsive to investor sentiment. High sentiment beta stocks also earn higher average returns than low sentiment beta stocks. This finding supports the cross-sectional effect of investor sentiment on stock returns documented by Baker and Wurgler (2006).

After providing the empirical evidence that the constructed sentiment factor is priced, I proceed to assess whether this sentiment factor, either alone or with other traditional risk factors, helps to explain the financial market anomalies discussed in Chapter 4. The findings are summarised as follows.

First, the presence of the sentiment risk factor in the asset pricing models significantly reduces the impact of size on the cross section of the stock returns. The pricing ability of the sentiment risk factor sustains even in the unconditional versions of the asset pricing models. The single sentiment factor model outperforms the unconditional versions of the traditional models such as the CAPM and Fama-French model in explaining the size effect, suggesting that noise trading is closely associated with the size effect. Second, when the sentiment factor is present along with other risk factors in the constant beta models, these models can further successfully capture the size effect. It is worth noting that my sentiment-augmented models demonstrate strong explanatory power for the size effect than the corresponding results of Avramov and Chordia (2006) when the same sample firms (NYSE, AMEX, and NASDAQ) are considered. The models proposed by Avramov and Chordia (2006) who do not consider investor sentiment in the first-pass regression generally fail to capture the size effect while the sentiment-augmented models discussed in Chapter 5 of this thesis shows pricing ability for the size effect.

Second, Chapter 5 shows that the short-term momentum effect dramatically reduces to a low level when the sentiment factor and Fama-French factors both appear in the time-varying models in which the factor loadings are conditional on the default spread. This finding, again, demonstrates the superiority of the sentiment-augmented models in capturing the financial market anomalies over the model of Avramov and Chordia (2006) which shows absolutely no capability in capturing the momentum effect on the risk-adjusted returns.

Third, the results show that the sentiment-augmented Fama-French-based models can generally successfully explain the size and value effects if the factor loadings are conditional on the default spread and firm-specific characteristics.

Overall, the findings of Chapters 4 and 5 indicate that investor sentiment actually helps to explain the financial market anomalies. Compared to other risk factors, the investor sentiment factor demonstrates notable ability in explaining the financial market anomalies, particularly the small and momentum effects, suggesting that the behaviour of noise traders could be one of the primary causes of these two anomalies.

In Chapter 6, this thesis turns its focus to the impact of investor sentiment on stock volatility and returns at the market level and explores this relationship beyond the U.S. market. The analysis of Chapter 6 also distinguishes itself from the framework of Lee, Jiang, and Indro (2002) in that it controls for the macroeconomic variables when examining the investor sentiment effect on stock returns and allows the investor sentiment measure to lag one period as opposed to stock returns. The empirical results of Chapter 6 show that the impacts of investor sentiment on stock volatility and returns are actually country specific. In general, consistent with the literature, the study finds high investor sentiment level is followed by low excess market returns for most of the countries such as the U.S., France, and Italy, with Japan as the only exception where there exists a positive sentiment-return relation. Investor sentiment has no significant effect on stock returns for the rest of the sample countries examined. Chapter 6 also documents that investor sentiment plays an important role in the formation of the conditional volatility of stock returns at the market level. Similar to the direct effect of sentiment on returns, its impact on stock volatility is also country specific. Investor sentiment changes the stock volatility for most of the countries examined except for Australia and New Zealand.

The tests of the relationship between the macroeconomic variables and market returns indicate that dividend yield and inflation rate have strong predictive power for the subsequent stock returns for most of the countries. As a result, it is important to filter out this inherent rational component regarding fundamental information from the investor sentiment measures in order to obtain the irrational investor sentiment component in the analysis of sentiment-return relation. Finally, unlike the significant effect of consumer confidence on stock returns for the European countries, the Economic Sentiment Indices show no predictive power for the subsequent stock returns, suggesting that production- or investment-based asset pricing theory is less likely to appropriately the stock price behaviour for these countries compared to the consumption-based theory.

Overall, the results of this thesis show that investor sentiment plays an important role in determining not only stock returns but also volatility of returns. Investor sentiment helps to explain the financial market anomalies when it is considered in the traditional asset pricing models such as the CAPM and Fama-French model. The influence of investor sentiment on stock price behaviour varies across countries. One should avoid applying the U.S. evidence to other countries.

7.3 Possible Future Research

Despite enormous effort has been devoted to understanding the roles that investor sentiment could possibly plays in stock market, this thesis does not address several interesting issues due to data availability and time constraints. Further research in the following directions is worth pursuing in order to enhance our understanding of the roles of investor sentiment plays in asset pricing.

First, this thesis provides empirical evidence that using investor sentiment individually as conditioning information or a risk factor helps to capture the financial market anomalies. It would be interesting to study whether such explanatory power could further improve if the roles of investor sentiment as information variable and a risk factor are both incorporated in asset pricing model.

Second, the thesis constructs the investor sentiment risk factor on the basis of the absolute value of the sentiment beta of individual stock returns. Alternatively, the sentiment risk factor could be constructed based on the raw value of the sentiment beta so that the sign of the sentiment beta is considered. It would be worth examining whether an alternative sentiment factor constructed in this manner is also priced and exhibits similar explanatory power as the one used in the thesis.

Third, both theoretical and empirical studies claim that noise trader risk deters rational investors from betting against noise traders, and hence investor sentiment drives stock price away from fundamental value. Further research could concentrate on how the sentiment-induced pricing error is related to the investor sentiment risk factor developed in this thesis. Relevant questions include whether high sentiment beta stocks tend are hard to arbitrage due to higher arbitrage costs and lower institutional ownership.

Fourth, despite this thesis has found that high sentiment level is followed by lower subsequent stock returns, it does not specifically explore any further more complicated investment strategies that could be formed on the basis of investor sentiment. Future research could enquire whether any profitable investment strategies exist either from the perspective of individual investors or institutional investors.

Fifth, most existing studies on investor sentiment focus on shorter investment horizons. It would be worth investigating the long-run relationship between investor sentiment, fundamental value, and stock price. A similar issue that future research may address is whether investor sentiment could also explain return reversals (De Bondt and Thaler, 1985).

Finally, this thesis shows that the sentiment-volatility-return relation is actually country specific; however, it does not further discuss what factors lead to this variation. Further research on what factors determine the extent to which investor sentiment affects stock price behaviour would help to improve our understanding of the interactive effects of these factors with the sentiment-volatility-return relation. For example, a question worth asking is whether investor sentiment would have larger impacts on stock volatility and returns if the market participation of individual investors is relatively high as opposed to institutional investors; or domestic investors dominate foreign investors in numbers within a stock market.

References

Akhtar, S., Faff, R., Oliver, B., Subrahmanyam, A., 2011. The power of bad: The negativity bias in Australian consumer sentiment announcements on stock returns. Journal of Banking and Finance 35, 1239-1249.

Alexander, G. J., Sharpe, W. F., Bailey, J. V., 2001. Fundamentals of Investments, 3rd edition. Upper Saddle River, NJ: Prentice Hall.

Ali, A., Huang, L, Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. Journal of Financial Economics 69, 355-373.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics 17, 223-249.

Avramov, D., Chordia, T., 2006. Asset pricing models and financial market anomalies. Review of Financial Studies 19, 1001-1040.

Baker, M., Stein, J. C., 2004. Market liquidity as a sentiment indicator. Journal of Financial Market 7, 271-299.

Baker, M., Wurgler, J., 2006. Investor sentiment and cross-section of stock returns. Journal of Finance 61, 1645-1680.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. Journal of Economic Perspectives 21, 129-152.

Bansal, R., Dittmar, R. F., Lundblad, C. T., 2005. Consumption, dividends, and the cross section of equity returns. Journal of Finance 60, 1639-1672.

Banz, R., 1981. The relation between return and market value of common stocks. Journal of Financial Economics 9, 3-18.

Basu, S., 1983. The relationship between earnings yield, market value and return for NYSE common stocks: further evidence. Journal of Financial Economics 12, 129-156.

Barberis, N., Shleifer, A., Vishny, R. W., 1998, A model of investor sentiment, Journal of Financial Economics 49, 307-343.

Barberis, N., Thaler, R., 2003. A survey of behavioural finance. Handbook of the Economics of Finance. Elsevier Science B.V.

Basu, S., 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient hypothesis. Journal of Finance 34, 663-682.

Bauer, R., Cosemans, M., Schotman, P., 2010. Conditional asset pricing and stock market anomalies. European Financial Management, 16, 165-190.

Black, F., 1986. Noise. Journal of Finance 41, 529-543.

Bollerslev, T., 2008. Glossary to ARCH (GARCH), in Festschrift in Honor of Robert F. Engle, edited by Tim Bollerslev, Jeffry R. Russell and Mark Watson.

Braun, P., Nelson, D., Sunier, A., 1995. Good news, bad news, volatility, and betas. Journal of Finance 50, 1575–1603.

Brav, A., Heaton, J. B., Li, S., 2010. The limits of the limits of arbitrage. Review of Finance 14, 157-187.

Breen, W., Glosten, L. R., Jagannathan, R., 1989. Economic significance of predictable variations in stock index returns. Journal of Finance 44, 1177-1189.

Brown, G. W., 1999. Volatility, sentiment, and noise traders. Financial Analysts Journal 55, 82-90.

Brown, G., Cliff, M., 2004. Investor sentiment and the near-term stock market, Journal of Financial Economics 11, 1-27.

Brown, G. W., Cliff, M. T., 2005. Investor sentiment and asset valuation. Journal of Business 78, 405-440.

Campbell, J. Y., 1987. Stock returns and the term structure. Journal of Financial Economics 18, 373-399.

Campbell, J. Y., Hentschel, L., 1992. No news is good news: An asymmetric model of changing volatility in stock returns. Journal of Financial Economics 31, 281-318.

Campbell, J. Y., Kyle, A. S., 1993. Smart money, noise trading, and stock price behaviour. Review of Economic Studies 60, 1-34.

Campbell, J. Y., Lo, A. W., Mackinlay, A. C., 1997. The Econometrics of Financial Markets. Princeton University Press.

CFTC-SEC, 2010. Preliminary Findings Regarding the Market Events of May 6 2010. US Commodity Futures Trading Commission, and U.S. Securities and Exchange Commission.

Chan, K. C., Chen, N., Hsieh., D. A., 1985. An explaratory investigation of the fim size effect. Journal of Financial Economics 14, 451-471.

Chan, K., Hamao, Y., Lakonishok, J., 1991. Fundamentals and stock returns in Japan. Journal of Finance 46, 1739-1764.

Chan, K., Hameed, A., Tong, W., 2000. Profitability of momentum strategies in the international equity markets. Journal of Financial and Quantitative Analysis, 35, 153-172.

Chan, K. C., Karolyi, G. A., Stulz, R. M., 1992. Global financial markets and the risk premium on the U.S. equity. Journal of Financial Economics 32, 137-167.

Charoenrook, A., 2005. Does Sentiment Matter?. Working Paper, Vanderbilt University.

Chen, N., Roll, Richard, Ross., S., 1986. Economic forces and the stock market. Journal of Business 59, 383-403.

Chopra, N., Lee, C., Shleifer, A., and Thaler, R., 1993. Yes, discounts on closed-end funds are a sentiment index, Journal of Finance 48, 801-808.

Chordia, T., Shivakuman L., 2002. Momentum, business cycle, and time-varying expected returns. Journal of Finance 57, 985-1020.

Christie, A. A., Hertzel, M., 1981. Capital asset pricing anomalies: Size and other correlations. Unpublished manuscript, Rochester, N. Y.: University of Rochester.

Chuang, W.-I., Lee, B.-S., 2006. An empirical evaluation of the overconfidence hypothesis. Journal of Banking and Finance 30, 2489-2515.

Cochrane, J. H., 1991. Production-based asset pricing and the link between stock returns and economic fluctuations. Journal of Finance 46, 209-237.

Cochrane, J. H., 1996. A cross-sectional test of an investment-based asset pricing model. Journal of Political Economy 104, 572-621.

Cochrane, J. H., 2005. Asset Pricing. Princeton, NJ: Princeton University Press.

Conrad, J., Kaul, G., 1998. An anatomy of trading strategies. Review of Financial Studies 11, 489-519.

De Bondt, W. F. M. Thaler, R., 1985. Does the stock market overreact? Journal of Finance, 40, 793-805.

De Long, J., Shleifer A., Summers L., Waldmann, R., 1990. Noise trader risk in financial markets. Journal of Political Economy 98, 703-738.

Deuskar, P., 2008. Market structure and effect of sentiment liquidity. Working Paper, University of Illinois at Urbana-Champaign.

Dijk, M. A., 2011. Is size dead? A review of the size effect in equity returns. Journal of Banking and Finance 35, 3263-3274.

Fama, E. F., 1965. The behaviour of stock market prices. Journal of Business 38, 34-105.

Fama, E. F., 1970. Efficient capital markets: A review of theory and empirical work. Journal of Finance 25, 383-417.

Fama, E. F., Schwert, G. W., 1977. Asset returns and inflation. Journal of Financial Economics 5, 115-146.

Fama E. F., French, K., 1988. Dividend yields and expected stock returns. Journal of Finance 22, 3-25.

Fama E. F., French, K., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427-465.

Fama, E., French K., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama E. F., French, K., 1998. Value vs. growth: The international evidence. Journal of Finance 53, 1975-1999.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607-636.

Ferson, W., Harvey, C, R., 1991. The variation f economic risk premiums. Journal of Political Economy 99,385-415.

Ferson, W., Kandel, S., Stambaugh, R., 1987. Tests of asset pricing with time-varying expected risk premiums and market betas. Journal of Finance 42, 201-220.

Ferson, W.E., and Schadt, R.W., 1996, Measuring fund strategy and performance in changing economic conditions, Journal of Finance 51, 425-462.

Fisher, K. L., Statman, M., 2000. Investor sentiment and stock returns. Financial Analysts Journal (March/April), 16-23.

Fisher, K. L., Statman, M., 2003. Consumer confidence and stock returns. Journal of Portfolio Management Fall, 115-127.

French, K. R., Schwert, G. W., Stambaugh, R. E., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3-29.

Friedman, M., 1953. The case for flexible exchange rates. Essays in Positive Economics. Chicago: University of Chicago Press.

Ghysels, E., 1998. On stable factor structures in the pricing of risk: Do time-varying betas help or hurt? Journal of Finance 53, 549-573.

Gibbons, M. R., Ferson, W., 1985. Testing asset pricing models changing expectations and nobeservable market portfolio. Journal of financial Economics 14, 217-236.

Glosten, L. R., Jagannathan, R., Runkle, D. E., 1993. On the relation between the expected value and the volatitlity of the nominal excess return on stocks. Journal of Finance 48, 1779-1801.

Glushkov, D., 2006. Investor sentiment, firm characteristics, and institutional behaviour. Working paper. University of Texas at Austin.

Gomes, J., Kogan, L., and Zhang, L., 2003. Equilibrium cross-section of returns. Journal of Political Economy 111, 693-732.

Griffin, J. M., Ji, S., Martin, S., 2003. Momentum investing and business cycle risk: Evidence from pole to pole. Journal of Finance 63, 2515-2547.

Griffin, J. M., Ji, S., Martin, S., 2003. . Global momentum strategies: A portfolio perspective. Journal of Portfolio Management (Winter), 23-39.

Guo, H., 2006. Time-varying risk premia and the cross section of stock returns. Journal of Banking and Finance 31, 2087-2107.

Hansen, L., Richard, S. F., 1987. The role of conditioning information in deducing testable restrictions implied by dynamic asset pricing models. Econometrica 55, 587-613.

Harvey, C., 1989. Time-varying conditional covariances in tests of asset pricing models. Journal of Financial Economics 24, 289-317.

Hibbert, A. M., Daigler, R. T., Dupoyet, B., 2008. A behavioural explanation for the negative asymmetric return-volatility relation. Journal of Banking and Finance 32, 2254-2266.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading and overreaction in asset markets. Journal of Finance 54, 2143-2184.

Hong, H., Stein, J. C., 2007. Disagreement and the stock market. Journal of Economic Perspectives 21, 109-128.

Horowitz, J. L., Loughran, T., Savin, N. E. , 2000.The disappearing size effect. Research in Economics 54, 83-100.

Hwang, Y.-S., Min, H.-G., McDonald, J.A., Kim, H., Kim, B.-H., 2010. Using the credit spread as an option-risk factor: Size and value effects in CAPM. Journal of Banking and Finance34, 2995-3009.

Jansen, W. J., Nahuis, N. J., 2003. The stock market and consumer evidence: European evidence. Economics Letters 79, 89-98.

Jagannathan, R., Wang, Z., 1996. The conditional CAPM and the cross-section of expected returns. Journal of Finance 51, 3-53.

Jagannathan, R., Wang, Z., 1998. An asymptotic theory for estimating beta-pricing models using cross-sectional regression. Journal of Finance 53, 1285-1309.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency, Journal of Finance 48, 65-91.

Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. Journal of Finance 56, 699-720.

Jensen, M. C., 1978. Some anomalous evidence regarding market efficiency. Journal of Financial Economics 6, 95-101.

Jones, C., Lamont, O., 2002. Short-sale constraints and stock returns, Journal of Financial Economics 66, 207-239.

Kalotay, E., Gray, P., Sin, S., 2007. Consumer expectations and short-horizon return predictability. Journal of Banking and Finance 31, 3102-3124.

Kelly, M., 1997. Do noise traders influence stock prices. Journal of Money, Credit, and Banking 29, 351-363.

Kleidon, A. W., 1986. Anomalies in financial economics: Blueprint for change? Journal of Business, 59, 469-499.

Kleim, D. B., 1983. Size-related anomalies and stock return seasonality: Further empirical evidence. Journal of Financial Economics 12, 13-32.

Kumar, A., Lee., M.C., 2006. Retail investor sentiment and return comovements. Journal of Finance 61, 2451-2486.

Kurov, A., 2008. Investor sentiment, trading behaviour and informational efficiency in index futures markets. The Financial Review 43, 107-127.

La Porta, R., Lakonishok, J., Shleifer, A., Vishny, R., 1997. Good news for value stocks. Journal of Finance 52, 859–873.

Lakonishok, J., Shleifer, A., Vishy, R., 1994. Contrarian investment, extrapolation and risk. Journal of Finance 49, 1541-1578.

Lee, C., Shliefer, A., Thaler, R. H., 1991. Investor sentiment and the closed-end fund puzzle. Journal of Finance 46, 75-109.

Lee, W. Y., Jiang, C. X., Indro, D. C., 2002. Stock market volatility, excess returns and the role of investor sentiment. Journal of Banking and Finance 26, 2277-2299.

Lemmon, M., Portniaguina, E., 2006. Consumer confidence and asset prices: Some empirical evidence. Review of Financial Studies 19, 1499-1529.

Leroy, S. F., Porter, R. D., 1981. Stock price volatility: Tests based on implied variance bounds. Econometrica 49, 97-113.

Leory S. F., Porter R. D., 1981. The present-value relation: Tests based on implied variance bounds. Econometrica, 3, 555-574.

Lesmond, D.A., Schill, M.J., Zhou, C., 2004. The illusory nature of momentum profits. Journal of Financial Economics 71, 349–380.

Lettau, M., Ludvigson, S., 2001. Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying. Journal of Political Economy 109, 1238-1287.

Lewellen, J., 1999. The time-series relations among expected return, risk, and book-to-market. Journal of Financial Economics 54, 1999.

Lewellen, J., Nagel, S., Shanken, J., 2008. A skeptical appraisal of asset-pricing tests. Working paper, Dartmouth College, Stanford University, and Emory University.

Li, G., 2007. Time-varying risk aversion and asset prices. Journal of Banking and Finance 31, 243-257.

Li, X., Miffre, J., Brooks, C., O'Sullivan, N., 2008. Momentum profits and time-varying unsystematic risk. Journal of Banking and Finance 32, 541-558.

Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital Budgets. Review of Economics and Statistics 47, 13-37.

Liu, S., 2006. Investor sentiment and stock market liquidity. Working Paper, University of Texas at Austin.

Moskowitz, T.J., Grinblatt, M., 1999. Do industries explain momentum? Journal of Finance 54,1249-1290.

Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics 78, 277-309.

Neal, R, and Wheatley, M. S., 1998. Do measures of investor sentiment predict returns? Journal of Financial and Quantitative Analysis 33, 523-547.

Nelson, D. B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59, 347-370.

Otoo, M. W., 1999. Consumer sentiment and the stock market. Finance and Economic Discussion Paper 1999-60. Federal Reserve Board, Washington, D. C.

Pagan, A. R., Hong, Y. S., 1991. Nonparametric estimation and the risk premium, in: Barnett, W. A., Powell, J., Tauchen, G. E. (Eds.), Nonparametric and Semiparametric Methods in Econometrics and Statistics. Cambridge University Press, Cambridge, pp. 51-75.

Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642-685.

Pesaran, M. H., Timmermann, A., 1994. Forecasting stock returns. Journal of Forecasting 13, 335-367.

Petkova, R., 2006. Do the Fama-French factors proxy for innovations in predictive variables? Journal of Finance 61, 581-612.

Pettengill, G.N., Sundaram, S., Mathur, I., 2002. Payment for risk: Constant beta vs. dual-beta models. The Financial Review 37, 123-136.

Post, T., Vliet, P., 2006. Downside risk and asset pricing. Journal of Banking and Finance 30, 823-849.

Reinganum, M. R., 1981. Misspecification of capital asset pricing: Empirical anomalies based on earnings yields and market values. Journal of Financial Economics 9, 19-46.

Roll, R., 1970. The Behaviour of Interest Rates: An Application of the Efficient Market Model to U.S. Treasury Bills (New York: Basic Books).

Rouwenhorst, K.G., 1998. International momentum strategies. Journal of Finance 53, 267-284.

Samuelson, P. A., 1965. Proof that properly anticipated prices fluctuate randomly. Industrial Management Review 6, 41-49.

Schmeling, M., 2009. Investor sentiment and stock returns: Some international evidence. Journal of Empirical Finance 16, 394-408.

Shanken, J., 1990. Intertemporal asset pricing: An empirical investigation. Journal of Econometrics 45, 99-120.

Shanken, J., 1992. On the estimation of beta-pricing models. Review of Financial Studies 5, 1-33.

Sharpe, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance 19, 425-442.

Shiller, R. J., 1981. Do stock prices move too much to be justified by subsequent changes in dividends? American Economic Review 71, 421-436.

Shiller, R. J., 1984. Stock prices and social dynamics. Brooking Papers on Economic Activity 2, 457-498.

Shleifer, A., Summers, L. H., 1990. The noise trader approach to finance. Journal of Economic Perspectives 4, 19-33.

Shleifer, A., Vishny, R., 1997. The limits of arbitrage. Journal of Finance 52, 35–55.

Shleifer, A., Summers, L. H., 1990. The noise trader approach to finance. Journal of economic perspectives 4, 10-33.

Skinner, D., Sloan, R., 2002. Earnings surprises, growth expectations, and stock returns, or, don't let an earnings torpedo sink your portfolio. Review of Accounting Studies 7, 289-312.

Subrahmanyam A., 2007. Behavioural finance: A review and synthesis. European Financial Management 14, 12-29.

Swaminathan, B., 1996. Time-varying expected small firm returns and closed-end fund discounts. Review of Financial Studies 9, 845-887.

Turner, C. M., Startz, R. Nelson, C. R., 1989. A Markov model of heteroskedasticity, risk, and learning in the stock market. Journal of Financial Economics 25, 3-22.

Vassalou, M., Xing, Y., 2004. Default risk in equity returns. Journal of Finance 59, 831-868.

Verma, R., Verma, P., 2007. Noise trading and stock market volatility. Journal of Multinational Financial Management 17, 231-243.

Wang, K.Q., 2003. Asset pricing with conditional information: A new test. Journal of Finance 58, 161–195.

Wang, Y. H., Keswani, A., Taylor, S. J., 2006. The relationships between sentiment, returns and volatility. International Journal of Forecasting 22, 109-123.

Wu, X., 2002. A conditional multifactor model of return momentum. Journal of Banking and Finance 26, 1675–1696.

Yu, J., Yuan, Y., 2011. Investor sentiment and the mean–variance relation. Journal of Financial Economics 100, 367-381.

Zweig, M. E., 1973. An investor expectations stock price predictive model using closed-end fund. Journal of Finance 28, 67-78.