Investor Sentiment and Cross-Sectional Stock Returns

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Abstract

This thesis consists of three essays on investor sentiment and the cross-section of stock returns.

The first essay extends Delong, Shleifer, Summer and Waldmann's (1990) noise trader risk model into a model with multiple risky assets to show the asymmetric effect of sentiment in the cross-section. Guided by my model, I also find that the effect of investor sentiment can be decomposed into long- and short-run components. The empirical tests in the first essay of the thesis present a negative relationship between long-run sentiment component and subsequent stock returns and a positive association between the short-run sentiment and contemporaneous stock returns.

The second essay explores a previously unexamined sentiment channel through which technical analysis can add value. I construct a daily market TA sentiment indicator from a spectrum of commonly used technical trading strategies. I find that this indicator significantly correlates with other popular sentiment measures. An increase in TA sentiment indicator is accompanied by high contemporaneous returns and predicts high near-term returns, low subsequent returns and high crash risk in the cross-section. I also design trading strategies to explore the profitability of my new TA sentiment indicator. My trading strategies generate remarkable and robust profits.

The third essay focuses on exploring the profitability of trading strategies based on Implied Volatility indicator (VIX) from the sentiment perspective. My trading strategies involve holding sentiment-prone stocks when VIX is low and sentiment-immune stocks when VIX is high. This shifting asset allocation strategies are based on Abreu and Brunnermeier's (2003) delayed arbitrage theory and the asymmetric effect of investor sentiment in the cross-section. I find sentiment-prone stocks have larger one-day forward returns following high sentiment and vice versa. My trading strategies generate substantial higher returns than benchmark portfolios, and the excess returns are not subsumed by well-known risk factors or transaction costs.

Thesis Supervisor: Dr. Qingwei Wang

Thesis Supervisor: Prof. Khelifa Mazouz

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Chapter 1

Preface

This thesis explores the effect of investor sentiment on the US market cross-sectional stock return. My focus is on 1) demonstrating the asymmetric effect of investor sentiment in the cross-section as stocks have different sentiment-prone level, 2) investigating not only the reversal effect of investor sentiment on future return in the long-run but also the momentum effect of investor sentiment in the short-run based on the delayed arbitrage theory, and 3) testing the profitability of the short-run momentum caused by investor sentiment and delayed arbitrage. This thesis aims at contributing to existing literature on investor sentiment and asset pricing.

1.1 Background

> "I could calculate the motions of the heavenly bodies, but not the madness of the people."

The quote may have or have not been uttered by Issac Newton but the story that he pocketed massive profit during the South Sea Bubble and suffered a greater loss during the following burst of that bubble is grounded in truth. Even one of the greatest physicists in human history found it hard to be entirely rational and form an unbiased belief on asset prices.

Traditional finance models assume agents are rational. Rational investors have the correct belief on asset pricing following Bayes' Law and make decisions on Savage's notion of Subjective Expected Utility. Though traditional finance models deliver appealingly clear and straightforward message, they do not match with data in reality very well. Prof. Richard Thaler, the laureate of 2017 Nobel Memorial Prize in Economic Sciences, once said that "When an economist says the evidence is 'mixed', he or she means that the theory says one thing and the data says the opposite". The most striking anomalies that traditional finance models fail to explain include the Equity Premium Puzzle (i.e., the stock market generates a substantial excess return), the Volatility Puzzle (i.e., the stock market returns are more volatile than expected in models), and the Return Predictability Puzzle (i.e., the stock returns are predictable, which does not fit the Efficient Market Hypothesis).

Behavioural Finance relaxes the assumption on investor rationality, allowing some agents to be not fully rational. Another important founding block of behavioural finance is the concept of limit on arbitrage. The traditional finance campus may argue that rational agents will push irrational ones out of the market through arbitrage action in an economy without market friction. However, a series of theoretical and empirical studies show that limits on arbitrage exist in the market (e.g., Shleifer and Vishny, 1997), which enables irrational investors to be long-lived and have an essential impact on asset prices.

Irrationality arises when people form beliefs and arises on people preferences. Ample experiments compiled by cognitive psychologists demonstrate extensive evidence that investors can have biased belief, such as Overconfidence, Representativeness, Conservatism, Anchoring, Belief Perseverance, and so on (see Barberis and Thaler (2003) for a more detailed description). The following are some examples of biased behaviour. One kind of

Overconfidence is that investors place more weight on the private information they work hard to obtain. A typical example of Representativeness behaviour is that people expect a small sample reflect the properties of the whole population. Conservatism means the tendency of investors underweight new information compared with the prior information. The irrationality assumption better fits the reality.

The two cornerstones for behavioral finance is the investors' irrationality and the limit of arbitrage. The first core argument of behavioural finance is that the market is not perfect and investors are not always rational. Irrational investors matter when there is limit on arbitrage. The irrational bullish/bearish belief can leads to overprice/underprice, and the mispricing persists when arbitragers fail to effectively bet against irrational investors.

The limit of arbitrage is a theory that price could remain in a non-equilibrium state for protracted periods due to the restrictions on the rational investors' capital to arbitrage away the mispricing. Different from the textbook definition, arbitrage in reality requires capital and entails risk. The restrictions on arbitrage comes from several sources[1]. For example, arbitragers might be forced to liquidate their position when the asset price move against them; short-selling are costly and not always available; the arbitragers fund managers has short investment horizon as their performance are evaluated frequently by their creditors/investors.

To better understand the effect of agents' irrationality on asset prices, this thesis investigates the effect of investor sentiment on stock market returns in the first essay. The other two essays focus on a certain kind of limit of arbitrage, i.e. the delayed arbitrage action due to the lack of coordination among arbitragers. I show that sentiment-induced mispricing can deepen in the short-run because of the delayed arbitrage.

Broadly defined, investor sentiment is a biased belief about future cash flows and investment risk. When there is a limit to arbitrage, investor sentiment pushes asset prices away from fundamental values. The link between investor sentiment and asset returns has

[1] Shleifer and Vishny (1997) provides a detailed description on how arbitrage are constrained in their model.

received considerable attention in the past two decades. The concept of investor sentiment is repeatedly mentioned in the studies of bubbles and crashes. Investor sentiment has been demonstrated to have a vital influence on the stock market. For instance, Datst (2003) shows that the effect of investor sentiment on stock return far exceeds the effect of fundamental factors during the extreme low or high sentiment periods.

This thesis consists of three essays on the relationship between investor sentiment and the cross-section of stock returns. This research on investor sentiment is of essential importance to better understand the patterns in the stock market and of practical value in forming investment decisions. In short, I theoretically demonstrate how sentiment-sensitivity leads to stronger predictability of investor sentiment in the cross-section than on the aggregate market in the first essay. The second essay shows that the usefulness of technical analysis could be connected with investor sentiment. Combining the delayed arbitrage theory with the effect of investor sentiment, I find a strongly profitable sentiment-induced return momentum in the cross-section. Table 1.1 gives a map road of this thesis.

Table 1.1 A Brief Summary of Research Topics in This Thesis

	Fisrt Essay	**Second Essay**	**Third Essay**
Research issues	What is the theoretical support for the effect of investor sentiment in the cross-section?	Can investor sentiment explain the value of technical analysis?	Is it profitable to ride the sentiment-induced short-run momenutm?
Where we stand	Empirical literature find extensive evidence of investor sentiment in the cross-section and inconclusive evidence on the aggregate market. However, previous models on investor sentiment are all applicable for explaining the effect of investor sentiment on the aggregate market.	Most papers on technical analysis focus on testing the profitablity of technical trading rules. Only a few theoretical studies explain the usefulness of technical analysis through the fundamental channel; it takes time for the market to incorporate fundamental information into price and technical analysis helps capture the fundamental information.	Ample papers look into the long-run reversal effect of investor sentiment and deem investor sentiment as a contrarian indicator of future returns. The behavorial economists who act as fund managers also claim that their trading phylosophy is to benefit from the return reversal predicted by investor sentiment.Abreu and Brunnermeier (2003) propose that lack of coordination among arbitragers lead to delayed arbitrage actions, which implies that bubbles persist when investors are bullish. Yet empirical studies have paid little attention on the profitability of sentiment-induced momentum.
What I do	My contribution is to extend the DSSW noise trader risk model by introducing another risky asset and differentiate the two risky assets by assigning them with different sentiment-prone level to the overall market sentiment and idiosyncratic sentiment component. This additional assumpition directly depicts the intuitive observation of Baker and Wurgler (2006) that stocks varies in their sentiment-prone level.	I argue that techincal analysis captures investor sentiment in the market. To support our argument, I propose a new market-wide sentiment measure based on the forecasts of a wide spectrum of technical trading rules. I verify my TA sentiment index by showing its correlation with other sentiment indicators and its predictability on the sentiment-induced future return momentum and reversal.	I use the daily VIX, a widely-accepted "fear guage", to time the market and shift asset allocation across stocks. The trading strategy is to hold sentiment-immune stocks when VIX is substantially high and to hold sentiment-prone stocks otherwise. My investment phylosophy combines the delaged arbitrage theory with the flight-to-quality argument to benefit from the sentiment-driven bubble and to dodge the sentiment-induced crash.
My findings	1) My model derivations captures well that sentiment has asymmetric effect on the assets with different sentiment-level, and asset that are more sentiment-prone aslo tend to have higher noise trader risk. 2) The extended model gives a new hypothesis that both long term and short investor sentiment jointly affect cross-section stock returns and my empirical tests confirms long-term sentiment componet negatively predicts return while short-term sentiment postively varies with return.	My TA index, the forecasts of technical trading rules on the overall market, signficantly correlates with other sentiment indicators. TA index has a short-run momentum effect and long-run reverasl effect on future returns just as a sentiment indicator has. Furthermore, this TA indicator performs well in profiting from the sentiment-induced return premium in the cross-sectional stock market.	The annualized returns of VIX trading strategies range from 22.05% to 42.38%. VIX-based trading strategies generally outperform the benchmark portfolios by over 17%, and the excess abnormal returns adjusted for well-known pricing factors are all signficantly higher than 10%. The returns of VIX trading strategies survive the transaction test and could not be totally explained by market microeconomic or microstructure factors. In short, VIX is strongly profitable when seen as a sentiment indicator to benefit from the sentiment-induced momentum.

1.2 Motivations

1.2.1 Asymmetric Effect of Sentiment in the Cross-Section

There are some interesting gaps in the existing literature on investor sentiment. For instance, empirical studies predominately show that investor sentiment has a strong predictive effect in the cross-section but little effect on the aggregate market level, despite almost all investor sentiment models containing only one risky assets. With one risky asset in the model setting, the model provides propositions for the aggregate market rather than the cross-sectional market. Whatever conclusion holds in the aggregate market does not necessarily hold in the cross-section in the existing theoretical models. Therefore, Chapter 3 presents the first rigorous and parsimonious model demonstrating the effect of sentiment on the cross-sectional return of a sentiment-prone asset over a sentiment-immune asset.

Why is it essential to look into the cross-sectional stock market for the effect of investor sentiment? The reason is that stocks differs in their sensitivity to investor sentiment. Sentiment-prone stocks are more attractive to speculative demands and more difficult to arbitrage. This thesis extends the DSSW model by introducing multiple risky assets that differ in their exposure to market-wide sentiment. Suppose that there are two risky assets, A and B, and that irrational investors' beliefs are biased more upwards (downwards) towards A than B when market sentiment is high (low). Thus, asset A has higher exposure to market-wide sentiment (more sentiment prone) than asset B. When investor sentiment is unpredictable, this assumption also implies that the equilibrium returns of asset A will fluctuate more with the shifts in market sentiment, hence posing higher noise trader risk to rational arbitrageurs, than those of asset B. My extended model effectively captures the intuitive observation that stocks more prone to investor sentiment are also more difficult to arbitrage (Baker and Wurgler, 2006). It also predicts that market-wide sentiment leads to relatively higher contemporaneous returns and lower subsequent returns for stocks more prone to sentiment and difficult to arbitrage.

Guided by my extended noise trader risk model, I also find that the effect of investor sentiment could be decomposed into long- and short-run components. Prior studies has investigated the relationship between investor sentiment and short-run return and long-run returns, but the effect of long-run investor sentiment and short-run sentiment on the future return are not explicitly clarified. In reality, investor sentiment could be persistently bullish for several periods; hence, decomposing investor sentiment into the long-run component and the short-run shock is of essence. Empirical studies either show that stock return is positively related to contemporaneous investor sentiment changes or that it is negatively associated with the previous investor sentiment level. By decomposing investor sentiment into the short-term incremental component and the long-term average component, I integrate the opposite effect of the two decomposed components. The empirical evidence shows that long-run sentiment negatively predicts cross-sectional returns while short-run sentiment contemporaneously correlates with the returns.

1.2.2 Technical Analysis: Mumbo Jumbo or A Crystal Ball

Technical analysis is a method of forecasting the direction of price movement through studying past price (volume) pattern. Long deemed as 'mumbo jumbo' by financial economists, technical analysis (TA) has been puzzlingly popular among experienced traders over hundreds of years.

Financial economists generally have unbalanced views on technical analysis. The most prevailing view is that technical analysis is of no value. Traditional academic wisdom posits that publicly available information such as past prices or trading volumes, which serve as the basis of technical analysis, should have already been incorporated into current asset prices, with any attempt to predict future returns based on technical analysis having to "share a pedestal with alchemy" (see Page 157 in Burton G. Malkiel (1973)). A less popular view is that technical analysis is an effective means of extracting useful fundamental information (Lo et al., 2000). Despite the lack of supporting theories for technical analysis, majority of empirical tests favor technical analysis. However, one may cast doubt on the strong empirical evidence on technical analysis because of publication bias or data snooping bias (Sullivan et al., 1999).

The financial industry, on the other hand, sees technical analysis as a crystal ball. Technical analysis has been part of industrial practice over many years: it was first documented in Dutch markets in the 17th century, and in Japan in the early 18th century. Technical analysis is popular among practitioners; according to the survey conducted by Taylor and Allen (1992), 90% of experienced traders place some weight on it during costly trading activities. It is also widely discussed in media and commonly covered in education. Even someone transferring from academia to practice admitted that "overcoming the prejudice against technical analysis was the most important lesson he had to learn when moving from the ivory tower into the laboratory of real-life experience as a trader" (Sushil Wadhwani, an LSE academic, a central banker and later a fund manager, said in an interview by Financial Times)[2].

To solve this conundrum, I argue that technical analysis captures investor sentiment. Chapter 4 is the first attempt to bridge the gap between academic finance and industry practice through the sentiment channel. The connection between investor sentiment and technical analysis is indicated in the previous literature. For instance, Menkhoff (1997) states that "technical analysis is a means of processing non-fundamental information". Technical analysis, especially positive feedback trading, is also a prominent example of biased belief in investor sentiment models, for instance, De Long et al. (1990b). To quote Zhou (2017),

"In technical analysis, there are many over-bought and over-sold indicators,

[2] See "Technical analysis pulled out of the bin", October 17, 2010, Financial Times.

> which are precisely designed to capture the unsustainable levels of optimism and pessimism".

I propose and validate a market-wide sentiment measure based on forecasts of a broad spectrum of technical trading rules. I apply 2,127 technical trading rules on S&P 500 Index every day, assign values to the forecasts of those 2,127 technical trading rule (buy forecast=1, sell forecast=-1, neutral=0), and then calculate the average of 2,127 forecast as the daily TA sentiment indicator.

The theoretical motivation is that equilibrium price is a function of cross-generation sentiment and current sentiment level in De Long et al. (1990a) model. Accordingly, current sentiment could also be valued through current equilibrium price and historical equilibrium prices. Combining past prices and current price potentially allows more accurate investor sentiment inferences. Some of those who use technical trading rules to make investment decisions believe that the forecasts actually give signals about how optimistic the investors in the market are. A broad spectrum of technical trading rules provide more information on the investor sentiment level.

In Chapter 4, there are two ways to validate that this TA indicator captures sentiment. The first way is to show that this sentiment measure significantly correlates with other sentiment indicators. The second way is to test whether this TA indicator could predict the returns in the same pattern that a sentiment indicator does. I find that high TA sentiment indicator indicates the returns of more sentiment-prone stocks relative to sentiment-immune stocks are contemporaneously higher, subsequently remain higher due to the delayed arbitrage theory before they eventually reverse. High TA indicator also indicates higher future crash risk, and this predictability is stronger among sentiment-prone stocks than among sentiment-immune stocks. In this way, I connect technical analysis with investor sentiment to demonstrate that technical analysis has value in capturing investor sentiment.

1.2.3 Profitability of Exploring Sentiment-Driven Momentum

One of the contributions of this thesis is to look into the momentum effect of investor sentiment on short-run returns. Most prior studies use monthly investor sentiment to predict monthly returns and therefore only capture the reversal effect. I find that not only investor sentiment can predict long-term return reversal but also can predict short-term return momentum. A high-frequency investor sentiment indicator enables the test the momentum effect of investor sentiment on short-run returns. I find that investor sentiment positively relates to the short-run return before the return reverses, and this return momentum is due to the lack of coordination among arbitrageurs. Both Chapter 4 and Chapter 5 rely on the hypothesis of the momentum effect of investor sentiment from the delayed arbitrage model.

Mispricing arises from the irrational bias and limit on arbitrage. Abreu and Brunnermeier (2003) propose the delayed arbitrage model to show how mispricing persists due to the lack of coordination among arbitrageurs. In their model setting, sentiment-driven overpricing emerges, and arbitrageurs become sequentially aware of it but do not know their sequence or their peers' opinions. For a bubble to burst, a critical mass of rational arbitrageurs need to agree on coordinated arbitrage actions. In actuality, rational arbitrageurs face performance evaluations in short horizon and care about the resale price and liquidation risk. Hence, instead of arbitraging right after realizing there has been mispricing, they become reluctant to arbitrage at an early stage and try to forecast their peers' action. Some rational arbitrageurs may even jump on the bandwagon, ride the bubble, and try to "beat the gun" before it collapses. With them switching sides from the rational to the irrational group, the mispricing could be enlarged by an increase in sentiment-induced trading. The lack of coordination among arbitrageurs leads to delayed arbitrage actions that make the bubble persist. If the investor sentiment become more extreme or the arbitrageurs decide to ride the bubble, the bubble may even grow bigger. Eventually, the bubble becomes prominent enough to trigger coordinated arbitrage actions and the return reverses. Hence, high investor sentiment has a momentum effect on the return before the reversal effect starts to take place.

While Chapter 4 focuses on explaining the predictability and profitability of technical analysis through an investor sentiment channel, Chapter 5 focuses on two things: to better predict future return and to profit from the predictive power of investor sentiment. I find that not only investor sentiment predicts long-term return reversal but it also predicts short-term return momentum. However, the predictive power of a factor does not necessarily guarantee its strong profitability. Therefore, I implement the investor sentiment in trading and test the profitability of investor sentiment.

Due to existing literature generally seeing investor sentiment as a contrarian indicator of future return, the trading strategies based on sentiment in existing literature are mostly contrarian trading strategies that aim to profit from the return reversal predicted by investor sentiment. The predictive power of a factor does not necessarily guarantee its strong profitability. After demonstrating the predictability of investor sentiment on the short-run return, I test the profitability of the momentum effect of investor sentiment caused by delayed arbitrage. I design trading strategies that aim at benefiting from the momentum effect of investor sentiment.

Every trading strategy has to answer two key questions: when to buy/sell and what to buy/sell. Chapter 4 and Chapter 5 answer the first question with a similar method using two different sentiment indicators, a newly-proposed TA sentiment indicator and VIX indicator. However, the two chapters differ in their answer to the second question. Unlike Chapter 4, Chapter 5 chooses to shift asset allocation among stocks to generate higher profitability and avoid short-selling constraints and high short-selling costs.

This shifting asset allocation strategy is based on delayed arbitrage theory and the asymmetric effect of investor sentiment in the cross-section. My trading strategies involve holding sentiment-prone stocks when VIX is low and sentiment-immune stocks when VIX is high. I also find that following low sentiment periods the sentiment-immune stocks outperform the sentiment-prone stocks. I test the robustness of the profitability of my trading strategy and also demonstrate that this profitability is not subsumed by the well-known risk factors and can survive transaction costs.

In summary, this thesis contributes to existing literature in three aspects. Initially, the first essay provides the first theoretical model illustrating the asymmetric effect of investor sentiment on cross-sectional stock returns. Second, the second essay connects technical analysis with investor sentiment and provide evidence on the value of technical analysis as a sentiment indicator from a behavioural finance perspective. Third, the last two essays emphasize the momentum effect of investor sentiment and the profit opportunity provided by sentiment-induced return momentum, which has not been thoroughly tested in previous research. The profitability of my sentiment-based trading strategies demonstrates a practical significance for studying investor sentiment.

Chapter 2

Literature Review

This section summarizes the findings and gaps in the previous literature. In short, strong empirical evidence of the predictability of investor sentiment has been found in the cross-sectional stock market. Almost all theoretical models looks into an economy with only one risky asset. Such a gap in the literature motivates me to build a two-risky-asset model to demonstrate the asymmetric effect of investor sentiment rigorously. Empirical studies also focus on the reversal effect of investor sentiment on future returns, and therefore most papers test the contrarian trading strategies based on investor sentiment.

This session also sums up the research related to the delayed arbitrage model proposed by Abreu and Brunnermeier (2003) to draw attention to the momentum effect of investor sentiment. The delayed arbitrage theory inspires me to test the momentum effect of investor sentiment and to investigate the profitability of exploring the momentum caused by investor sentiment and delayed arbitrage.

Finally, I review the literature on the connections between investor sentiment and technical analysis. I briefly sort out the opinions of the academia on the effectiveness of technical analysis and use existing research to support my attempt to explain technical analysis from a sentiment channel.

2.1 Investor Sentiment Measures

The literature on investor sentiment measures answers two key questions: 1) how to measure investor sentiment; 2) how to tell it is a good proxy or not. Generally speaking, the choice the sentiment index should be based on the economic logic and theoretical rationale. Apart from the theoretical reasoning, there are practically three ways to validate the performance of sentiment index. First is to see whether the high and low sentiment period matches with anecdotal bubbles and crashes history. Second is to calculate and test the correlation of any new sentiment index with sentiment-related macroeconomic variables and other widely-acknowledged sentiment indicators. More importantly, those papers use the remarkable performance of a sentiment index in explaining or predicting the equity premium as validity evidence of the index.

Investor sentiment measures fall into three categories, namely the survey-based sentiment, textual analysis based sentiment, and market-based sentiment.

2.1.1 Survey-Based Sentiment Indicators

The survey-based measures include University of Michigan Consumer Sentiment Index, Conference Board Consumer Confidence Index, Investors' Intelligence Index, the institutional (individual) Bull-Bear spread surveyed by the American Association of Individual Investor, etc.

Different types of interviewees of the survey make the sentiment indicator measure the sentiment of different groups of people. University of Michigan Consumer Sentiment Index is a retail-based sentiment measure (Fisher and Statman, 2003). Conference Board

Consumer Confidence Index (CCI) is a more widely employed survey-based sentiment indicator. Investor Intelligence Index is a measure of institutional sentiment, as it represents the bullish/bearish expectation of over 120 market newsletters. This sentiment proxy could either be the percentage difference or the ratio of bullish and bearish newsletters (e.g., Brown and Cliff, 2005; Kurov, 2010; Lee et al., 2002).

The complex index could also be constructed from the several survey-based sentiment indicators. Ho and Hung (2009) use all three survey indexes and create an index containing the common component of those three indexes to examine the role of investor sentiment in conditional asset-pricing models.

2.1.2 Textual-Analysis Sentiment Indicators

The textual analysis sentiment measures are not the mainstream, yet it is attracting attention. Different types of text content one analyses measure the sentiments of different agent groups. Most textual analysis on sentiment digs into the corporate filings and disclosures to gauge corporation-expressed sentiment. For example, Jiang et al. (2017) construct managers' sentiment from the textual analysis of financial reports, earning disclosure conference, and they show that the overall market managers' sentiment performs very well as a contrarian predictor of future aggregate stock market returns. Tetlock (2007), Garcia (2013) and Engelberg et al. (2012), among many others, point out the importance of media-expressed sentiment. Those papers analyses the tones in major newspapers the Wall Street Journal, the New York Times, and the Dow Jones News Service.

This thesis is more interested in the Internet-based sentiment from textual analysis, which measures the mood of investors all over the market. Da et al. (2014) create a market-wide sentiment measure called Financial and Economic Attitudes Revealed by Search (FEARS) index by aggregating the US household Google Trend search volume of negative words such as "bankruptcy", "unemployment", "recession". Da et al. (2014) find that their FEARS index is a contrarian measure of investor sentiment; high FEARS index indicates low investor sentiment and vice versa. Sun et al. (2016) provide an intraday sentiment measure from textual analysis and find their half-hour lagged sentiment measure strongly predicts the hourly return of S&P 500 index.

2.1.3 Market-Based Sentiment Indicators

The market-based sentiment indicators include retail investor trades; mutual fund flows; trading volume; premium on dividend-paying stocks; closed-end fund discounts; option implied volatility; first-day returns on initial public offerings; number of initial public offerings; new equity issues; insider trading; complex index constructed from several market-based indexes.[1]

Retail Investor Trades. Retail investors' intention to buy or sell proxies investor sentiment. (Barber et al., 2008; Kumar and Lee, 2006) find that retail investors tend to buy or sell stocks in concert, and their behavior pattern is consistent with the systematic sentiment. Ritter and Welch (2002) conjecture that the bullish investor sentiment among retail investors explains the IPOs' high first day return and low future return. Greenwood and Nagel (2009) find that inexperienced retail investors tend to hold more stocks during the peak of the Internet Bubble than the sophisticated institutional investors. In addition, retail investors are more likely to be sentiment-prone than sophisticated investors. A series of papers support this argument by showing that retail investors prefer sentiment-prone stocks more than sophisticated investors. Qiu and Welch (2004) see the retail investors demand as a proxy for sentiment-prone level and build cross-sectional portfolios based on the characteristics representing retail investors' demand. Stocks held disproportionately by retail investors (such as young and small stocks) are more sentiment-prone than stocks held by institutional

[1] see a comprehensive survey in Baker and Wurgler (2007).

investors. In addition, they argue that the reason closed-end fund discount captures investor sentiment is due to the fact that closed-end funds are predominately held by retail investors.

Mutual fund flows. Neal and Wheatley (1998) use the closed-end fund discount, the ratio of odd-lot sales to purchases, and net mutual fund redemptions to measure the investor sentiment level, and they find mutual fund redemption predictive for the small premium. Similar to the net mutual fund redemption, Liao et al. (2011) employ net mutual fund purchase to proxy for sentiment. Brown and Cliff (2004) argue that net purchases by mutual funds positively indicate the optimistic magnitude in the stock market. Investors tend to buy when they are bullish about the market and prefer to sell when lack of confidence or in a bad mood. Ben-Rephael et al. (2012) use aggregate net exchanges of equity funds, the monthly shift between bond funds and equity funds, to gauge investor sentiment. They find it weakly correlates with sentiment the measures used in Lemmon and Portniaguina (2006), but it works well in explaining contemporaneous excess return especially for small and growth stocks. Frazzini and Lamont (2008) use mutual fund flow to measure the sentiment of individual stocks.

Trading Volume. Liquidity measures such as trading volume, market turnover and bid-ask spread can predict future return on the firm- and market-level (Baker and Stein, 2004). When irrational investors overreact to private signals, both negative and positive sentiment shock tend to boost the liquidity in a market without short-selling constraints. However, irrational investors are usually kept out of the market in face of the short-selling constraints when sentiment is negative. Baker and Stein (2004) build a mathematical model to demonstrate that an increases in trading volume implies higher participation of bullish irrational investors in the market, and hence high trading volume indicates bullish investor sentiment. Another line of studies demonstrate that innovations in trading volume proxy for the divergence of opinion among investors (Chen et al., 2001; Hong and Stein, 1999), and hence Scheinkman and Xiong (2003) and Baker and Wurgler (2007) point out that the aggregate trading volume level measures the bullishness of investors when short-selling is difficult. However, with the development of high-frequency trading algorithm in the stock market, turnover is no longer suitable for capturing investor sentiment. Therefore, Jeffrey Wurgler leave the turnover out of the construction of the latest version of Baker-Wurgler Sentiment.

Option Implied Volatility. VIX is, by definition, a measure of market expectation of stock return volatility implied from the supply and demand of S&P index options over the next 30 calendar days. The Chicago Board Options Exchange's implied volatility index (VIX) is first introduced by Whaley (2000) as a premier barometer of investor sentiment by scholars and practitioners (Bekaert and Hoerova, 2014; Da et al., 2014; Giot, 2005). The Wall Street Journal and many other major media assigned VIX the nickname "the fear gauge" or "the sentiment index". Fleming et al. (1995) show that though VIX is a good predictor for future volatility, it contains misperception. Low (2004) argues that VIX is a collective best guess of all option traders on the S&P index options and therefore regardless of its forecast accuracy VIX encompasses the bias and exuberance of a sample of sophisticated, well-informed professional market participants.

Closed-End Fund Discount. A strand of research presents a very intriguing and heated debate on whether closed-end fund discount (CEFD) associates with investor sentiment (Chen et al., 1993; Chen and Miller, 1993; Chopra et al., 1993a,b). Lee et al. (1991) infer that CEFD proxy for investor sentiment and the changes in CEFD highly correlates with returns of stock stocks. Elton et al. (1998) consider CEFD as an indicator of investor mood of individual investors because closed-end funds are disproportionately held by retail investors. A more prominent discount value means a more bearish investor sentiment. Neal and Wheatley (1998) find the net redemption captures investor sentiment in CEFD.

Complex Index. Baker and Wurgler (2006) use principal component analysis to extract the common component of six measures of investor sentiment, which are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. They provide a detailed illustration on the relation of each measure with sentiment. They also compare the fluctuation of the BW sentiment index with anecdotal history from 1961 to 2002 and find it consistent with reality. Huang et al. (2015) point out a potential problem of using principal component analysis: the six indexes all contain approximation error and those errors contribute partially to their variations, thus the first principal component of the six indexes may also contain the common component of approximation errors which has no explanatory power on the future return. They use partial least square method (PLS) to gather the common component of those six proxies that most aligned with the aggregate market return. They consider PLS index a better proxy, as it has better performance in predicting the future aggregate market return and it highly correlates with macroeconomic variables.

2.1.4 Comparison of the Three Categories of Sentiment Measures

The survey-based sentiment indicators are the most direct measures for sentiment and quite often serve as the benchmark indicator in the validation of other sentiment measures. The correlations with the direct survey-based sentiment indicators have been widely used to test the validity of other market-based or textual-based sentiment measures. For instance, Lemmon and Portniaguina (2006) argue that consumer confidence measures are good proxies for sentiment as they are highly correlated to the Bull-Bear spread. Qiu and Welch (2004) also argue that correlations of a new measure with direct survey indicators provide a more convincing validation because direct survey indicators directly show opinions of investors.

Previous literature points out two disadvantages of survey-based indicators. First, those measures are usually in low frequency. Second, Singer et al. (2002) cast doubts on the quality of survey-based indicators due to the lack of incentives for interviewees to truthfully and carefully answer the survey questions, especially when the questions are sensitive.

The advantage of textual sentiment indicator is that it could be measured in different frequency and have easier access than the survey-based sentiment indicator. However, the quality of textual analysis based sentiment indicator, to a large extent, relies on finding the right and comprehensive negative and positive words dictionary.

The advantage of market-based sentiment indicators is their availability and high-frequency availability relative to survey-based sentiment indicator. The disadvantage is that the market-based sentiment indicators are the equilibrium of many economic forces other than investor sentiment. Also, it faces a problem pointed out by Qiu and Welch (2004) succinctly: "How does one test a theory that is about input $\rightarrow$ outputs with an output measure?". This is why current literature mostly verify a market-based sentiment indicator by testing its correlation with survey-based sentiment indicator. To better address this issue, future research should contribute more on designing a better framework or finding a better test-field for the validation of market-based sentiment indicators.

2.2 Investor Sentiment and Stock Returns

2.2.1 Effect on Aggregate Market and Cross-Sectional Returns

Theoretical Models

Models like Grossman and Stiglitz (1980), Black (1986), Shleifer and Vishny (1997), Daniel et al. (1998), among others, are designed to illustrate the effect of sentiment on asset returns from the aspect of limits on arbitrage. Another strand of theoretical works illustrates the effect of investor sentiment on asset price with belief-based models. For instance, Barberis et al. (1998) propose a model which measures investors' attention on the strength and the statistical weight of information; they prove investors' overreaction or underreaction to information cause cross-section return premium. They argue that investors wrongly allocate their attention on the strength and the statistical weight of information, and therefore their biased perceptions will lead to cross-section return disparity between stocks. Barberis et al. (1998) incorporate the conservatism and representativeness bias in this belief-based model. Daniel et al. (2001) model the effect of overconfidence in private information on asset prices.

Instead of capturing only a few aspects of biased belief, De Long et al. (1990a) propose a noise trader model to incorporate all kinds of biased belief into one parameter and theoretically relate prices to sentiment level and returns to sentiment changes. The selling point of DSSW model is that the uncertainty of stochastic investor sentiment create noise trader risk can prevent rational investors to eliminate the mispricing with limits on arbitrage entirely, and investor sentiment can drive a wedge between the price and the fundamental value. This model also shows that current sentiment change positively varies with current return and the lagged sentiment negatively predicts returns.

Aggregate market and Cross-Sectional Returns

Almost all theories of investor sentiment including De Long et al. (1990a) apply most appropriately to market portfolios since there is only one risky asset in the models (Huang et al., 2015), yet empirical literatures suggest that the role of sentiment is at best controversial at the aggregate market level (Baker et al., 2012; Brown and Cliff, 2004; Elton et al., 1998; Solt and Statman, 1988). Instead, there is ample evidence that market sentiment helps explain the asset returns in the cross-section (Baker and Wurgler, 2007, ,among others.).

Why is the effect of investor sentiment is stronger in the cross-section than in the aggregate market? The answer is that stocks may have asymmetric sensitivities to investor sentiment (Baker and Wurgler, 2006; Zhou, 2017). Baker and Wurgler (2007) explain with a see-saw graph to show that the predictive effect of investor sentiment weakens if the sentiment-immune stocks possibly have opposite response to a sentiment shock compare with the sentiment-prone stocks due to "flight to quality".

Sentiment often acts at the level of categories (Barberis and Shleifer, 2003; Barberis et al., 2005). Cohen and Lou (2012) find when facing up with the same information, complicated firms are more difficult to categorise, and therefore they are less likely to be affected by investor sentiment which acts at the categorical level. Baker and Wurgler (2006) indicate that sentiment-prone stocks tend to be small, young, volatile, unprofitable, non-dividend-paying, distressed or with extreme growth potential and contains relatively high percentage of intangible assets, because this kind of stocks is more difficult to evaluate and more likely to be misperceived by sentiment-biased investors. Berger and Turtle (2012) look into whether stocks with those characteristics are sentiment prone. They use each characteristic to construct ten decile portfolios and calculate the average sentiment sensitivity measured by sentiment beta in the asset pricing regression. They conclude that investor sentiment sensitivities are significantly correlated with those categorisation measures in the cross-section, and greater extent of opacity means higher sentiment sensitivities. Therefore, it is practical to divide the stocks into categories based on its sensitivity to investor sentiment and check how they react differently to investor sentiment.

Long-Run and Short-Run Effect

Shleifer and Vishny (1997), who illustrate that the agency problem, arbitrage cost, long liquidation risk and funding constraints of rational investors will prevent them from taking long-term positions against mispricing. If investors are not sophisticated enough to understand a money manager's strategies, they will use short-term returns as a way of judging his competence and withdraw funds after a poor performance, which threatens arbitrageurs to take a short-term view. The holding cost of counteracting the mispricing is high for the long-run holding period, especially for short selling. Arbitragers may even be forced to liquidate their positions at a loss when running out of capital. However, the mutually-exclusive effects of long- and short-term sentiment on predicting future return have so far not been emphasised in the literature. Most researchers focus on the short-term relation between sentiment and return, while few look into how long-term and short-term investor sentiments affect either long-term or short-term return. For example, Brown and Cliff (2005) prove that short-term sentiment will have a stronger predictive power on long-term future return than on short-term future return. It is of essential importance to look at the effect of investor sentiment in both the long and the short run.

2.2.2 Momentum and Reversal Effects of Sentiment on Returns

In short, previous empirical studies on the link between investor sentiment and stock returns generally show two findings: first, investor sentiment is negatively related to future stock returns; second, the predictive power of investor sentiment on stock returns is more pronounced in the cross-section. The contrarian predictive power of investor sentiment on future returns is usually tested with low-frequency data. Most of the commonly used investor sentiment measures, such as mutual fund flow, consumer confidence index, closed-end fund discount, Baker Wurgler index, are in monthly frequency (Baker and Wurgler, 2007; Brown and Cliff, 2005; Neal and Wheatley, 1998, among many others.). Those papers look into the predictability of those monthly sentiment level on monthly, quarterly or longer-term future return. They argue that bullish investor sentiment pushes current price high and the mispricing will be corrected in the future which means lower future return, and vice versa.

It has come to my attention that the negative relationship between investor sentiment and future returns may not hold in the short run with high-frequency data. A strand of studies demonstrates the prominent profitability of trading strategies that capture the return momentum induced by the news-based sentiment (Huynh and Smith, 2017; Sun et al., 2016; Uhl, 2017). Even without using intraday data, Lee et al. (2002) show the positive short-term relationship between investor sentiment and stock return with weekly data. Recently, more empirical works show that investor sentiment also predicts short-term momentum (see, e.g., Chou et al., 2016; Han and Li, 2017).

Mispricing arises due to uninformed demand and limit of arbitrage. Investor sentiment indicates how far the price is away from the fundamental value. Assume the sentiment-induced momentum comes through the uninformed demand channel. Liang (2016) argue that the momentum effect of sentiment shock may come from the underreaction of sentiment-driven investors, i.e. the persistent high return after a positive shock is due to the delayed reaction of sentiment-driven investors. However, the under reaction proposition does not explain the future return reversal. In another word, bubbles exist in a market where some investors are biased and arbitrage trading is constrained.

Consider the momentum comes from the limit of arbitrage channel. Limit of arbitrage comes from various sources, namely fundamental risk, noise trader risk, implementation costs, short-selling constraints and synchronisation risk. One source of limit on arbitrage, synchronisation risk, could serve well in explaining the momentum effect of investor sentiment. Abreu and Brunnermeier (2003) argue that arbitrageurs may fail to coordinate their betting against the mispricing due to the dispersion of strategies to find the market turning points. Rational arbitrageurs may even choose to capture the momentum gains and ride the bubble, and they correct mispricing until a sufficient mass of arbitrageurs takes synchronised actions.

A series of empirical works support the argument that rational arbitrageurs delay arbitrage. McQueen and Thorley (1994) assume the probability to predict the end of a sentiment episode is low at the beginning and this probability increases when coming to the end of a sentiment episode. Multiple anecdotal studies have contended that institutional investors managerially ride the bubble and exacerbate mispricing (Brunnermeier and Nagel, 2004; DeVault et al., 2014; Griffin et al., 2011; Xiong and Yu, 2011). Rather than selling to bring the price back to fundamental value, some institutional investors choose to buy, knowing that positive feedback will attract more irrational traders, leading to a higher price where they can exit a profit. The market timing behaviour of institutional investors makes the mispricing sustaining for the more extended consecutive period before correction. This mispricing component accumulates till the point that it becomes attractive enough for sophisticated investors to counteract the mispricing (Berger and Turtle, 2015).

Previous studies on the behaviour of individual investors versus institutional investors justify this thesis using delayed arbitrage theory to explain the profitability of technical analysis. Empirical findings show sophisticated investors ride the bubbles and benefit from chasing the trend, while individual investors are the contrarian traders. In line with Abreu and Brunnermeier (2003) model, Griffin et al. (2011) find that during tech bubble period institutional investors were the major buyers of technology stocks and they were also the dominant selling force when bubble crashed. Brunnermeier and Nagel (2004) report hedge funds ride the technology bubble by heavily investing in technology stocks. In the same vein, Temin and Voth (2004) present through a case study that one sophisticated investor knowingly invested in the South Sea bubble and earned profits from riding the bubble. Since no short-selling constraints or agency problems exist for this sophisticated investor, Temin and Voth (2004) argue that it is synchronisation problem among rational investors that lead to the bubble and the subsequent crash.

2.3 Technical Analysis and Investor Sentiment

2.3.1 The Efficiency of Technical Analysis

Earlier empirical works about the efficiency of technical analysis are inconclusive. Generally speaking, evidence of the profitability of technical analysis is much stronger in foreign exchange markets (Allen and Taylor, 1990; Lui and Mole, 1998; Narayan et al., 2015; Neely and Weller, 2003; Osler, 2003; Qi and Wu, 2006; Taylor and Allen, 1992). With regard to other asset classes, Goh et al. (2013) find that technical indicators have salient forecasting power on bond risk premium. Lukac et al. (1988) find supporting evidence in the commodity futures market. Glabadanidis (2014) shows the predominate profitability of applying the Moving Average trading rule on REIT indexes.

Efficacy of technical analysis in the stock market is much weaker relative to futures markets or foreign exchange markets during the 1960s and 1970s. One of the earliest work, Cowles (1933), shows that Hamilton's forecasts based on Dow Theory over 1904 to 1929 only have a success rate of 55%. Fama and Blume (1966) find the Filter Rules was not profitable over 1956-1962. Allen and Taylor (1990) see little profitability of generic algorithms in the stock market. Sullivan et al. (1999) find profitability of technical analysis vanishes after adjusting for data-snooping bias[2]. Their finding indicates that profits of technical analysis are not due to fundamental changes but rather driven by sentiment.

There are also various studies supporting the effectiveness of technical trading rules in stock markets. Take some recent papers for instance, Brock et al. (1992) present evidence that uptrend signals of technical analysis indicators made by DJIA consistently predict higher subsequent returns than downtrend signals. Nagel (2012) strengthens the liquidity

[2]Data-snooping bias arises when a set of data is over-reused for the purposes of model selection or making inference. When data is used repeatedly, there is always a chance that the satisfactory results are obtained due to pure-luck rather than to any underlying economic rationale. In a case of data-snooping bias, the significant statistical tests results are overvalued and does not show merit.

explanation with proof that both the short-term reversal strategies and trend factors do well during recessions because of evaporating liquidity. Ülkü and Prodan (2013) show that return persistence is a principal determinant of trend-following rules' profitability, and return volatility will also contribute to the profitability. Antoniou et al. (2013) test specific technical rules in isolation. Consistent with the informational diffusion model, Han et al. (2016) construct a pricing factor from trend-following strategy and find it performs better when information is more uncertain.

Park and Irwin (2007) point out the difficulty of proving the efficiency of technical analysis lies in statistical methodology. The riskiness of technical trading rules should be taken into consideration; the trading rule profits should be adjusted for data snooping biases and be tested for its statistical significance. Data-snooping bias occurs when a given set of data is used more than once for the purpose of inference or model selection. Sullivan et al. (1999) test 7846 trading rules that belongs to five commonly used classes, namely the Filter Rules, Moving Averages, Support and Resistance, Channel Breakouts and On-balance Volume Averages. They find that during the 1987 to 1996 technical trading rules are of little value after applying Bootstrap Reality Check methodology to account for the data-snooping bias. There is also a possibility that certain technical analysis rules may perform well due to pure luck. The universe of technical trading rules should be set up to show the profitability of technical trading strategies is artificial by data-mining and picking out the trading strategies that work well.

2.3.2 Theoretical Explanations for the Use of Technical Analysis

Typical theoretical explanations for the use of technical analysis include the following three groups. The first group argue technical analysis users are not fully rational. The second group argues that technical analysis is valuable in processing information of fundamental influences on price. The third group proposes that technical analysis exploit information of the non-fundamental impacts on price.

Irrational Action. Some argue that using technical analysis is an unreasonable action. Technical analysis challenges the Efficiency Markets Hypothesis, which indicates technical analysis is of no value when information on past prices has been embedded into the current price (Fama and Blume, 1966; Jensen and Benington, 1970). However, the consistent popularity of technical analysis does not fit EMH. The Efficient Market Hypothesis suggests that irrational investors will be forced out of the market after making losses to rational investors. Some hold the opinion that technical analysis users have suboptimal behaviour. For instance, Ebert and Hilpert (2016) point out that even when technical analysis is not profitable it is still attractive due to investors' preference for positive skewness return, and technical analysis induces lottery-like returns that is more right-skewed. De Long et al. (1990b) propose that technical analysis users may underestimate the asset risk. Some claim that financial intermediaries promote technical analysis as its forecasts generate fee and commission.

However, many economists do not agree with the irrational behavioural explanation and insist that technical analysis is of value in making investment decisions. Technical analysis is still appealing and popular among financial practitioners, including a large part of sophisticated investors who are from the buy-side and are not likely to have suboptimal behaviour or underestimate the risk. For example, Lo and Hasanhodzic (2010) and Schwager (2012) find in their interviews that many top traders and fund managers believe in and employ technical analysis to make decisions accordingly. Their interviewees see technical analysis at least as critical as fundamental analysis. Menkhoff (2010) finds technical analysis is the most important form of analysis among fund managers at a forecasting horizon of weeks, and it is more popular in smaller asset management firms.

Under the irrational explanation, technical analysis is deemed as much less profitable for individual investors relative to institutional investors. Smith et al. (2016) demonstrate that hedge fund managers who use technical analysis have superior performance, lower risk and better market-timing ability than the non-users during high sentiment periods, and those advantages disappear and even reverse in low sentiment periods. However, individual technical analysis users have poor performance. Neely (1997) points out that it is much less useful for individual investors in foreign exchange market due to higher transaction cost, the opportunity cost of time and the risk entailed in the trading strategy. Hoffmann and Shefrin (2014) show that individual technical analysis users are disproportionately less capable of earning higher returns. These findings are all consistent with the predictions in Abreu and Brunnermeier (2003), that when unsophisticated investors sentiment is predictable to some extent, rational speculators profit from riding the bubble supported by inexperienced investors.

Fundamental Explanation. The second group sees technical analysis as an approach to obtain information of fundamental influences on price. The notion that the process towards equilibrium prices could be time-consuming throws a lifeline to the efficacy of technical analysis. In an economy where investors receive information at different times, past prices are useful in assessing whether the information has been incorporated into current price (Brown and Jennings, 1989; Hellwig, 1982; Treynor and Ferguson, 1985). Even if investors receive information at the same time, when investors are heterogeneously informed or process information at different speeds, past price are also valuable to help investors to make more price inferences about the signals contained in the information (Brown and Jennings, 1989; Grundy and McNichols, 1989).

Technical analysis is valuable in analysing the information that reveals in a sequence of security prices rather than a single price. Treynor and Ferguson (1985) argue that the value of technical analysis is to evaluate whether the non-public information has been priced into current price, so it is the non-public information that creates profit opportunity rather than technical analysis. Lo et al. (2000) propose that technical analysis adds value to the investment process based on their novel approach by comparing the distribution conditional on technical patterns with the unconditional distribution. Edmans et al. (2015) theoretically validate the use of positive feedback trading strategy by showing that firm decision makers learn information from market trading and improve the underlying asset value, which increases the profitability of buying on good news and reduces the profitability of selling on bad news.

Liquidity Explanation. In the same vein, liquidity is another reason for the use of technical analysis. Cespa and Vives (2015) and Guo and Xia (2012) show that price can differ from the fundamental value in a market with liquidity traders, and that technical analysis can be used to capture price trend. Hence, the trend-following strategies based on past prices could be profitable. In Blume et al. (1994) model, traders receive signals with differing quality, and volume provides information on the quality of these signals, which enables traders to use technical analysis as a method of learning. They show that technical analysis users could do better than the non-users.

Some other fundamental theories try to explain technical analysis from different aspects, such as better asset allocation, better prediction of market intervene, and so on. Neely and Weller (2001) argue that technical analysis may capture the trend or support and resistance levels created by major market participants in a market. The test-ground for this idea is foreign exchange markets, where central banks are influential traders and can intervene foreign exchange rates. LeBaron (1999) find the profitability of technical analysis diminishes after removing the sample periods intervention happens. However, evidence supporting the overall market intervention argument for the consistent use of technical analysis in the stock markets is thin.

Behavioural Explanation. The behavioural rationale for the use of technical analysis is the foundation of this thesis. Some argue that technical analysis is applied to processing information of the non-fundamental influence on price. Noise traders' demand for stocks could be somewhat disconnected from the news or fundamental factors. Other models highlight that market participants' bounded rationality is the reason why technical analysis is profitable, which enables me to connect technical analysis indicator with investor sentiment. In Shleifer and Summers (1990) model, noise traders are momentum traders. In Shleifer and Summers (1990) noise trader models, noise traders buy when prices rise and sell when prices fall, and the non-fundamental behaviour is not chaotic but has a systematic component. Their paper infers that technical analysis may serve as an instrument to analyze this component. Zhu and Zhou (2009) demonstrate that technical analysis improves an investor's utility substantially in a standard asset allocation model due to the presence of irrational noise traders. Some argue that technical analysis predicts the intervene of traders with influential power, for instance, the intervene of central banks in foreign exchange markets. The profitability of technical analysis can also stem from investors' underreaction to relevant public information in the past prices (Chan et al., 1996; Jegadeesh and Titman, 2001).

Menkhoff and Taylor (2007) argue that the last group of behavioural explanation for technical analysis is most plausible. However, formal evidence supporting this argument is weak. My empirical findings are strongly consistent with theories in the last group. The first three groups do not explain the spike-reversal pattern in cross-sectional returns after a high technical analysis forecast. On one hand, some models such as information diffusion model cannot explain the asymmetric profitability of applying technical analysis in the cross-sectional stock market. On the other hand, theories such as asset allocation model could not explain why the long-short portfolio returns spike immediately after high technical analysis forecasts and reverse in subsequent trading days.

Current literature challenges the first group's opinion that sees technical analysis as a pure irrational behaviour of irrational investors. It is found that, institutional investors and experienced practitioners, who are commonly deemed as rational investors, also use technical analysis. For instance, Taylor and Allen (1992) find in their survey that over 90% of experienced traders place some weight on technical analysis in trading activities.

2.3.3 Connections between Sentiment and Technical Analysis

Technical analysis users argue that technical analysis reflect investor sentiment. Menkhoff (2010) claims that technical analysis could be an instrument to analyze the systematic component of noise traders trading if the non-fundamental behaviour is assumed not all chaotic but has a symmetric component. Menkhoff (2010) shows that fund managers who use technical analysis hold the view that prices are heavily determined by psychological influences and consequently they react to this view with trend-following strategies. Feng et al. (2016) state that "One of the core foundational assumptions of technical analysis is that prices reflect all economically rational factors, as well as all irrational or psychological factors". One essential technical trading strategy, feedback trading, is primarily driven by sentiment-related noise trading (Chau et al., 2011; Feng et al., 2016; Kurov, 2008). De Long et al. (1990b) also explain the mispricing with a model where rational speculators can actively induce positive feedback trading of more forward-looking speculators.

Another strand of literature links technical analysis with sentiment by looking into the existence and efficacy of technical analysis during high and low sentiment period. Kurov (2008) find that positive feedback trading in index futures markets increases when sentiment is optimistic. Chau et al. (2011) model that feedback traders' demand for shares also partially depends on investor sentiment, and they empirically prove that for the largest three US ETF contracts positive feedback trading significantly exists and the level of feedback trading increases during high sentiment period. Feng et al. (2016) find that profitability of technical trading is more prevalent in high sentiment period and is stronger on difficult-to-arbitrage securities due to impediments on short-selling. When the market is in negative or neutral sentiment environment, asset prices should be close to fundamental value as arbitragers can eliminate mispricing simply by buying. Short-selling constraints lead to higher and long-lasting asset overpricing in high sentiment periods, therefore making technical analysis more effective and valuable. Smith et al. (2016) compare the performance of technical analysis users and non-users among hedge funds and find that technical analysis users exhibit better performance than non-users, especially during high sentiment periods.

Another vein of studies links sentiment with technical analysis is on anomalies such as momentum. Numerous studies show asset-pricing anomalies, indicating that predictable patterns exist in stock returns. Shleifer and Summers (1990) argue that empirical findings of positive serial correlation of returns in short horizon in the market imply the presence of positive feedback trading which could not be fully eliminated by arbitragers. Antoniou et al. (2013) find that momentum effect is stronger during high sentiment period and weaker in low sentiment period. They suggest that investors may underreact more strongly to information when it contradicts their sentiment due to cognitive dissonance and subsequently momentum effect may have asymmetry effect between high and low sentiment period because of short-selling constraints. Taylor (2014) finds the profits of momentum-based technical trading rules evolve slowly over time and profits positively rely on investors' short-selling ability. All those studies connect technical analysis with sentiment by showing the effectiveness of technical analysis in different investor sentiment environment.

Technical trading has also long been a prominent example of investor sentiment in theoretical papers, where investors form their belief based on mechanical trading rules without consideration of fundamentals. In the noise trader models, irrational noise trader may employ trading strategies that is based on technical analysis rules, for instance, positive feedback trading and momentum trading. In Shleifer and Summers (1990), positive feedback trading leads to an autocorrelation of returns over a short horizon and negative autocorrelation of returns over a long horizon. Technical analysis is valuable when prices are predictable.

Menkhoff and Taylor (2007) review literature and argue the most plausible explanation for technical analysis is that historical prices may reflect not only fundamental information but also the influences of noise traders or self-fulfilling effect of technical analysis. When mispricing could be predicted, technical analysis will be valuable. Pring (1991) also argues that technical analysis holds the key to monitoring investor sentiment. Zhou (2017) highlights that the importance of linking investor sentiment with technical analysis as well. He points out that many over-bought and over-sold indicators are designed to capture the unsustainable sentiment level in the market. With the popularity of technical analysis in practice, technical analysis provides concrete examples and ways of how investors' biased beliefs are formed and therefore could be used to capture investor sentiment.

Chapter 3

Investor Sentiment and the Cross-Section of Stock Returns: New Theory and Evidence

3.1 Introduction

Several theoretical studies, such as Delong, Shleifer, Summer and Waldmann (1990) (hereafter referred to as DSSW), demonstrate that investor sentiment affects asset prices when rational arbitrageurs face limits to arbitrage.[1] These studies focus on a single risky asset and accordingly their models are more suitable for empirical tests involving aggregate market portfolios (Huang et al., 2015). However, while there is ample evidence that market sentiment affects the cross-section of asset returns[2], there is no rigorous theory on the role of investor sentiment in the context of multiple assets.

[1] Several other models, including Campbell and Kyle (1993), Daniel et al. (1998), Barberis et al. (1998), Hirshleifer (2001), also illustrate the effect of sentiment on signal asset returns.

[2] For example, Brown and Cliff (2004), Brown and Cliff (2005), Baker and Wurgler (2006), Lemmon and Portniaguina (2006), Qiu and Welch (2004), Kumar and Lee (2006), Frazzini and Lamont (2008), Stambaugh et al. (2012), Ben-Rephael et al. (2012), Da et al. (2014), Huang et al. (2015), among many others.

The DSSW illustrate that investors' stochastic biased misperception (which is interpreted as investor sentiment in this thesis) affect the risky asset's price in a single risk-asset market. Predictions from a single-asset model do not necessarily hold in multi-asset economies (Verrecchia, 2001). For example, Cochrane et al. (2008) show that contrary to a constant price-dividend ratio and i.i.d. returns in one-tree model of Lucas (1978), the price-dividend ratio varies over time and predicts future returns in a two-tree model. Therefore, it is unclear whether DSSW's predictions can be generalized to markets with more than one risky assets.

In this chapter, I provide a parsimonious model of how investor sentiment affects the cross-section of stock returns. I introduce the idea that in a multiple risky-asset market risky assets are prone to two kinds of sentiment: the overall market sentiment and the idiosyncratic sentiment component. By introducing this new assumption into the DSSW model, I demonstrate the effect of investor sentiment in the cross-section, which has not been derived in theory.

Suppose that there are two risky assets, asset A and B. Assume irrational investors' beliefs are biased upwards (downwards) more towards A than B when market sentiment is high (low). Thus, asset A has higher exposure to market-wide sentiment (more sentiment prone) than asset B. When investor sentiment is unpredictable, this assumption also implies that the equilibrium returns of asset A will fluctuate more with the shift in market sentiment,hence posing higher noise trader risk to rational arbitrageurs, than those of asset B. My tractable model effectively captures the intuitive observation that stocks more prone to investor sentiment are also more difficult to arbitrage (Baker and Wurgler, 2006).

When market sentiment changes and rational investors trade against the misperception of irrational investors only partially due to noise trader risk, the contemporaneous returns of asset A change more than those of asset B. In the subsequent periods, asset A's returns reverse more as investor sentiment reverts to its mean. Therefore, my model predicts the return difference between the more sentiment-prone asset and the less sentiment-prone asset to be positively associated with the change in contemporaneous sentiment and negatively related to the level of lagged sentiment. These predictions are consistent with the existing empirical evidence on the link between sentiment and cross-sectional stock returns.

Similar to DSSW, my model features the long- and short-run investor sentiment components. The long-run sentiment reflects the average bullishness of noise traders, while the short-run sentiment represents the transitory deviations from the long-run sentiment. Both components affect the price of the single risky asset in the DSSW model. Unlike DSSW, the two components in my model have cross-sectional implications. When the short-run component increases relative to the long-run component, irrational investors become more bullish and drive up the relative returns of more sentiment-prone stocks. Hence, I predict a positive correlation between contemporaneous changes in short-run sentiment and the relative returns of sentiment-prone stocks. However, a higher long-run sentiment exerts more upward pressure on the prices of more sentiment prone stocks, reducing the expected future return on these stocks.[3] Therefore, I predict the long-run component to be a contrarian predictor of cross-sectional returns.

Motivated by my model, I empirically decompose investor sentiment into a short-run sentiment component constructed as incremental changes of sentiment, and a long-run sentiment component measured by a moving average of investor sentiment during the past two years.[4] I test the cross-sectional pricing effect of both components with all common stocks on NYSE, AMEX, and NASDAQ between July 1965 and Sep 2015. I follow Baker and Wurgler (2006) and construct sixteen long-short portfolios that take a long position on more sentiment-prone stocks and a short position on less sentiment-prone stocks. Sentiment-prone stocks tend to be small, young, more volatile, unprofitable, non-dividend-paying, financially

[3] I do not model the time-varying long-run sentiment explicitly. Instead, I rely on comparative statics to obtain predictions on the pricing effect of long-run sentiment. Allowing long-run sentiment varying with time complicates the model, although I expect the effect of long-run sentiment to remain the same.

[4] I also consider alternative measures of short-run and long-run sentiment components and find similar results.

distressed, with extreme growth potential or with a relatively high percentage of intangible assets.

Consistent with my theoretical predictions, I find a positive association between short-run sentiment and the contemporaneous cross-sectional stock returns and a negative association between long-run sentiment component and the subsequent cross-sectional stock returns. These findings are robust after accounting for systematic risk and time-varying factor loadings as well as to alternative sentiment measures, alternative constructions of portfolios, and alternative decomposition of sentiment. Further analysis suggests that the effect of the sentiment components on returns is generally stronger for stocks that are small, young, volatile, unprofitable/non-dividend paying, financially distressed and have high growth potential.

The contribution of this chapter is twofold. First, I contribute to theory by presenting the first parsimonious model that explicitly examines the effect of market-wide sentiment on the cross-sectional asset returns. My model formalises Baker and Wurgler's (2006) idea that more sentiment-prone assets are also more difficult to arbitrage. The type of limits to arbitrage I consider here is the noise trader risk, while limits to arbitrage in Baker and Wurgler (2006) take many other forms, such as transaction costs and idiosyncratic risk. My model complements existing knowledge on investor sentiment with a single risky asset by providing theoretical support for the well-documented evidence that investor sentiment affects the cross-sectional asset returns.

Second, I contribute to the empirical literature on investor sentiment by decomposing investor sentiment into short- and long-run components, showing that both components affect cross-sectional stock returns. Existing empirical studies on the pricing impact of investor sentiment find that change in investor sentiment is positively associated with contemporaneous returns (e.g., Ben-Rephael et al., 2012; Brown and Cliff, 2004; Lee et al., 2002) and that the sentiment level is negatively related to future returns(e.g., Baker and Wurgler, 2007;

Brown and Cliff, 2004; Lemmon and Portniaguina, 2006; Stambaugh et al., 2012, 2014). These studies do not decompose sentiment into long- and short-run components. Instead, most focus on the short-run relations between (undecomposed) sentiment and returns, with only a few papers investigating the long-run sentiment-return relationship. For example, Brown and Cliff (2005) document a strong predictive effect of sentiment level on long-run pricing error in size and value portfolios. Unlike existing studies, I examine the empirical predictions of my theoretical model by simultaneously examining the effects of long- and the short-run sentiment components on cross-sectional returns. I find that stock returns are negatively associated with the long-run sentiment component and positively related to the short-run sentiment component.

The rest of this chapter is organized as follows. Section 3.2 illustrates the model and derives the two main hypotheses. Section 3.3 describes the data. Section 3.4 discusses the empirical results and the robustness checks. Section 3.5 summarises the conclusions.

3.2 A Cross-Sectional Noise Trader Risk Model

DSSW (1990) propose a simple overlapping generation model of a market with one risky asset, one risk-free asset, and two types of two-period-lived agents, rational investors and irrational noise traders with stochastic misperception. The uncertainty of noise traders' misperception creates "noise trader risk" that deters rational investors from fully arbitraging. Because of its focus on a single risky asset, DSSW model is presumably better suited for examining the impact of investor sentiment at the aggregate levels (Huang et al., 2015). Since the claims or results in a single-asset model can sometimes be reversed in multi-asset economies (Verrecchia, 2001), it is unclear whether predictions of DSSW can be generalized to markets with more than one risky assets. In this study, I extend the single risky asset model of DSSW to a noise trader risk model with multiple risky assets that vary in their exposure to market-wide investor sentiment.

Similar to DSSW, my model is also an overlapping-generation model with two-period-lived agents. There are two agents in the economy: sophisticated investors (denoted as i), who have rational expectations, and noise traders (denoted as n), who hold biased beliefs and trade on noise. The percentage of noise traders in the market is given as μ, and the percentage of sophisticated investors is $1-\mu$. Both noise traders' and sophisticated investors' utility function is a CARA (constant absolute risk aversion) function of wealth, $\mathrm{U} = -e^{-(2\gamma)\omega}$, where γ is the coefficient of absolute risk aversion and ω is wealth. If holding period returns are normally distributed, solving expected utility optimization is equivalent to maximizing $\overline{\omega} - \gamma\sigma_{\omega}^2$, where $\overline{\omega}$ is the expected final wealth, and σ_{ω}^2 is one period ahead variance of wealth.

Unlike DSSW, my model has one risk-free asset and two risky assets, u_1 and u_2.[5] The difference between the risk-free asset and the unsafe assets lies in their supply. The risk-free asset is in perfectly elastic supply, which implies that its price is fixed. However, the supply of each unsafe asset is set at one unit, which means that their prices fluctuate along with the change in demand. In each period the risk-free asset has a fixed real rate of r and the risky assets have fixed dividend rate r, which means both risk-free asset and risky asset have the same fixed income rate of r. Sophisticated investors choose a portfolio of holding $\lambda_{t,1}^{i}$ amount of risky asset u_1 and $\lambda_{t,2}^{i}$ amount of risky asset u_2 to maximize their expected utility. However, given their misperception, noise traders maximize their expected utility by choosing a portfolio of holding $\lambda_{t,1}^{n}$ amount of risky asset $u_1$and $\lambda_{t,2}^{n}$ amount of risky asset u_2.

I assume that the overall market sentiment ρ_t follows a normal distribution with $\rho_t \sim N(\rho^*, \sigma_\rho^2)$. To examine the cross-sectional effect of investor sentiment and noise trader risk,

[5] Extending the model further with more than two risky assets is straightforward. I focus on the two risky assets model since it is sufficient to shed the lights on the cross-sectional effect of investor sentiment.

I further assume that noise traders have different misperceptions of the risky assets $u_1$and u_2.

$$\rho_{t,1} = \alpha_1 \rho_t + \varepsilon_{t,1},\ \varepsilon_{t,1} \sim \mathcal{N}(0, \sigma^2_{\varepsilon_1}) \tag{3.1}$$

$$\rho_{t,2} = \alpha_2 \rho_t + \varepsilon_{t,2},\ \varepsilon_{t,2} \sim \mathcal{N}(0, \sigma^2_{\varepsilon_2}) \tag{3.2}$$

$$cov(\varepsilon_{t,1}, \rho_t) = 0,\ cov(\varepsilon_{t,1}, \varepsilon_{t,2}) = 0 \tag{3.3}$$

For simplicity, I also assume $\sigma^2_{\varepsilon_1} = \sigma^2_{\varepsilon_2}$. Equations (3.1) and (3.2) show that noise traders' misperception of a risky asset contains a systematic component proportional to market sentiment and an idiosyncratic component. The equations above also imply that $\sigma^2_{\rho_1} = {\alpha_1}^2 \sigma^2_{\rho} + \sigma^2_{\varepsilon_1}$ and $\sigma^2_{\rho_2} = {\alpha_2}^2 \sigma^2_{\rho} + \sigma^2_{\varepsilon_2}$.Without the loss of generality, assume $\alpha_1 > \alpha_2 > 0$, then u_1 are more exposed to market sentiment than asset u_2.[6] This implies $\sigma^2_{\rho_1} > \sigma^2_{\rho_2}$. Later I show that equilibrium price volatility of asset u_1 is larger than that of asset u_2 due to higher noise trader risk ($\sigma^2_{\rho_1} > \sigma^2_{\rho_2}$). Higher noise trader risk poses stronger limits to arbitrage for rational investors to trade against irrational investors. As a result, my model parsimoniously captures the intuitive observation of Baker and Wurgler (2006) that more sentiment-prone assets are also more difficult to arbitrage, although the limits to arbitrage in Baker and Wurgler (2006) are broader and not necessarily related to noise trader risk.

For sophisticated investors maximization of their expected utility is equivalent to maximize

$$\begin{aligned} \overline{w^i} - \gamma \sigma^2_{w^i} &= c_0 + \lambda^i_{t,1}(r + {}_t p_{t+1,1} - p_{t,1}(1+r)) + \lambda^i_{t,2}(r + {}_t p_{t+1,2} - p_{t,2}(1+r)) \\ &\quad - \gamma[{\lambda^i_{t,1}}^2 {}_t\sigma^2_{p_{t+1,1}} + {\lambda^i_{t,2}}^2 {}_t\sigma^2_{p_{t+1,2}} + 2\lambda^i_{t,1}\lambda^i_{t,2t} cov(p_{t+1,1}, p_{t+1,2})] \end{aligned} \tag{3.4}$$

[6] I relax the assumption of positive $\alpha_1$and α_2 in the discussions at the end of this section.

For noise traders maximization of their expected utility is equivalent to maximize

$$\begin{aligned}\overline{w^n} - \gamma\sigma_{w^n}^2 = c_0 &+ \lambda_{t,1}^n\left(r + {}_tp_{t+1,1} - p_{t,1}(1+r)\right) + \lambda_{t,2}^n\left(r + {}_tp_{t+1,2} - p_{t,2}(1+r)\right) \\ &- \gamma[{\lambda_{t,1}^n}^2\, {}_t\sigma_{p_{t+1,1}}^2 + {\lambda_{t,2}^n}^2\, {}_t\sigma_{p_{t+1,2}}^2 + 2\lambda_{t,1}^n\lambda_{t,2}^n\, {}_tcov(p_{t+1,1}, p_{t+1,2})] \\ &+ \lambda_{t,1}^n(\alpha_1\rho_t + \varepsilon_{t,1}) + \lambda_{t,2}^n(\alpha_2\rho_t + \varepsilon_{t,2})\end{aligned} \tag{3.5}$$

where ${}_tp_{t+1,1}$ is the conditional expectation of the one-step-ahead price of risky asset u_1 at time t, ${}_t\sigma_{p_{t+1,1}}^2$ is the conditional expectation of one-step-ahead variance of $p_{t+1,1}$, and ${}_t\sigma_{p_{t+1,2}}^2$ is the conditional expectation of one-step-ahead variance of $p_{t+1,2}$, and ${}_tcov(p_{t+1,1}, p_{t+1,2})$ is the conditional expectation of the covariance of the one-step-ahead risky assets' price $p_{t+1,1}$ and $p_{t+1,2}$. The anterior subscript t means that an expectation is taken at time t. Solving the above optimization problem with first-order condition yields the portfolio holdings of the two risky assets:

$$\lambda_{t,1}^i = \frac{kR_{t+1,2} - \sigma_2^2 R_{t+1,1}}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)} \tag{3.6}$$

$$\lambda_{t,2}^i = \frac{kR_{t+1,1} - \sigma_1^2 R_{t+1,2}}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)} \tag{3.7}$$

$$\lambda_{t,1}^n = \frac{k(R_{t+1,2} + \alpha_2\rho_t + \varepsilon_{t,2}) - \sigma_2^2(R_{t+1,1} + \alpha_1\rho_t + \varepsilon_{t,1})}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)} \tag{3.8}$$

$$\lambda_{t,2}^n = \frac{k(R_{t+1,1} + \alpha_1\rho_t + \varepsilon_{t,1}) - \sigma_1^2(R_{t+1,2} + \alpha_2\rho_t + \varepsilon_{t,2})}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)} \tag{3.9}$$

where $R_{t+1,1} = r + {}_tp_{t+1,1} - p_{t,1}(1+r)$, $R_{t+1,2} = r + {}_tp_{t+1,2} - p_{t,2}(1+r)$, $k = {}_tcov(p_{t+1,1}, p_{t+1,2})$, and $\sigma_1^2 = {}_t\sigma_{p_{t+1,1}}^2$, $\sigma_2^2 = {}_t\sigma_{p_{t+1,2}}^2$.

Market clearing requires the holding of the two risky assets from the noise traders and the sophisticated investors to be equal to their supply.

$$\begin{cases}(1-\mu)\lambda_{t,1}^i + \mu\lambda_{t,1}^n = 1 \\ (1-\mu)\lambda_{t,2}^i + \mu\lambda_{t,2}^n = 1\end{cases} \tag{3.10}$$

By assuming that equilibrium prices in all periods have identical distributions, I can obtain the equilibrium pricing functions by solving the following function recursively:

$$p_{t,1} = \frac{1}{1+r}[r + {}_t p_{t+1,1} - 2\gamma(k+\sigma_1^2) + \mu(\alpha_1 \rho_t + \varepsilon_{t,1})] \tag{3.11}$$

$$p_{t,2} = \frac{1}{1+r}[r + {}_t p_{t+1,2} - 2\gamma(k+\sigma_2^2) + \mu(\alpha_2 \rho_t + \varepsilon_{t,2})] \tag{3.12}$$

If the conditional variance of the price is constant, substituting the conditional one-step-ahead price forward yields:

$$p_{t,1} = 1 + \frac{\mu\alpha_1(\rho_t - \rho^*)}{1+r} + \frac{\mu\alpha_1\rho^*}{r} - \frac{2\gamma(k+\sigma_1^2)}{r} + \frac{\mu\varepsilon_{t,1}}{1+r} \tag{3.13}$$

$$p_{t,2} = 1 + \frac{\mu\alpha_2(\rho_t - \rho^*)}{1+r} + \frac{\mu\alpha_2\rho^*}{r} - \frac{2\gamma(k+\sigma_2^2)}{r} + \frac{\mu\varepsilon_{t,2}}{1+r} \tag{3.14}$$

The equilibrium price is a function of both the misperception and the risk induced by stochastic misperception. The second term in the equilibrium price functions shows the change in the price caused by the fluctuations of the overall market misperception around its long-run mean. When noise traders become more bullish relative to the average overall market misperceptions, their demand pushes the price up. The third term captures the deviation of the price from the fundamental value caused by the average overall market misperception. The fourth term captures the compensation for bearing the "noise trader risk" caused by uncertainty of the next period's misperception. Noise trader risk makes sophisticated investors unwilling to trade fully against noise traders since future misperceptions of noise traders can become extreme. The last term captures the fluctuation in price caused by the variation of idiosyncratic misperceptions towards risky asset u_1. Equations (3.13) and (3.14) imply that the unconditional price volatility and the price covariance of the two risky assets at time $t+1$

are given as:

$$\sigma^2_{t+1,1} = \frac{\alpha_1^2\mu^2\sigma_\rho^2}{(1+r)^2} + \frac{\mu^2\sigma^2_{\varepsilon_1}}{(1+r)^2} \tag{3.15}$$

$$\sigma^2_{t+1,2} = \frac{\alpha_2^2\mu^2\sigma_\rho^2}{(1+r)^2} + \frac{\mu^2\sigma^2_{\varepsilon_2}}{(1+r)^2} \tag{3.16}$$

$$cov(p_{t+1,1}, p_{t+1,2}) = \frac{\alpha_1\alpha_2\mu^2\sigma_\rho^2}{(1+r)^2} \tag{3.17}$$

I also solve the Equation (3.6) to (3.9) to obtain the portfolio holdings for sophisticated investors and noise traders:

$$\lambda^i_{t,1} = 1 - \frac{\mu(k\alpha_2 - \sigma_2^2\alpha_1)}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)}\rho_t - \frac{\mu(k\varepsilon_{t,2} - \sigma_2^2\varepsilon_{t,1})}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)} \tag{3.18}$$

$$\lambda^i_{t,2} = 1 - \frac{\mu(k\alpha_1 - \sigma_1^2\alpha_2)}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)}\rho_t - \frac{\mu(k\varepsilon_{t,1} - \sigma_1^2\varepsilon_{t,2})}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)} \tag{3.19}$$

$$\lambda^n_{t,1} = 1 + \frac{(1-\mu)(k\alpha_2 - \sigma_2^2\alpha_1)}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)}\rho_t + \frac{(1-\mu)(k\varepsilon_{t,2} - \sigma_2^2\varepsilon_{t,1})}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)} \tag{3.20}$$

$$\lambda^n_{t,2} = 1 + \frac{(1-\mu)(k\alpha_1 - \sigma_1^2\alpha_2)}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)}\rho_t + \frac{(1-\mu)(k\varepsilon_{t,1} - \sigma_1^2\varepsilon_{t,2})}{2\gamma(k^2 - \sigma_1^2\sigma_2^2)} \tag{3.21}$$

Given the obtained price volatility and covariance, $2\gamma(k^2 - \sigma_1^2\sigma_2^2) < 0$, $k\alpha_2 - \sigma_2^2\alpha_1 < 0$, and $k\alpha_1 - \sigma_1^2\alpha_2 < 0$. Thus, the sophisticated investors' holdings of the two risky assets are inversely proportional to current market sentiment, while the noise traders' holdings of these risky assets are proportional to current market sentiment. That is, sophisticated investors reduce their demand for sentiment-prone assets while noise traders increase their demand for sentiment-prone assets when overall market sentiment becomes more bullish.

The exposure of the risky assets to the overall market misperception also affects the cross-section of holdings. The sophisticated investors' holdings of $u_1(u_2)$ are positively related to $\alpha_1(\alpha_2)$. Since $\alpha_1 > \alpha_2$, the current market sentiment will have a greater effect on investors' (both sophisticated and irrational) holdings of asset u_1. This also means that when overall market sentiment becomes more bullish, sophisticated investors will reduce their demand for asset u_1 more than asset u_2 and irrational investors will increase their demand for asset u_1 more than on asset u_2.

Recall that the excess return from date t to date $t+1$ is defined as: $R_{t+1} = r + {}_t p_{t+1,1} - p_{t,1}(1+r)$. Plugging this in the equilibrium price, I obtain the return for asset u_1 and asset u_2 at time $t+1$

$$R_{t+1,1} = \frac{\mu\alpha_1[\rho_{t+1} - (1+r)\rho_t]}{1+r} - \frac{\alpha_1\mu\rho^*}{1+r} + 2\gamma(k+\sigma_1^2) + \theta_1 \tag{3.22}$$
$$R_{t+1,2} = \frac{\mu\alpha_2[\rho_{t+1} - (1+r)\rho_t]}{1+r} - \frac{\alpha_2\mu\rho^*}{1+r} + 2\gamma(k+\sigma_2^2) + \theta_2 \tag{3.23}$$

where $\theta_1(\theta_2)$ are functions of $\varepsilon_{t,1}$ and $\varepsilon_{t+1,1}$ ($\varepsilon_{t,2}$ and $\varepsilon_{t+1,2}$). Hence, the return difference between the two risky assets is

$$R_{t+1,1} - R_{t+1,2} = (\alpha_1 - \alpha_2)[\frac{\mu[\rho_{t+1} - (1+r)\rho_t]}{1+r} - \frac{\mu\rho^*}{1+r}] + 2\gamma(\sigma_1^2 - \sigma_2^2) + \theta_1 - \theta_2 \tag{3.24}$$

The equilibrium returns can also be expressed as functions of the deviation of current sentiment from its long-run mean, denoted as η_t ($\eta_t = \rho_t - \rho^*$).

$$R_{t+1,1} = \frac{\mu\alpha_1[\eta_{t+1} - (1+r)\eta_t]}{1+r} - \alpha_1\mu\rho^* + 2\gamma(k+\sigma_1^2) + \theta_1 \tag{3.25}$$
$$R_{t+1,2} = \frac{\mu\alpha_2[\eta_{t+1} - (1+r)\eta_t]}{1+r} - \alpha_2\mu\rho^* + 2\gamma(k+\sigma_2^2) + \theta_2 \tag{3.26}$$

Hence, the return difference between asset u_1 and asset u_2 at time $t+1$ can be written as

$$R_{t+1,1} - R_{t+1,2} = (\alpha_1 - \alpha_2)[\frac{\mu[\eta_{t+1} - (1+r)\eta_t]}{1+r} - \mu\rho^*] + 2\gamma(\sigma_1^2 - \sigma_2^2) + \theta_1 - \theta_2 \tag{3.27}$$

Take the unconditional expectations of Equation (3.27), I obtain:

$$E(R_{t+1,1} - R_{t+1,2}) = (\alpha_1 - \alpha_2)[-\mu\rho^*] + 2\gamma(\sigma_1^2 - \sigma_2^2) \tag{3.28}$$

I consider the average of the overall market misperception ρ^* as the long-run sentiment component, and the incremental sentiment change as the short-run sentiment component. The latter is measured by either sentiment increment, $\rho_t - (1+r)\rho_{t-1}$, or the changes of sentiment's derivation from its long-run mean, $\eta_{t+1} - (1+r)\eta_t$.

Equations (3.22) and (3.23) show that the short-run sentiment is positively related to the returns of both risky assets. The effect is stronger for u_1 than u_2 because $\alpha_1 > \alpha_2$ (see Equation (3.27)). As a result, I have the following hypothesis on the pricing effect of the short-run component of investor sentiment:

Hypothesis 1. *The short-run sentiment component is positively related to the contemporaneous difference in returns of more sentiment-prone and less sentiment-prone assets.*

Inspection of Equations (3.22) and (3.23) also reveals that returns of a risky asset depend on the exposure of the misperception about its price to the overall market misperception. High long-run sentiment implies lower equilibrium returns for both risky assets (α_1 and α_2 are positive), and the returns of u_1 are more adversely affected by the long-run sentiment than u_2 ($\alpha_1 > \alpha_2$). This leads to my hypothesis on the pricing effect of the long-run component of investor sentiment.

Hypothesis 2. *The long-run sentiment component predicts lower returns for more sentiment-prone assets than less sentiment-prone assets.*

If I relax the assumption that $\alpha_1 > \alpha_2 > 0$ by allowing $\alpha_2 < 0$ while keeping $\alpha_1 > 0$, the effect of long- and short-run investor sentiment are inversed for the risky asset u_2. In this case, when the average market sentiment becomes more bullish, it exerts an adverse effect on contemporaneous returns due to the short-run sentiment effect, and a positive effect on future returns due to the long-run sentiment effect. The opposite is true in case of the risky asset u_1, as it still has a positive exposure to market sentiment. Hence, the returns of the two risky assets move in the opposite directions, and the effect of long- and short-run sentiment will be muted at the aggregate market level. Baker and Wurgler (2007) make a similar argument that if the price of a low sentiment-prone stock is inversely related to sentiment, due to reasons such as "flight to quality”, then the effect of sentiment on aggregate market returns is unlikely to be significant. This implication may also explain the inconclusive evidence on the impact of investor sentiment on aggregate market returns (Baker and Wurgler, 2007; Baker et al., 2012; Brown and Cliff, 2004; Elton et al., 1998). However, for a given positive α_1 when $\alpha_1 > \alpha_2$, a negative (instead of positive) α_2 makes the cross-sectional returns difference between u_1 and $u_2$4 more dispersed. Hence, it is not surprising that several empirical studies find that market sentiment affects asset returns in the cross-section (Baker and Wurgler, 2007; Lemmon and Portniaguina, 2006, among others).

3.3 Data

3.3.1 Portfolio Construction

To substantiate my theory, I follow Baker and Wurgler (2006) to construct long-short portfolios to obtain the relative returns of more sentiment-prone stocks over less sentiment-prone stocks. Baker and Wurgler (2006) argue that firms that are small, young, volatile, non-dividend-paying/non-profitable, informationally opaque, financially distressed and with more growth opportunities are more prone to sentiment. Similar to Baker and Wurgler (2006), I construct sixteen long-short portfolios based on 10 characteristics. These characteristics include market capitalization (ME), firm age (Age), total risk (Sigma), earnings-book ratio for profitable firms (E/BE), dividend-book ratio for dividend payers (D/BE), fixed assets ratio

(PPE/A), research and development ratio (RD/A), book-to-market ratio (BE/ME), external finance over assets (EF/A) and sales growth ratio (GS).[7] The ten firm characteristics are winsorized at 99.5 and 0.5% annually. The breakpoints for deciles are defined by only using NYSE firms. The top three, middle four, and bottom three decile portfolios are noted as H, M, and L respectively.

The firm-level accounting data are from Compustat and the firm-level stock monthly returns are from CRSP. I adopt the Fama and French (1992) approach and match the year-end accounting data of year t-1 to monthly returns from July t to June t+1. The stock market data include all common stocks (share codes 10 and 11) on NYSE, AMEX, and NASDAQ (with stock exchange codes 1, 2, and 3) between January 1962 and Sep 2015. My final sample consists of 18175 firms. I only consider the RD/A from 1972 because the RD/A data are not available until 1971. I follow Baker and Wurgler (2006) to construct the portfolio when possible.[8]

To facilitate the interpretation of my results, I use the returns of more sentiment-prone stocks minus the returns of less sentiment-prone stocks to calculate the returns of the long-short portfolios. For example, the returns of the long-short portfolio based on BE/ME (L-M) represents the return difference between the bottom three deciles and the middle four deciles when using BE/ME as the sorting characteristic. All the portfolio returns are equal-weighted.[9]

The sixteen long-short portfolios can be categorised into six groups. The first group is named 'Size, Age, and Risk'. Small, young, and volatile firms are more sentiment-prone; hence, the long-short portfolios associated with these variables are constructed and noted as ME(L-H), Age(L-H) and Sigma(H-L). The second group is referred to as 'Profitability and

[7] Definitions of these characteristics variables are provided in the Appendix B.

[8] I use the same variable definition of Baker and Wurgler (2006) except for RD/A, which I do not replace any missing value with zero. Replacing R&D missing values with zeros will cause some problem after mid 2000 where almost half of the observations are zero. I focus on the stocks that have non-missing R&D values. Monthly returns are adjusted for delisting.

[9] I also conduct all the tests in this chapter with value-weighted returns and find similar results.

Dividend Policy'. In this group, non-profitable stocks or stocks with low dividend payments are considered to be more prone to sentiment. The third group is labelled 'Tangibility' and contains portfolios constructed by PPE/A and RD/A. Stocks with less tangible asset or more intangible asset are considered to be more informational opaque and therefore more prone to sentiment. The last three groups are called 'Growth Opportunity and Distress', 'Growth Opportunity' and 'Distress' respectively, which are constructed according to BE/ME, EF/A and GS.

The reason for constructing nine long-short portfolios in the last three groups based on the three characteristics (BE/ME, EF/A, and GS) is that those three characteristics have a multidimensional nature. Stocks at the top and the bottom deciles sorted on BE/ME, EF/A or GS represent either extreme growth or extreme value stocks, while firms in the middle deciles are more stable and safe. In the meantime, those three characteristics could be used as a generic pricing factor. Take BE/ME as an example. High BE/ME implies that a firm is in distress, while the low BE/ME indicates extreme growth potential. On one hand, since financially distressed stocks are highly appealing to the speculative demand of irrational investors, firms with high BE/ME, low EF/A, and low GS are likely to be more prone to sentiment. On the other hand, as high growth firms are hard to value, the returns of firms with low BE/ME, high EF/A, and high GS are likely to be affected more by shifts in investor sentiment.

Panel A in Table 3.1 presents the summary statistics for the long-short portfolio returns during the sample period. Generally, most of the long-short portfolios have positive average returns. The negative average portfolio returns of EF/A(H-L) and GS(H-L) are not surprising because EF/A and GS measures the growth opportunity and financial stress in an opposing way from BE/ME.[10] The returns of those sixteen long-short portfolios are all positively

[10]One may find it more appropriate to construct long-short portfolios as EF/A(L-H) and GS(L-H). However, due to the multidimensional nature of EF/A and GS, I would not expect decomposed investor sentiment to perform well in predicting the long-short portfolios constructed with top and bottom deciles of EF/A or GS, whatever the long-legs or short-legs are. Accordingly, I use EF/A(H-L) and GS(H-L) to be consistent with

skewed. The last two columns of Panel A report the first-order autoregression coefficients (AR(1)) and the correlation between the variable and one-month lagged Baker Wurgler sentiment (Corr), respectively. Although the portfolio returns of ME(L-H) and BE/ME (H-L) have little autocorrelations, the returns of all other long-short portfolios are significantly autocorrelated. Furthermore, except for BE/ME(L-H), GS(H-L) and BE/ME(H-M), Baker Wurgler sentiment negatively predicts future returns with strong statistical significance. The negative correlation coefficients between the long-short portfolio returns and one-month lagged investor sentiment are in line with previous studies showing that investor sentiment is a good contrarian predictor of future cross-sectional returns.

Baker and Wurgler(2006).

Table 3.1 Summary Statistics

This table reports the descriptive statistics of dependent variables and decomposed Baker-Wurgler sentiment measures. High is defined as a portfolio of top three deciles; Medium is the middle four deciles; Low contains the bottom three deciles. AR(1) represents the first-order autocorrelation and Corr represents the correlation between the summarised variable and one-term lagged Baker-Wurgler sentiment index. Panel A contains summary statistics for all the return premiums of the sixteen long-short strategies. In Panel A, the first column is the characteristic used and the second column is the portfolio construction. Panel B contains the statistics of long-run sentiment measure $\rho_{LR,t}$ and two proxies for short-run sentiment. $\eta_t - \eta_{t-1}$is the changes of the sentiment deviation from long-run sentiment, and $(\rho_t - \rho_{t-1})^{\perp}$ is the sentiment increment orthogonalized to long-run sentiment of previous period. $***p < 0.01, **p < 0.05, *p < 0.1$. The sample period is from Jul 1965 to Sep 2015.

Variable		Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	AR(1)	Corr
Panel A Dependent Variables										
ME	L-H	606	0.28	3.43	-12.73	17.1	0.78	6.29	0.08	-0.14***
Age	L-H	606	0.07	3.34	-12.69	23.89	1.23	10.03	0.15*	-0.17***
Sigma	H-L	606	0.12	4.48	-13.88	24.26	0.76	6.03	0.22***	-0.18***
E	$<0->0$	606	0.13	4.06	-14.44	28.5	1.36	9.60	0.18**	-0.18***
D	$=0->0$	606	0.1	3.73	-13.46	24.39	1.03	8.74	0.19**	-0.18***
PPE/A	L-H	606	-0.07	2.68	-7.99	15.12	0.60	5.51	0.24***	-0.09**
RD/A	H-L	516	0.25	2.28	-6.93	18.04	1.16	10.77	0.16*	-0.09**
BE/ME	H-L	606	0.54	2.62	-11.13	12.89	0.20	5.86	0.12**	0.03
EF/A	H-L	606	-0.48	1.44	-5.52	6.33	-0.01	4.50	0.11**	-0.08**
GS	H-L	606	-0.29	1.63	-6.01	4.78	-0.19	3.76	0.14***	0.00
BE/ME	L-M	606	-0.23	2.08	-10.53	14.03	0.33	10.05	0.09	-0.11***
EF/A	H-M	606	-0.29	1.66	-6.36	10.43	0.67	7.21	0.14**	-0.18***
GS	H-M	606	-0.23	1.81	-6.87	10.52	0.36	6.25	0.15**	-0.16***
BE/ME	H-M	606	0.33	1.52	-5.26	9.78	0.97	7.57	0.18***	-0.09**
EF/A	L-M	606	0.18	1.20	-2.98	6.06	0.9	5.45	0.13***	-0.15***
GS	L-M	606	0.06	1.68	-5.79	9.89	1.21	7.88	0.21***	-0.17***
Panel B Sentiment Proxies Based on Baker-Wurgler Sentiment										
ρ_{LR}		604	-0.03	0.91	-2.08	2.09	-0.17	-0.19	0.99***	0.72***
$\eta_t - \eta_{t-1}$		601	0.00	0.02	-0.09	0.07	-0.24	1.35	0.15**	-0.26***
$(\rho_t - \rho_{t-1})^{\perp}$		601	0.00	0.02	-0.07	0.08	0.11	1.41	0.08	0.05
BN_LR		602	0.00	1.06	-2.32	3.34	0.28	3.67	0.99***	0.98***
BN_SR		602	0.00	0.22	-0.85	0.77	-0.41	4.64	0.91***	-0.26***

3.3.2 Decomposition of Investor Sentiment

To test my theoretical predictions on the cross-sectional effect of the long- and short-run sentiment, I empirically decompose the overall market sentiment, as measured by the original monthly sentiment index constructed by Baker and Wurgler (2006), into long- and short-run sentiment components.

One innovation in my empirical tests is allowing long-run investor sentiment to vary over time. In the DSSW model, both the constant level of long-run investor sentiment and the fluctuation of short-run investor sentiment affect the asset price. However, the long-run sentiment is included in their model as a constant and has a time invariant impact on returns of the risky asset in the equilibrium. Empirical tests of investor sentiment typically examine how the short-run lagged level of investor sentiment affects the cross-section of returns, while long-run sentiment is usually ignored. Omitting long-run sentiment from the empirical tests probably reflects the lack of a theory that allows long-run sentiment to vary over time, implying that regressions of returns on constant long-run sentiment will make its coefficients unidentifiable from the intercept. For this end, I modify the empirical tests by assuming that the long-run sentiment component is a time-varying first-order autoregressive progress. In this way, the empirical tests show that the time-varying long-run investor sentiment is a contrarian predictor of the returns of the long-short portfolio that buys the more sentiment-prone risky assets and sells the less sentiment-prone risky assets.

In my baseline regressions, I choose Baker-Wurgler Sentiment indicator as the investor sentiment measure, because it is extensively accepted in the empirical studies. Choosing Baker-Wurgler Sentiment also enables me to compare my results with Baker and Wurgler (2006) to see whether my decomposed sentiment performs better at explaining the cross-sectional return. Baker and Wurgler (2006) use the principal component analysis method to extract the common component of five sentiment proxies, including closed-end fund discount

(CEFD), the number and the first-day returns of IPOs (NIPO, RIPO), the equity share in total new issues (S), and the dividend premium (DP).[11] The Baker-Wurgler index, Sent_BW, is orthogonalized to macroeconomic variables, including the growth in industrial production, the growth in durable, nondurable, and services consumption, the growth in employment and a NBER dummy variable for recessions. The sample period is from July 1965 to September 2015.[12]

I implement two approaches to decompose the original investor sentiment index. The first one uses a moving average of the original sentiment index as a crude yet intuitive measure for the long-run sentiment component. More specifically, at each time t, the long-run sentiment component $\rho_{LR,t}$ is the moving average of the original sentiment index over a two-year period between $[t-25, t-2]$. While the choice of a 24-month window is admittedly somewhat arbitrary, it is partially motivated by the observation that periods of high/low sentiment often persist for around two years. For example, the US stock market experienced a "new-issue mania" between 1961 and 1962, high investor sentiment for firms with strong growth potential between 1967 and 1968, and a bubble in gambling issues in 1977 and 1978. Concerning the bubbles and crashes, it also usually takes around two years for stock price to come back to earth in the anecdotal history. For instance, following the high-tech bubble in early 1980s, investors' demand shifted to dividend paying stocks between 1987 and 1988. For robustness purposes, I also consider alternative windows of the moving average for long-run sentiment, including 12-month, 36-month and 48-month,with my primary conclusions remaining unchanged.

When the long-run sentiment component is measured crudely by smoothing average, there are two ways to construct the corresponding short-run sentiment component. One measure for the short-run component $(\rho_t - \rho_{t-1})^{\perp}$ is the change in the current sentiment

[11] Jeffery Wurgler provide these data on his personal website http://people.stern.nyu.edu/jwurgler/.

[12] I choose the Baker-Wurgler index as my baseline sentiment measure to make it easier to compare my regression results with the findings in Baker and Wurgler (2006). I also use other sentiment measures to obtain their long-run and short-run components and find similar results.

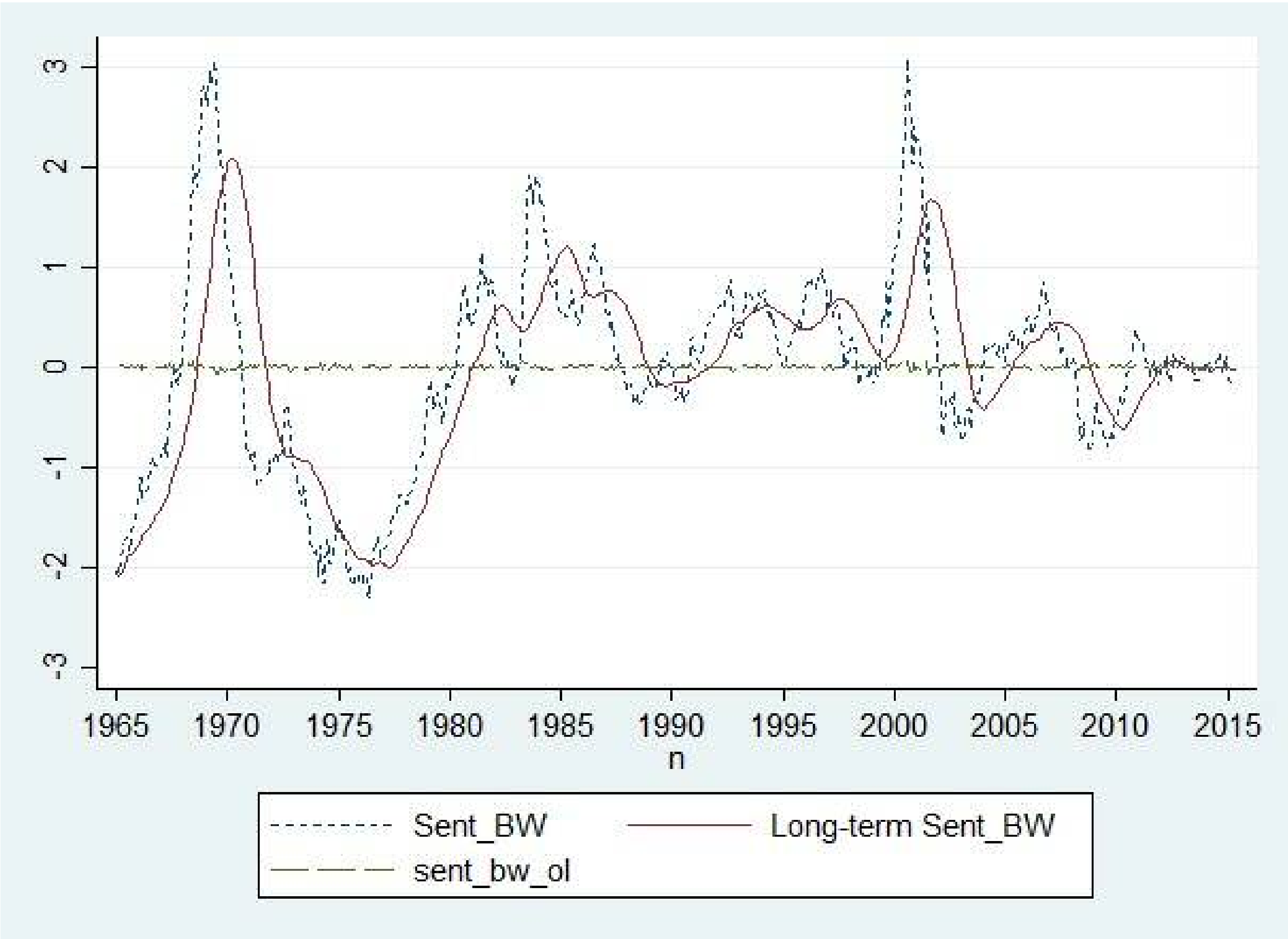
from its previous level, which is also orthogonalized to the long-run sentiment component. $\rho_t - \rho_{t-1}$ is orthogonalized from the long-run sentiment component to obtain a measure of the short-run sentiment fluctuation that is uncorrelated with the long-run sentiment. Another measure for short-run sentiment $\eta_t - \eta_{t-1}$ is the change in the deviation of current sentiment from its corresponding long-run sentiment $(\rho_t - \rho_{LR,t}) - (\rho_{t-1} - \rho_{LR,t-1})$.[13]

Our second approach to decompose sentiment is from Beveridge and Nelson (1981).[14] The Beveridge-Nelson decomposition is an approach to decompose the Autoregressive Integrated Moving Average ARIMA(p,1,q) process into two components: a permanent component that is a random walk with drift and a transitory component that is a stationary process with a mean of zero. I consider the permanent component of the decomposed sentiment index as the long-run sentiment (BN_LR), and the transitory component of decomposed sentiment index as the short-run sentiment (BN_SR).

Figure 3.1 depicts the time series of decomposed long- and short-run sentiment and the original Baker-Wurgler index when using a moving average to obtain long-run sentiment. The long-run sentiment is $\rho_L R$ and the short-run sentiment is $\eta_t - \eta_{t-1}$. The graph shows that the long-run sentiment is strongly correlated with the original Baker-Wurgler sentiment index, albeit with some lags. The long-run sentiment is smoother than the original Baker-Wurgler index, while the short-run sentiment is relatively small and fluctuates around zero. The short-run sentiment component is generally smaller in magnitudes than the long-run sentiment component.

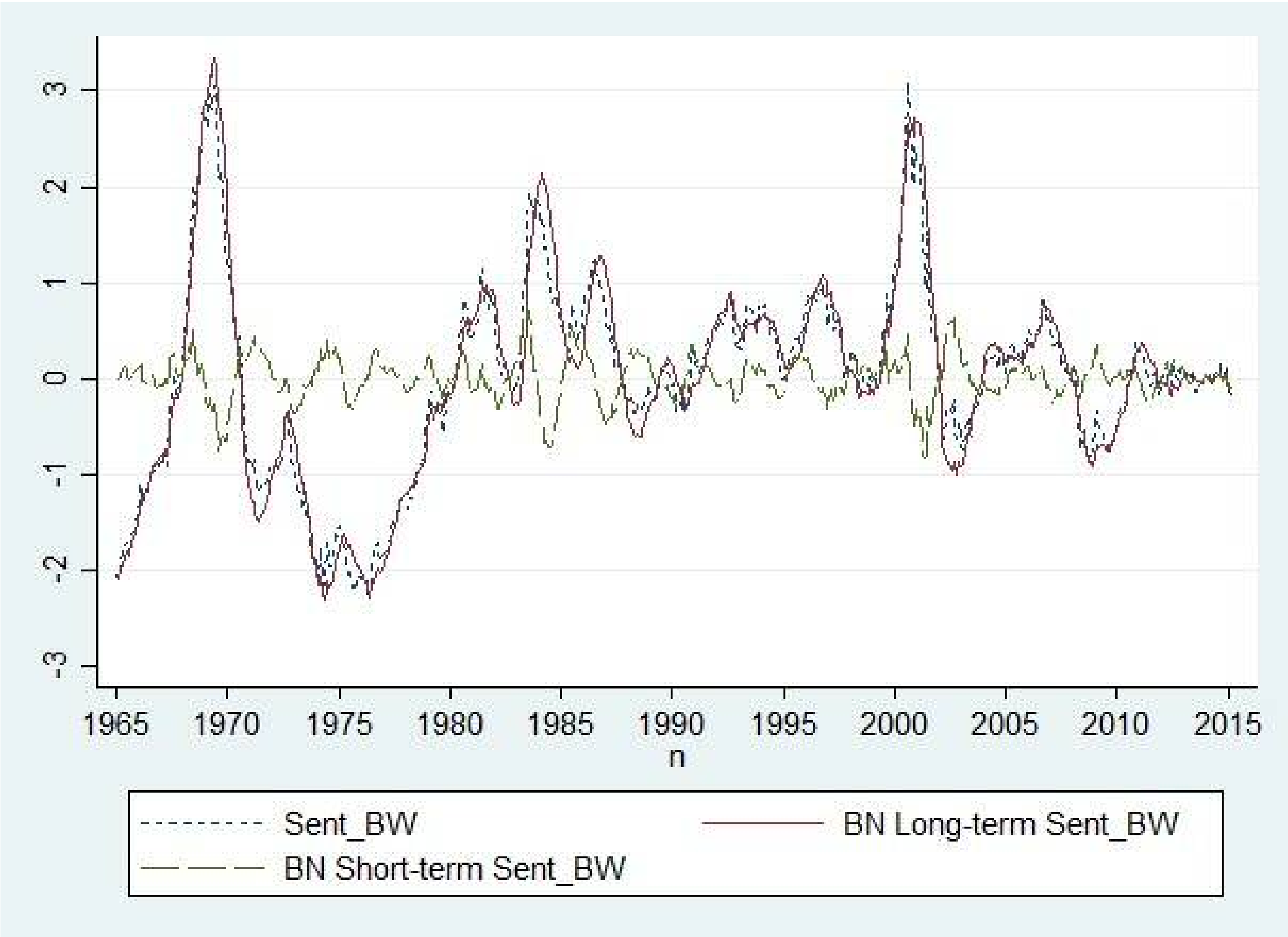
[13] Based on my model, the short-run sentiment should be $(\rho_t - (1+r)\rho_{t-1})^{\perp}$. I nevertheless follow the previous literature and ignore the effect of risky-free rate to obtain a short-run sentiment proxy, $(\rho_t - \rho_{t-1})^{\perp}$. I also use $(\rho_t - (1+r)\rho_{t-1})^{\perp}$ to run the tests and the regression results are strongly consistent with the results of using $(\rho_t - \rho_{t-1})^{\perp}$. The monthly risky-free rate is small and does not affect my main results.

[14] I thank Dominique Ladiray for providing the algorithm codes.



Moving Average Based Decomposition of BW Sentiment Index, 1965:07-2015:09.
The long-dashed blue line depicts the original Baker-Wurgler sentiment index during July 1965 and September 2015. The solid red line depicts the long-run component of Baker-Wurgler sentiment index, which is measured by the moving average of previous 24-month sentiment. The green short-dashed line depicts the short-run component $\eta_t - \eta_{t-1}$, which is the change in the deviation of current sentiment from its corresponding long-run sentiment.

Fig. 3.1 Moving Average Based Decomposition of BW Sentiment Index



Beveridge-Nelson Decomposition of BW Sentiment Index, 1965:07-2015:09.
The short-dashed blue line depicts the original Baker-Wurgler sentiment index. The red solid line depicts the long-run component of Baker-Wurgler sentiment index decomposed by Beveridge and Nelson (1981) method. The long-dashed green line depicts the short-run component of Baker-Wurgler sentiment index decomposed by Beveridge and Nelson (1981) method.

Fig. 3.2 Beveridge-Nelson Decomposition of BW Sentiment Index

Figure 3.2 plots Beveridge-Nelson decomposed sentiment and the original Baker-Wurgler index. It shows that BN_LR is highly correlated with the original Baker-Wurgler sentiment. Comparing Figure 3.2 with Figure 3.1, the long-run sentiment is no longer a lagged version of original sentiment. The correlation coefficient between the long-run sentiment and the original sentiment is higher when I use BN_LR as the long-run sentiment indicator. Figure 3.2 also shows that BN_SR has a broader range than other short-run sentiment measures, such as $\eta_t - \eta_{t-1}$ and $(\rho_t - \rho_{t-1})^{\perp}$.

Panel B of Table 3.1 reports the descriptive statistics of the decomposed investor sentiment during the sample period from July 1965 to September 2015. Regarding the magnitudes of decomposed sentiment components, the long-run sentiment is generally much bigger than the short-run sentiment. The standard deviations of the long-run sentiment ρ_{LR} and BN_LR are 0.91 and 1.06, respectively. The standard deviations of the two short-run sentiment components,$\eta_t - \eta_{t-1}$ and $(\rho_t - \rho_{t-1})^{\perp}$, are both 0.02. The Beveridge-Nelson decomposition generates a short-run sentiment with a relatively larger scale than $\eta_t - \eta_{t-1}$ and $(\rho_t - \rho_{t-1})^{\perp}$. The short-run sentiment component BN_SR has a standard deviation of 0.22.

Panel B also shows that the long-run sentiment measures, namely ρ_{LR} and BN_LR, have a significant first-order autocorrelation coefficient with a value of 0.99. Short-run sentiment measure $(\rho_t - \rho_{t-1})^{\perp}$ does not have significant correlation with its own lagged term, as it has been orthogonalized to the strongly persistent long-run sentiment component. The short-run sentiment BN_SR is still significantly auto-correlated, with a first-order autocorrelation coefficient of 0.91. The last column of Panel B presents the correlation between each decomposed sentiment and the one-term lagged Baker-Wurgler sentiment. Apart from $(\rho_t - \rho_{t-1})^{\perp}$, the long- and short-run sentiment measures are significantly associated with the original sentiment, although the correlation coefficients for the short-run sentiment are relatively small in term of magnitude. With the exception of $(\rho_t - \rho_{t-1})^{\perp}$, the short-run sentiment measures are negatively associated with the one-period lagged original Baker and Wurgler sentiment.

3.4 Empirical Results

3.4.1 Decomposed Sentiment and Cross-Sectional Returns

Our theoretical model predicts that both the long- and short-run sentiment components affect cross-sectional stock returns. To examine this prediction, I run the following regression:

$$R_{t,1} - R_{t,2} = \alpha + \beta_1 \rho_{LR,t} + \beta_2 \Delta\rho_{s,t} + \gamma X + \varepsilon_t \tag{3.29}$$

where $R_{t,1} - R_{t,2}$ represents the relative returns of a more sentiment-prone portfolio over a less sentiment-prone portfolio, $\rho_{LR,t}$ refers to the long-run sentiment component at time t, $\Delta\rho_{s,t}$ represents the short-run sentiment increments, and X is a vector of control variables. The control variables include Fama-French (2015) five factors (RMRF, SMB, HML, RMW, CMA) and the Carhart (1997) momentum factor (UMD).[15] Specifically, RMRF is the market return premium over risk-free rate; SMB is the average return on the three small portfolios minus the average return on the three big portfolios; HML is the average return on the two value portfolios minus the average return on the two growth portfolios; RMW is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios; CMA is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios; UMD is the average return of high prior return portfolio over low prior return portfolio. The control variable SMB (HML) is excluded when the long-short portfolio is constructed with ME (BE/ME). The control variable RMW is excluded when the long-short portfolio is

[15] The data are available on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

constructed with E/BE or D/BE.

The strong persistence of the long-run sentiment measure may raise the concern of spurious regressions. Stambaugh (1999) points out that the coefficient estimates of predictive regression with a small sample can be biased and distort the t-statistics when the predictor is highly persistent. Stambaugh bias exists if the autoregressive disturbance of a lagged stochastic regressor correlates with the regression error term. Under this circumstance, OLS regression results will lead to an erroneous conclusion that the lagged regressors have predictive power while in fact they do not. Thus, it is paramount that I account for Stambaugh bias in my predictive regressions. To this end, I adopt the multi-predictor augmented regression method of Amihud et al. (2009) to adjust for the Stambaugh bias in the estimated coefficients and report the t-statistics of coefficients estimated from a wild bootstrap procedure. The detailed methodology of this wild bootstrap procedure is in Appendix C. I also calculate Newey-West standard errors (Newey and West, 1987) that are robust to heteroscedasticity and serial correlation, and I choose a maximum lag of 12 throughout the regressions.

Table 3.2 Regressions of Monthly Cross-Sectional Returns on Decomposed Sentiment

This table reports the regressions of long-short portfolio returns on both the long-run and short-run sentiment.

$$R_{t,1} - R_{t,2} = \alpha + \beta_1 \rho_{LR,t} + \beta_2 \Delta\rho_{s,t} + \gamma X + \varepsilon_t,$$

$R_{t,1} - R_{t,2}$ represents the return disparity of more sentiment-prone portfolio over the less sentiment-prone portfolio. The control variables (X) include the Fama-French Five factors (RMRF, HML, SMB, RMW, CMA), and the momentum factor (UMD). SMB (HML) will not be included in regression when return premium is constructed by ME (BE/ME). The first two columns show how the portfolio is constructed. H, M, L represents the top three, middle four and bottom three decile portfolios respectively. The long-run sentiment component $\rho_{LR,t}$ in Panel A and Panel B is the standardised smoothing average of prior $[-25,-2]$ monthly investor sentiment. Short-run component in Panel A and Panel B are respectively the standardised incremental change of sentiment deviation from long-run sentiment average $\eta_t - \eta_{t-1}$ and the standardised incremental sentiment orthogonalized to long-run sentiment $(\rho_t - \rho_{t-1})^{\perp}$. The long- and short-run sentiment in Panel C are decomposed with Beveridge and Nelson (1981) method and noted as BN_LR and BN_SR respectively. All coefficients are adjusted for Stambaugh-bias. The p-values reported in parentheses are obtained from wild bootstrap procedures in which all stimulation uses Newey West robust t-statistics. See Appendix C for details of the bootstrap simulation. $***p < 0.01, **p < 0.05, *p < 0.1$.

		Panel A		Panel B		Panel C	
		$\rho_{LR,t}$	$\eta_t - \eta_{t-1}$	$\rho_{LR,t}$	$(\rho_t - \rho_{t-1})^{\perp}$	BN_LR	BN_SR
ME	L-H	-0.262***	0.332***	-0.323***	0.312***	-0.236***	0.135***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	L-H	-0.017	0.187***	-0.051***	0.175***	-0.091***	0.109***
		(0.126)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sigma	H-L	-0.195***	0.147***	-0.222***	0.138***	-0.242***	-0.001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.273)
E/BE	<0->0	-0.335***	0.180***	-0.368***	0.170***	-0.453***	0.039***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D/BE	=0->0	-0.305***	0.059***	-0.316***	0.056***	-0.359***	-0.101***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PPE/A	L-H	0.060***	0.014	0.058***	0.013	0.062***	0.164***
		(0.000)	(0.377)	(0.000)	(0.310)	(0.000)	(0.000)
RD/A	H-L	-0.032***	0.010**	-0.033***	0.009**	-0.007***	-0.119***
		(0.002)	(0.038)	(0.000)	(0.040)	(0.000)	(0.000)
BE/ME	H-L	-0.084***	0.116***	-0.105***	0.109***	-0.104***	-0.004
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.188)
EF/A	H-L	0.002***	-0.003	0.003**	-0.003**	0.007***	-0.031***
		(0.002)	(0.136)	(0.011)	(0.035)	(0.002)	(0.000)
GS	H-L	-0.052***	-0.127***	-0.029***	-0.119***	0.020***	-0.092***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	L-M	-0.004***	-0.060***	0.007***	-0.057***	-0.016***	-0.002
		(0.001)	(0.000)	(0.000)	(0.000)	(0.005)	(0.114)
EF/A	H-M	-0.103***	0.008	-0.105***	0.008	-0.102***	-0.024***
		(0.000)	(0.335)	(0.000)	(0.195)	(0.000)	(0.000)
GS	H-M	-0.114***	0.020***	-0.118***	0.019***	-0.093***	-0.029***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	H-M	-0.088***	0.056***	-0.098***	0.052***	-0.120***	-0.006
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.419)
EF/A	L-M	-0.105***	0.010***	-0.107***	0.010***	-0.109***	0.008***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GS	L-M	-0.062***	0.147***	-0.089***	0.138***	-0.112***	0.063***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 3.2 shows the estimation coefficients of the standardised long- and short-run sentiment components of the Baker-Wurgler's (2006) sentiment indicator. All independent variables (including the long- and short-run sentiment measures) are standardised before running the regression to facilitate comparisons of coefficients. The short-run sentiment in Panel A $\eta_t - \eta_{t-1}$ is measured by changes in the sentiment deviation from the long-run sentiment. The short-run sentiment in Panel B, $(\rho_t - \rho_{t-1})^{\perp}$, is measured by the sentiment increment orthogonalized to the long-run sentiment component. The long-run sentiment component $\rho_{LR,t}$ in both Panels A and B is the moving average of prior $[-25,-2]$ monthly investor sentiment. The long- and short-run sentiment components in Panel C are Beveridge-Nelson decomposed long- and short-run sentiment, BN_LR and BN_SR, respectively. I report the Stambaugh-bias adjusted coefficients with bootstrapped p-values in parentheses.

Panel A in Table 3.2 shows that the long-run sentiment component $\rho_{LR,t}$ is a significant contrarian predictor for 13 out of 16 long-short portfolio returns, consistent with my theory. Furthermore, the short-run sentiment component $\eta_t - \eta_{t-1}$ is significantly and positively associated with 11 out of sixteen long-short portfolio returns, which is consistent with existing evidence that contemporaneous excess returns are positively related to shifts in sentiment (Ben-Rephael et al., 2012; Lee et al., 2002).

In general, the empirical results in Panel A provide strong support for my two main hypotheses. The signs of coefficients of both the long- and short-run sentiment components in 11 out of 16 regressions are consistent with the predictions of my theory. However, the coefficients of the long-run sentiment are significantly positive for the regressions involving PPE/A(L-H) and EF/A(H-L), while the coefficients of the short-run sentiment are significantly negative in the case of GS(H-L) and BE/ME(L-H). The portfolios with the unexpected coefficient signs are portfolios in the 'Tangibility' and in 'Growth Opportunity and Distress' group. Baker and Wurgler (2006) also find that investor sentiment is not a good predictor of the future returns of the portfolios in the 'Tangibility' group and argue that the multidimensional nature of BE/ME, EF/A, and GS makes the results unclear in the 'Growth Opportunity and Distress' group.

Panel B of Table 3.2 reports the estimation results of the long-run sentiment $\rho_{LR,t}$ and the short-run sentiment $(\rho_t - \rho_{t-1})^{\perp}$. The coefficients of the long-run sentiment component are significantly negative in 13 out of the 16 regressions. The coefficients of the short-run sentiment component are significantly positive in 11 out of 16 regressions, consistent with the results in Panel A. The coefficients of the short-run sentiment are significantly positive in 5 out of 16 regressions. The dependent variables in those regressions with unexpected coefficients of the long- and short-run sentiment belong to the 'Tangibility' and the 'Growth Opportunity and Distress' group. The magnitude of the coefficients of the long- and short-run sentiment measures in Panel B is in most cases comparable to their counterparts in Panel A.

Panel C in Table 3.2 presents the estimation results of the Beveridge-Nelson decomposed long- and short-run sentiment. The coefficients of the long-run sentiment BN_LR are almost all significantly negative, while those on the short-run sentiment BN_SR are significantly positive in 6 out of the 16 regressions. Under the Beveridge-Nelson decomposition, the long-run sentiment no longer exhibits a pattern lagged to original sentiment (recall that in Figure 3.2), and yet is still negatively associated with the subsequent long-short portfolio returns. Despite some differences in the magnitude, the coefficients of the long- and short-run sentiment components in Panel C have the same signs as their counterparts in Panel A.

Regressions with the long-short portfolio returns as the dependent variables may obscure the effects of the two sentiment components on individual decile portfolios. To obtain further insight into this issue, I run regressions of decile portfolio returns on both the long- and short-run sentiment variables and control variables:

$$R_{t,i,j} = \alpha + \beta_{1,i,j}\rho_{LR,t} + \beta_{2,i,j}(\eta_t - \eta_{t-1}) + \gamma X + \varepsilon_t \tag{3.30}$$

$R_{t,i,j}$ represents the return of the ith decile portfolio sorted by variable j, where i represents the decile portfolio rank and takes values from 1 to 10 and j is one of the ten firm characteristic variables used to construct the decile portfolios. The control variables (X) include the Fama-French five factors (RMRF, HML, SMB, RMW, CMA), and the Carhart (1997) momentum factor (UMD).

Table 3.3 reports the coefficients of the long- and short-run sentiment components. Panel A documents a large variation in the coefficients of the long-run sentiment component across the decile portfolios. The observed patterns are consistent with predictions of my theoretical model. Specifically, I find decile portfolios that are more prone to market-wide sentiment are usually more affected by the long-run sentiment. More specifically, for Size and Age sorted portfolios, the coefficients of the long-run sentiment increase from Decile 1 to Decile 10 most of the time, indicating that the reversal effect of long-run sentiment effect on decile returns is more salient on small and young stocks than large and old stocks. The coefficients of the long-run sentiment for Sigma sorted decile portfolios decrease almost monotonically with the decile rank, implying that high long-run sentiment leads to lower returns on more volatile decile portfolios than less volatile portfolios. For the two variables in the 'Tangibility' group, PPE/A and RD/A, there is no salient pattern in the long-run sentiment coefficients across different deciles. This finding is in line with the results in Table 3.2 and is consistent with the findings in Baker and Wurgler (2006).

Table 3.3 Decile Portfolio Returns and Decomposed Sentiment

This table reports the regressions of long-short portfolio returns on both the long-run and short-run sentiment.

$$R_{t,i,j} = \alpha + \beta_{1,i,j}\rho_{LR,t} + \beta_{2,i,j}(\eta_t - \eta_{t-1}) + \gamma X + \varepsilon_t,$$

$R_{t,i,j}$ represents the return of the ith decile portfolio sorted by variable j, where i is from 1 to 10 and j is one of the ten sentiment-prone characteristic variables. The control variables (X) include the Fama-French Five factors (RMRF, HML, SMB, RMW, CMA), and the momentum factor (UMD). SMB (HML) is not included in regression when the long-short portfolio is constructed by ME (BE/ME). Long-run sentiment component $\rho_{t-1}^{\perp}$ in is the standardised smoothing average of prior $[-25,-2]$ monthly investor sentiment, and short-run component is the standardised incremental change of sentiment deviation from long-run sentiment average $\eta_t - \eta_{t-1}$. Panel A and Panel B respectively reports the coefficients long- and short-run sentiment. The coefficients are adjusted for Stambaugh-bias. The p-values are obtained from wild bootstrap procedures in which all stimulation uses Newey West robust t-statistics. $***p < 0.01, **p < 0.05, *p < 0.1$.

	Decile1	Decile2	Decile3	Decile4	Decile5	Decile6	Decile7	Decile8	Decile9	Decile10
Panel A Coefficients of Long-run Sentiment Component $\rho_{t-1}^{\perp}$										
ME	-0.115***	-0.105***	-0.027***	-0.046***	-0.088***	-0.095***	0.040***a	-0.068***	-0.026***	-0.067***
Age	-0.116***	-0.033***	0.027***	0.092***	0.119***	-0.054***	-0.013***	0.025***a	-0.100***	-0.174***
Sigma	0.138***a	0.058***a	-0.009***	-0.024***	0.018***a	-0.071***	-0.023***	-0.097***	-0.139***	-0.158***
E/BE	-0.126***	-0.124***	-0.011***	-0.007***	-0.020***	-0.031***	0.029***	-0.068***	-0.113***	-0.140***
D/BE	-0.212***	-0.183***	-0.131***	-0.070***	-0.118***	-0.051***	0.042***	-0.295***	-0.244***	0.061***
PPE/A	-0.100***	-0.029***	-0.011***	-0.117***	-0.055***	-0.096***	-0.161***	-0.084***	-0.084***	-0.165***
RD/A	-0.121***	-0.326***	-0.333***	-0.207***	-0.252***	-0.200***	-0.042***	-0.122***	-0.085***	-0.024***
BE/ME	-0.117***	-0.092***	0.043***a	0.000***a	-0.001***	0.070***a	0.007	-0.006***	-0.059***	-0.005*
EF/A	-0.170***	-0.083***	0.032***a	0.016***a	0.044***a	0.014***a	0.043***a	-0.013***	-0.039***	-0.169***
GS	-0.171***	0.038***	-0.008***	0.062***a	0.015***a	-0.042***	0.001***a	-0.090***	-0.068***	-0.153***
Panel B Coefficients of Short-run Sentiment Component $\eta_t - \eta_{t-1}$										
ME	0.272***	-0.054***a	-0.012***	-0.119***	-0.081***	-0.152***	0.004	-0.028***a	0.023***	-0.064***a
Age	0.165***	0.162***	0.057***	0.028***	0.104***	0.058***	0.028***	-0.036***a	-0.027***a	-0.016***a
Sigma	0.024***	0.009***	-0.013***a	0.024***	0.022***	-0.009***a	0.069***	0.039***	0.113***	0.304***
E/BE	0.250***	0.017***	0.027***	-0.040***	-0.003**a	-0.048***a	-0.031***a	0.004**	-0.216***a	-0.019***a
D/BE	0.124***	-0.017***a	-0.054***a	-0.012***a	-0.088***a	-0.144***a	0.025***	-0.060***	0.011***	0.067***
PPE/A	0.094***	0.073***	0.106***	0.128***	0.093***	0.043***	0.073***	0.062***	0.080***	0.082***
RD/A	0.085***	-0.027***a	0.059***	0.096***	-0.078***a	0.006	0.070***	0.136***	0.277***	0.268***
BE/ME	0.136***	0.131***	0.071***	0.063***	0.173***	0.101***	0.058***	0.114***	0.109***	0.126***
EF/A	0.129***	0.050***	0.102***	0.104***	0.051***	0.082***	0.084***	0.014***	0.077***	0.183***
GS	0.236***	0.211***	0.103***	0.042***	0.083***	-0.024***a	0.043***	0.064***	-0.030***a	0.117***

For firm characteristics with the multidimensional nature, namely BE/ME, EF/A, and GS, I find that the coefficients of the long-run sentiment across deciles have an inverse U-shape, indicating that the middle deciles are less prone to overall market, while distressed stocks and stocks with strong growth potential are more prone to overall market. When sorted on ME, Sigma, and D/BE, the less sentiment-prone deciles and the more sentiment-prone deciles show opposite exposure to the long-run sentiment. For example, for deciles sorted on Sigma, the coefficients of long-run sentiment in the top two are negative, while those of the bottom two deciles are significantly positive. This indicates that the "bond-like" stocks with low return volatility have negative exposure to the long-run overall market sentiment. One plausible explanation proposed by Baker and Wurgler (2007) is "flights to quality". When overall market is pessimistic, bond-like stocks are more appealing to not only sophisticated investors but also noise traders, leading to rising prices of those stocks during low market sentiment periods. The reverse pattern I found in "bond-like" stocks helps explain the weak relationship between investor sentiment and aggregate market return documented in the literature. Indeed, I check the effects of decomposed sentiment on aggregate market returns, and find the coefficients of the long- and short-run sentiment are insignificant.

Panel B of Table 3.3 reports the coefficients of the short-run sentiment component. The coefficient of the short-run sentiment is positive and significant for almost all more sentiment-prone decile portfolios. There is a decreasing (increasing) pattern in the coefficients of the short-run sentiment across the deciles sorted by ME, Age, E/BE and D/BE (Sigma). However, the coefficients of the short-run sentiment follow a U-shaped pattern across the deciles sorted by BE/ME, EF/A, and GS and exhibit no clear pattern in the deciles sorted by PPE/A and RD/A. I also find significantly negative coefficients of the short-run sentiment in most of the less sentiment-prone deciles. In general, the results in Panel B confirm the conclusions drawn from Panel A that the effect of short-run sentiment on returns varies across deciles and the bond-like stocks have negative exposure to overall market sentiment.

3.4.2 Robustness Checks

This chapter presents a behavioural explanation to the variations in the cross-sectional stock returns. However, it is possible that variation in investor sentiment reflects changes in systematic risk and my results may not be entirely consistent with the behavioural story. For example, changes in my decomposed sentiment measures may coincide with time variation in the market beta. If that is the case, the cross-sectional patterns conditional on certain characteristics is the rational compensation for systematic risk. I examine this possibility with a time-varying CAPM beta model.

$$R_{t,1} - R_{t,2} = \alpha + \beta_1 \rho_{LR,t} + \beta_2 \Delta\rho_{s,t} + (b + \gamma_1 \rho_{LR,t} + \gamma_2 \Delta\rho_{s,t}) RMRF_t + \upsilon_t, \tag{3.31}$$

where $R_{t,1} - R_{t,2}$ represents the portfolio returns that long the more sentiment-prone portfolios and short the less sentiment-prone portfolios, $\rho_{LR,t}$ refers to the long-run sentiment component at time t, $\Delta\rho_s$ represents the short-run sentiment increments, and $RMRF_t$ is the market return premium. If the negative (positive) effect of long-run (short-run) sentiment on the cross-sectional return is driven by its negative (positive) effect on the beta loading of market return premium, the coefficients for the interaction terms will be significantly different from zero, and the sign of γ_i will be the same as the sign of β_i in Table 3.2; otherwise, the behavioural story holds. That is to say, γ_1 should be significantly negative and γ_2 should be significantly positive if the rational explanation holds.

Table 3.4 shows the sign and magnitude of the coefficients of both the long- and short-run sentiment components remain consistent with their counterparts in Table 3.2 even after including the interaction terms in the regressions. This evidence proves that the long- and short-run sentiment components do indeed affect the cross-sectional stock returns. I also consider another potential systematic risk explanation, which suggests that even when the market beta loadings are constant, the decomposed investor sentiment may reflect the variations in the market return premium. If this story holds, the decomposed investor sentiment should perform well in predicting the market return premium. However, in an regression of market return premium on decomposed investor sentiment, I find little evidence that decomposed investor sentiment components affect the aggregate market returns.

I also conduct a battery of other robustness checks (the results are reported in Appendix E.1). First, I re-run my regressions with decomposed sentiment indicators from other widely accepted investor sentiment proxies, such as the Conference Board Consumer Confidence Index (CCI) from Bloomberg, Consumer Confidence Index by Michigan (ICS), the closed-end fund discount (CEFD) and the aligned sentiment indicator (Sent_PLS) from Huang et al. (2015). See Table E.1. I find similar results when the decomposition of sentiment is based on CCI, CEFD and Sent_PLS, especially for the coefficients of long-run sentiment. The results from ICS are slightly mixed.

Second, I construct different measures of sentiment components by taking the moving average of the original Baker and Wurgler sentiment index over different horizons as the measure of the long-run sentiment. I consider both 12-month and 36-month horizon and my conclusions remain unchanged. See Table E.2.

Third, I divide the samples into high and low sentiment periods, where a low (high) sentiment period is defined as the period when the current sentiment is lower (higher) than the previous two-year smoothing average sentiment. See Table E.3. I find that the long- and short-run sentiment components perform better in explaining the cross-sectional returns during periods of high sentiment. This evidence may be explained by more binding short-selling constraints during high sentiment periods (Nagel, 2005; Stambaugh et al., 2012; Yu and Yuan, 2011).

Table 3.4 Time-Varying Market Betas

Regressions of long-short portfolio returns on the market risk premium and its interactions with both long-run sentiment and short-run sentiment.

$$R_{t,1} - R_{t,2} = \alpha + \beta_1 \rho_{LR,t} + \beta_2 \Delta\rho_{s,t} + (b + \gamma_1 \rho_{LR,t} + \gamma_2 \Delta\rho_{s,t}) RMRF_t + \upsilon_t,$$

The long-run sentiment component $\rho_{LR,t}$ is the standardised smoothing average of prior $[-25,-2]$ monthly investor sentiment. Short-run sentiment component $\Delta\rho_{s,t}$ is measured by $\eta_t - \eta_{t-1}$ and $\rho_t - \rho_{t-1}$ in Panel A and Panel B respectively. All regressors are standardised. The coefficients are adjusted for Stambaugh-bias. The label 'a' marks the coefficients of interaction terms significantly supports rational story. The p-values reported in parentheses are obtained from wild bootstrap procedures in which all stimulation uses Newey West robust t-statistics. $***p < 0.01, **p < 0.05, *p < 0.1$.

		Panel A				Panel B			
		$\rho_{LR,t}$	$(\eta_t - \eta_{t-1})$	$\rho_{LR,t} RMRF_t$	$(\eta_t - \eta_{t-1}) RMRF_t$	$\rho_{LR,t}$	$(\rho_t - \rho_{t-1})^{\perp}$	$\rho_{LR,t} RMRF_t$	$(\rho_t - \rho_{t-1})^{\perp} RMRF_t$
ME	L-H	-0.218***	0.301**	-3.122***a	0.005	-0.340***	0.233***	-3.110***a	0.007
		(0.000)	(0.046)	(0.008)	(0.367)	(0.000)	(0.000)	(0.004)	(1.000)
Age	L-H	-0.634***	0.232***	0.961*	0.187	-0.732***	0.143***	0.946	0.182***a
		(0.000)	(0.004)	(0.081)	(0.162)	(0.000)	(0.003)	(0.187)	(0.000)
Sigma	H-L	-1.507***	0.206	0.133***	0.293***a	-1.587***	0.107***	0.09	0.285
		(0.000)	(0.462)	(0.000)	(0.001)	(0.000)	(0.000)	(0.316)	(1.000)
E/BE	<0->0	-1.108***	0.367	2.419***	0.453***a	-1.255***	0.242***	2.394	0.447
		(0.000)	(0.385)	(0.000)	(0.000)	(0.000)	(0.000)	(0.153)	(1.000)
D/BE	=0->0	-1.094***	0.116	2.062**	0.242**a	-1.143***	0.015***	2.004	0.231***a
		(0.000)	(0.316)	(0.034)	(0.050)	(0.000)	(0.000)	(0.123)	(0.000)
PPE/A	L-H	-0.285***	-0.031*	0.271***	0.187***a	-0.273***	-0.030***	0.263***	0.185***a
		(0.000)	(0.096)	(0.000)	(0.008)	(0.000)	(0.002)	(0.000)	(0.000)
RD/A	H-L	-0.401***	-0.165***	2.419***	0.047	-0.341***	-0.219***	2.341***	0.032***a
		(0.000)	(0.000)	(0.000)	(0.234)	(0.000)	(0.000)	(0.002)	(0.000)
BE/ME	H-L	0.176***	0.275*	-3.766*	-0.06	0.061***	0.286***	-3.696**a	-0.048***
		(0.000)	(0.084)	(0.078)	(0.212)	(0.000)	(0.000)	(0.045)	(0.000)
EF/A	H-L	-0.145***	-0.078***	1.827**	-0.005	-0.114***	-0.104	1.790***	-0.012***
		(0.000)	(0.000)	(0.010)	(0.172)	(0.000)	(0.472)	(0.000)	(0.000)
GS	H-L	-0.125***	-0.247**	0.4	-0.099*	-0.023***	-0.239***	0.357***	-0.107***
		(0.000)	(0.019)	(0.131)	(0.074)	(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	L-M	-0.294***	-0.123***	1.506***	0.096	-0.243***	-0.167**	1.446	0.086***a
		(0.000)	(0.000)	(0.010)	(0.255)	(0.000)	(0.023)	(0.293)	(0.000)
EF/A	H-M	-0.420***	0.009***	1.598*	0.088***a	-0.426***	-0.039	1.559	0.081***a
		(0.000)	(0.000)	(0.094)	(0.000)	(0.000)	(0.376)	(0.420)	(0.000)
GS	H-M	-0.455***	-0.027***	2.256***	0.026	-0.444***	-0.082***	2.207***	0.016***a
		(0.000)	(0.007)	(0.000)	(0.122)	(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	H-M	-0.253***	0.138	-2.236	0.047	-0.310***	0.109	-2.225***a	0.048***a
		(0.000)	(0.228)	(0.375)	(0.143)	(0.000)	(0.200)	(0.000)	(0.000)
EF/A	L-M	-0.227***	0.090***	-0.348***a	0.082***a	-0.262***	0.063	-0.349	0.081***a
		(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.243)	(0.261)	(0.004)
GS	L-M	-0.521***	0.214	1.972**	0.134***a	-0.611***	0.157**	1.973***	0.133***a
		(0.000)	(0.241)	(0.029)	(0.000)	(0.000)	(0.017)	(0.006)	(0.000)

Fourth, I test whether the stocks that I argued as sentiment-immune ones are immune because they receive very little investor attention. Investor sentiment indicates the direction of the price movement: optimistic investor sentiment leads to price overpricing and pessimistic investor sentiment results in underpricing of an asset. Investor attention, on the other hand, indicates how effective investor attention could be. The effect of investor sentiment is stronger when investor pays more attention and is weaker when investor seldom cares. I employ the two investor attention measures proposed by Barber and Odean (2008), namely the abnormal trading volume index and the abnormal return index. I first calculate the monthly abnormal trading volume and abnormal return index for each firm and then I calculate the averaged investor attention of all portfolios. The abnormal trading volume (abnormal return index) is calculated as the ratio of the stock's trading volume (return) of that month to its average trading volume (return) over the prior one-year. I add the cross-sectional investor sentiment disparity measure as a control variable into the regressions. For every regression, I construct the attention disparity in the same way I calculate the return disparity of the sentiment-prone portfolio over the sentiment-immune portfolio. Take ME sorted long-short portfolio as an example, the dependent variable is the difference of bottom three-decile portfolio averaged return over the top three-decile averaged return, and the attention disparity control variable is the difference of bottom three-decile averaged attention over the top three-decile averaged attention, noted as $A_{t,1}) - A_{t,2}$. The regression results are shown in Table E.4. After taking the effect of investor attention into account, the effect of decomposed sentiment components on returns remain strong.

Finally, to isolate the size effect on the portfolio returns, I re-run my tests using value-weighted portfolio returns. The results are report on Table E.5. My conclusion does not alter when using value-weighted portfolio returns.

3.5 Conclusion

Chapter 3 fills a theoretical gap by showing that investor sentiment disproportionally affects the returns of different assets. I extend De Long et al. (1990a) model into a noise trader risk model with multiple risky assets. In my model, I allow the risky assets to have different exposure to overall market investor sentiment and provide theoretical predictions consistent with the empirical evidence on the effect of investor sentiment on the cross-sectional stock returns.

Motivated by the model, I also decompose investor sentiment into long- and short-run components. Consistent with the theory, I find that the long-run sentiment component is a contrarian predictor of future long-short portfolio returns and the short-run sentiment is positively correlated with contemporaneous long-short portfolio returns, where the long-short portfolios long the sentiment-prone stocks and short the sentiment-immune stocks.

Furthermore, I check whether the effect of the sentiment components can be attributed to the time-varying beta loading of the market premium (or other risk factors). My empirical findings show that the impact of sentiment components on the cross-sectional return is not related to systematic risk. Accordingly, the behavioural story holds. Further analysis suggests that my results are robust to alternative sentiment measures, different sample periods, additional control variables, and the use of value-weighted returns.

Chapter 4

Technical Analysis as a Sentiment Barometer and the Cross-Section of Stock Returns

4.1 Introduction

Technical analysis (hereafter TA) is one of the most debated issues between financial academics and investment practitioners. The traditional academic wisdom posits that publicly available information, such as past prices and trading volume, which serve as the basis of TA, is already incorporated into asset prices. Accordingly, any attempt to predict future returns using TA must "share a pedestal with alchemy" (Malkiel, 1999). However, TA continues to be popular among experienced traders and top fund managers.[1] For example, Sushil Wadhwani has stated that overcoming the prejudice against TA was the most important lesson he had to

[1] Taylor and Allen (1992) document that at least 90% of experienced traders place some weight on technical analysis. Schwager (2012) and Lo and Hasanhodzic (2010) report that many of the top traders and fund managers they interviewed believe that technical analysis works.

learn when moving from academia to the fund management industry.[2] This disparity between theory and practice raises important questions, such as the underlying reasons for traders' adoption of TA, and investors' reasons for paying them to do so.

This study aims to reconcile these conflicting views by proposing a new channel through which TA can add value. Explicitly, I argue that TA has the potential to serve as a barometer for investor sentiment. My view is based on the theoretical model of Brown and Jennings (1989), which considers TA as a vital tool for extracting information from current and past prices. Several models also acknowledge that asset prices can carry information about investor sentiment (e.g., De Long et al., 1990a). If investor sentiment is not directly observable (as is usually the case in reality) and if prices are noisy predictors of sentiment,[3] investors may find combining current and past prices helpful in drawing inferences about sentiment signals.

Despite the absence of empirical literature in this direction, the role of TA as a barometer of investor sentiment has been prevailingly recognised among practitioners and in the media. For example, some analysts argue that the term "technical analysis" is a misnomer and should be replaced by "investor sentiment analysis".[4] In one of the most popular books on TA, Pring (1991, pp. 2-3) states that:

> "... Since the technical approach is based on the theory that the price is a reflection of mass psychology ('the crowd') in action, it attempts to forecast future price movements on the assumption that crowd psychology moves between panic, fear, and pessimism on one hand and confidence, excessive optimism, and greed on the other."

In the same vein, an article in Forbes magazine[5] states that:

[2] See "Technical analysis pulled out of the bin", October 17, 2010, Financial Times.

[3] In De Long et al. (1990a), the spot price reveals contemporaneous sentiment fully and leaves no room for past prices (hence TA) to improve inference of sentiment. Such an implication does not hold when there is a random supply shock and current prices are a noisy predictor of sentiment.

[4] See http://www.centimetrics.com/explanation/

[5] See "Why Technical Analysis Matters", April 16, 2010, Forbes Magazine, by Michael Kahn

> "Technical analysis also attempts to measure the collective investor psyche, calling heavily on the psychology of crowds and the cycle of greed and fear."

This chapter provides the first empirical evidence on the link between TA and investor sentiment. To this end, I build a daily market sentiment indicator (hereafter TA sentiment) based on the average of trading signals generated from applying 2,127 technical trading strategies to benchmark stock market indices such as the S&P 500 index and DJIA. By averaging the trading signals across different trading rules helping remove the idiosyncratic noise contained in signals from individual trading rules, a buying (selling) signal indicates a sentiment increase (decline). I use the same universe of trading strategies as Qi and Wu (2006), which nests nearly all the technical trading rules studied in the top three finance journals. I show that the level and the change of TA sentiment are significantly correlated with the level and the change of both market- and survey-based sentiment indicators, such as the CBOE Volatility Indicator (VIX), the CBOE Options Total Put-Call ratio, the detrended trading volume of S&P 500 (VOL), and the Bull-Bear spread from surveys of retail investors and institutional investors. These correlations are not driven by persistence in TA and other sentiment indicators because I also observe strong contemporaneous positive associations between innovations in TA sentiment and innovations in other sentiment indicators. This evidence is consistent with some practitioners' view that TA reflects investor sentiment.

After demonstrating that TA reflects investor sentiment, I examine whether TA sentiment affects the cross-section of stock returns. I build my analysis on the delayed arbitrage models in Abreu and Brunnermeier (2002, 2003). In these models, a single arbitrageur cannot move the market and mispricing correction happens only when a sufficient mass of arbitrageurs arbitrage in coordination. If an arbitrageur attacks mispricing too early, she may find herself sailing against the wind and suffering substantial losses. Due to this synchronisation risk, rational arbitrageurs may be unwilling to correct mispricing when they are uncertain whether others are aware of the mispricing or hold similar opinions. Instead, rational arbitrageurs, who detect investor sentiment through TA, may delay arbitrage and ride mispricing. Thus, based on the delayed arbitrage models, I expect high TA sentiment to be contemporaneously accompanied with higher returns for sentiment-prone stocks than for sentiment-immune stocks. I also expect sentiment-prone stocks to continue to earn higher returns than sentiment-immune stocks following an increase in TA sentiment,[6] as rational arbitrageurs ride mispricing.[7] Such a cross-sectional predictive pattern will reverse when sentiment decays away and rational arbitrageurs manage to coordinate their attack on mispricing. A coordinated attack of rational arbitrageurs on overpricing also implies a sharper decline in the returns of more overpriced stocks. Therefore, a high TA sentiment predicts a higher subsequent crash risk among the sentiment-prone and difficult-to-arbitrage stocks.

To test the empirical implications of the delayed arbitrage models of Abreu and Brunnermeier (2002, 2003), I follow Baker and Wurgler (2006) to compute the returns of long-short portfolios that long the sentiment-prone and difficult-to-arbitrage stocks (e.g., small, young, and high volatility stocks) and short the sentiment-immune and easy-to-arbitrage stocks (e.g., big, old, and low volatility stocks). Consistent with the delayed arbitrage models, I find that the change in TA sentiment positively correlates with the contemporaneous returns of the long-short portfolios. I also find that a rise in TA sentiment predicts an increase in the next-day returns but a decline in the subsequent returns of the long-short portfolios. Controlling for the commonly used risk factors, such as the Fama-French five factors and liquidity risk, and time-varying factor loadings does not alter my results. Further tests also show that when

[6]While most previous studies consider that investor sentiment predicts future return reversal, several recent studies demonstrate that investor sentiment also predicts short-term momentum (see, e.g., Chou et al., 2016; Han and Li, 2017; Tu et al., 2016). Another strand of studies demonstrate the profitability of trading strategies that benefit from the return momentum induced by the news-based sentiment (Huynh and Smith, 2017; Sun et al., 2016; Uhl, 2017).

[7]Several studies also show that sophisticated investors ride mispricing (see, e.g., Bhojraj et al., 2009; Brunnermeier and Nagel, 2004; Griffin et al., 2011; Temin and Voth, 2004). Others also show that trend following is a predominant strategy of hedge funds (e.g., Hurst et al., 2013; Schauten et al., 2015) and commodity traders (Billingsley and Chance, 1996).

beginning-of- period TA sentiment is low, sentiment-prone stocks have higher crash risk than sentiment-immune stocks. Finally, consistent with the view that sophisticated investors earn higher returns by riding mispricing, I show that a simple 'trend chasing' trading strategy that buys portfolios of the sentiment-prone stocks after a TA sentiment increase and sells them following a TA sentiment decrease generates an average abnormal return of 12% per annum. The returns of out TA trading strategies remain sizable and saliently positive after controlling for the traditional risk factors and transactions costs.

Our study contributes to the literature in a number of ways. First, I provide a new explanation for how TA can create value. Several studies suggest that past prices (or volumes) are useful for inferring information that is not fully impounded into the current price (Brown and Jennings, 1989; Hellwig, 1982; Treynor and Ferguson, 1985). TA also arises naturally when traders learn about the quality of signals they receive from analyzing the sequences of price and volume (Blume et al., 1994), or inferring information about the market depth from limit order book (Kavajecz and Odders-White, 2004). Furthermore, TA improves asset allocation when returns are predictable and there exists uncertainty about their predictability (Zhu and Zhou, 2009). I contribute to this strand of research by demonstrating that TA reflects investor sentiment and assists sophisticated investors to time the market.[8]

Second, I test the profitability of TA strategies from a sentiment perspective. Most of the existing studies apply TA to a single asset or a market index to show that TA strategies generate prominent returns (e.g., Allen and Taylor, 1990; Brock et al., 1992; Lui and Mole, 1998; Neely and Weller, 2003; Osler, 2003; Taylor and Allen, 1992). To the best of my knowledge, this is the first attempt to apply TA to market indexes in order to construct a market-wide sentiment indicator, which is then used to devise trading strategies using portfolios of stocks with different exposures to investor sentiment. My new trading strategies are motivated by the cross-sectional effect of market sentiment, and generates substantial

[8]In line with my results, Smith et al. (2016) find that hedge funds that use TA perform better than non-users, although they do not consider TA as a measure of investor sentiment.

profitability in the cross-section. While Han et al. (2013) also report notable cross-sectional profitability from applying the Moving Average rules to individual portfolios constructed with proxies of information uncertainty, I consider a much broader spectrum of trading rules and apply TA to market indexes rather than individual stocks.

Finally, I introduce a novel, easy-to-construct, and real-time sentiment measure that is available at daily frequency. Since the only data required for constructing a TA sentiment indicator is historical prices, my approach can be useful when alternative sentiment indicators are difficult to convey due to data availability. Furthermore, although I restrict the analysis in this chapter to the stock market, my approach can be used to build sentiment indicators for other asset classes.

The rest of Chapter 4 is organized as follows. Section 4.2 explains my data and the construction of a TA sentiment index and various portfolios. Section 4.3 provides empirical evidence of the predictive power of TA sentiment on cross-sectional return premium and crash risk. Section 4.4 examines the profitability of timing strategies using TA sentiment. Section 4.5 concludes.

4.2 Data and Sample Construction

4.2.1 TA Sentiment Indicator

To build a sentiment indicator from the trading signals generated by TA, I need to decide on the number of trading rules I should use. Such a decision is difficult, as relying on a single technical trading rule may fail to capture the overall market sentiment, whereas considering all trading rules is inviable. As a balance, I employ the widely-acknowledged technical trading rules mentioned in top journals, including Filter Rules, Moving Average, Support and Resistance, and Channel Breakout Rules.[9] This universe of trading strategies is the same as the one documented in Qi and Wu (2006) and covers nearly all the trading rules studied in the top three finance journals.

To build a market-wide sentiment indicator, I apply the 2,127 technical trading rules to benchmark market indexes, including S&P 500 index and DJIA. Each trading rule generates a buy/sell/neutral recommendation for the next day at the end of each day. I assign value 1, 0, and -1 to each buy, neutral, and sell signal, respectively. Each day, I compute the equal-weighted average[10] of trading signals across all 2,127 strategies to obtain a time series, which I then use as my TA sentiment index. For example, if at a given day, 1,800 strategies recommend a buy, 127 strategies recommend a sell, and the remaining strategies are neutral, TA sentiment on that day would be (1800-127)/2127 or 0.78. I argue that my TA sentiment is a measure of the overall market sentiment (i.e., a high value of TA sentiment indicates a high overall market sentiment). Averaging trading signals across trading rules helps remove the idiosyncratic noise associated with individual trading rules.

I restrict ourselves to market-wide TA sentiment because validating TA sentiment at the individual stock level by investigating the correlations between TA sentiment and other sentiment indicators is constrained by the availability of other individual stock level daily sentiment indicators with sufficiently long history. I also focus on testing effect of TA sentiment on the cross-sectional stock returns because theory suggests that market-wide investor sentiment can have different (and even opposite) effects on individual stocks (Baker and Wurgler, 2007).

Our baseline TA sentiment is constructed by applying the technical trading rules on S&P 500 index. Since S&P 500 members are mainly large cap stocks that are less prone

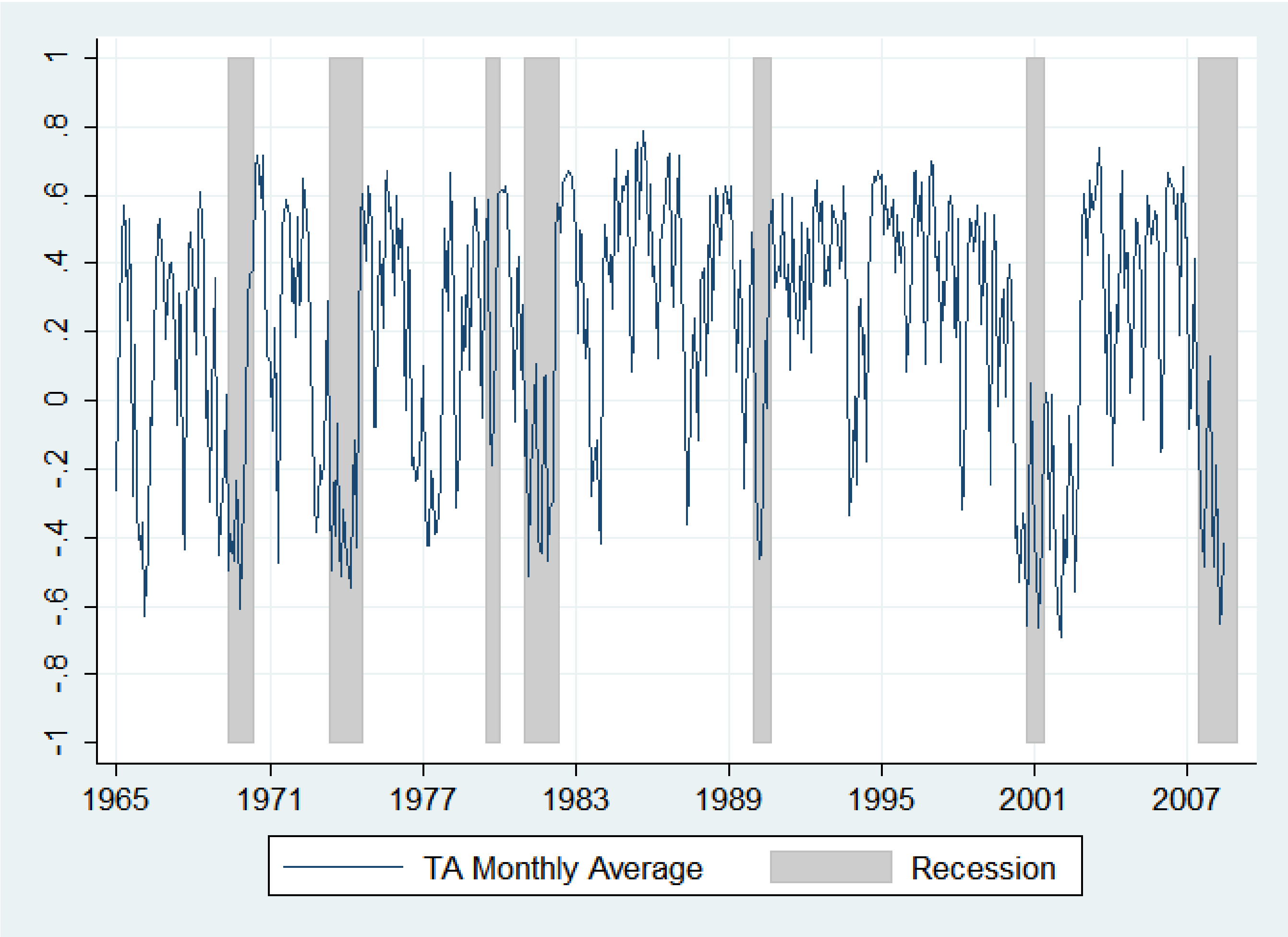
[9]The definitions of these trading strategies are the same as used by Qi and Wu (2006), and standard in the literature, with the parameters used to define these technical trading strategies documented in Appendix D.

[10]I also calculate a performance-weighted TA sentiment index, which is the average of the trading signals of 2,127 technical trading rules weighted by their returns in the past year. The use of performance-weighted TA sentiment index does not alter my conclusions.

to sentiment and are easier to arbitrage, a TA sentiment that is based on S&P 500 does not capture as much sentiment as that constructed from the small-cap stock index. However, although my baseline TA sentiment index is likely to be biased against my findings, I choose to focus on S&P 500 because of its popularity as the most closely monitored benchmark in the US stock market.

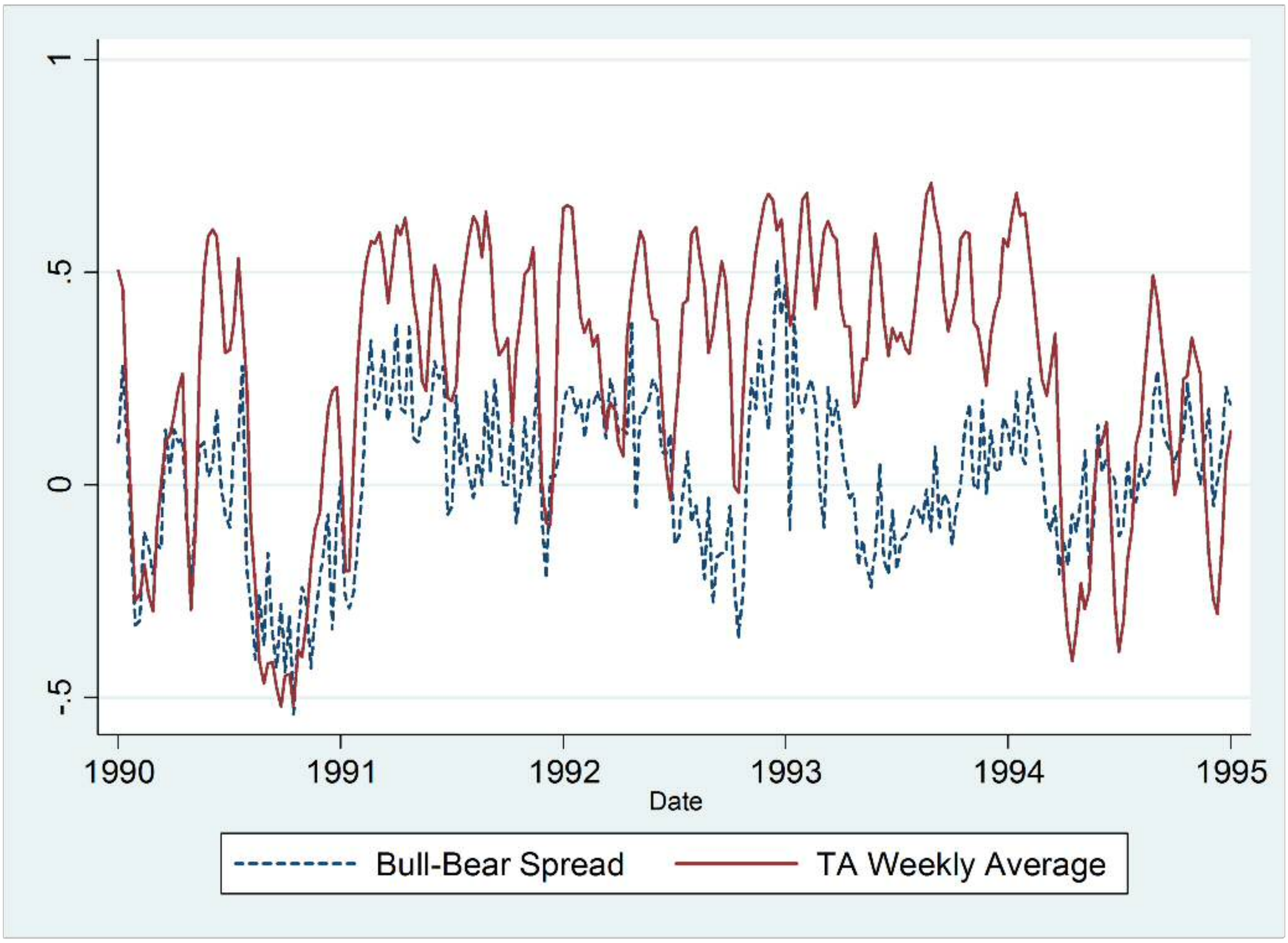
Figures 4.1 and 4.2 provide a simple eyeball check for the TA sentiment. Since the daily TA sentiment is highly volatile and difficult to visualize over 50 years, I compute and plot its monthly averages in Figure 4.1. The plotting of TA sentiment index roughly lines up with anecdotal accounts of market sentiment fluctuations. It drops sharply during the recession periods defined by the National Bureau of Economic Research (NBER) and is visibly consistent with historical bubbles and crashes. In addition, TA sentiment is largely positive in the high sentiment years as measured by the positive value of Baker and Wurgler's (2006) sentiment index.[11]

[11] Baker and Wurgler sentiment index is positive for 1968-1970, 1972, 1979-1987, 1994, 1996-1997, and 1999-2001.



Monthly Averaged TA Sentiment and NBER Recession, 1964:01-2008:12. This figure shows the monthly average TA sentiment from 1964 to 2008. The grey vertical bars represents NBER-dated recession periods.

Fig. 4.1 TA Sentiment Index and NBER-Dated Recession



Weekly Averaged TA Sentiment and Bull-Bear Spread, 1990:01-1995:01. This figure compares weekly averaged TA sentiment index with weekly Bull-Bear Spread of individual investors from a randomly selected sub-sample period (from 1990 to 1995). The solid line is the averaged TA sentiment index. The dashed line is the Bull-Bear Spread.

Fig. 4.2 TA Sentiment Index and Bull-Bear Spread

I also calculate a weekly average of TA sentiment to facilitate its comparison with the weekly Bull-Bear spread from surveys of individual investors. Figure 4.2 plots weekly average of TA sentiment and the weekly Bull-Bear spread for a randomly selected subsample period (from 1990 to 1995)[12]. The observed comovement between these two variables provides a first indication that my TA index tracks market sentiment.

To further validate my TA sentiment index as a sentiment measure, I examine its pair-wise correlations with other commonly used sentiment indicators, such as the daily CBOE Volatility Index (VIX), CBOE Options Total Put-Call ratio, the detrended trading volume of S&P500 (VOL), and the weekly individual Bull-Bear spread based on surveys of individual investors and institutional investors. VIX measures the market expectations of the volatility conveyed by the S&P500 stock index option prices over the next 30-day period. VOL is the detrended daily trading volume of the 500 stocks included in the S&P500 index. I detrend the trading volume by subtracting a one-year backward moving average from the log trading volume series. Higher trading volume means the market is more optimistic. The Put-Call ratio is a ratio of put volume to call volume[13], a contrarian indicator of market sentiment. The Bull-Bear spread is the percentage of investors who are bullish, minus the percentage of those who are bearish about the stock market performance over the next six months. I construct the Bull-Bear spread for individual investors using data from weekly surveys of members of American Associate of Individual Investors[14] and the Bull-Bear spread for institutional investors from the opinion polls of institutional investors available from Bloomberg.

[12]The reason I show a randomly selected sample period instead of the whole sample is that the two indicators prominently correlate with each other and they are also both very volatile during the sample period. As I have weekly data over a very long sample period, if I choose the whole sample it would be hard to distinguish the two lines and see the correlation pattern.

[13]The Put-Call ratio is downloaded from https://www.cboe.com/data/putcallratio.aspx.

[14]Bull-Bear spread is available from http://www.aaii.com/sentimentsurvey.

Table 4.1 Summary Statistics of the Sentiment Indicators

The table summarises the Pearson correlations of TA sentiment and other sentiment indicators and the descriptive statistics for each indicator. Panel A reports the results for sentiment level, while Panel B focuses on the change in sentiment. The descriptive statistics include the number of observations (Obs), mean (Mean), standard deviation (Std. Dev), minimum value (Min), maximum value (Max) and skewness (*Skew*).

Panel A Summary of the level of sentiment indicators

	Correlations		Descriptive statistics					
	correlation	p-value	Obs	Mean	Std. Dev.	Min	Max	*Skew*
VIX	-0.63	0.000	4788	19.70	7.88	9.31	80.86	2.28
VOL	0.22	0.000	11329	0.08	0.23	-3.29	1.25	-0.42
Put-Call ratio	-0.24	0.000	3336	0.78	0.20	0.30	1.70	0.60
Individual Bull-Bear Spread	0.46	0.000	5399	9.39	18.93	-54.00	62.86	-0.10
Institutional Bull-Bear Spread	0.29	0.000	3474	10.01	13.65	-29.30	40.90	-0.67
TA			11329	0.20	0.39	-0.74	0.80	-0.53

Panel B Summary of the change in sentiment indicators

	Correlations		Descriptive statistics					
	correlation	p-value	Obs	Mean	Std. Dev.	Min	Max	*Skew*
VIX	-0.39	0.000	4784	0.01	1.45	-17.36	16.54	0.43
VOL	0.05	0.000	11328	0.00	0.20	-3.23	3.33	-0.07
Put-Call Ratio	-0.19	0.000	3331	0.00	0.15	-0.70	0.70	-0.08
Individual Bull-Bear Spread	0.32	0.000	1110	-0.07	15.15	-56.97	51.00	-0.14
Institutional Bull-Bear Spread	0.41	0.000	713	0.00	4.88	-20.50	22.30	0.17
TA			11328	0	0.03	-0.15	0.13	-0.11

Table 4.1 reports the Pearson correlation coefficients and p-values from testing the null hypothesis that two sentiment indicators are uncorrelated. Panel A shows the results of correlations between the level of the TA sentiment and the level of other sentiment measures. All five sentiment indicators significantly correlate with TA sentiment. The correlation between TA sentiment and VIX is -0.63 with a corresponding p-value smaller than 1%. The negative correlation is expected since high VIX proxies for low investor sentiment, whereas high TA sentiment indicates high investor sentiment. The correlation of daily VOL and TA sentiment is both positive (which means it has the right sign) and statistically significant.

As expected, the Put-Call ratio varies negatively with TA sentiment, with a statistically significant correlation coefficient of -0.24. The Bull-Bear spread data for both individual and institutional investors are strongly and positively correlated with my TA sentiment. Panel B reports the correlation between the change in TA sentiment and the change in other sentiment measures. All the signs of the correlations remain the same as in Panel A. While the magnitude of the correlations are smaller than those in Panel A, they are all statistically significant, and three out of five correlation coefficients have a correlation coefficient greater than 0.3. This suggests that TA sentiment strongly correlates with other sentiment indicators both in levels and in changes.

When measuring investor sentiment with trading volume or turnover, most literature measures detrend trading volume/turnover by substracting a one-year/five-year backward moving average of log series (eg: Campell, Grossman and Wang, 1993; Baker and Wurgler, 2006; Huang et al, 2015). I employed this detrending approach in this section to measure detrended trading volume. VOL is highly correlated with TA sentiment and other sentiment indicators.

One can plausibly argue that TA may generate rather than monitor investor sentiment because of positive feedback trading. To address this issue, I do some more tests on the correlations. If TA creates sentiment, I would expect current innovation in TA sentiment to be positively associated with next period's innovations in other sentiment indicators. However, if TA reflects sentiment, I would expect a contemporaneous positive correlation between innovations in TA sentiment and innovations in other sentiment indicators. To check these predictions, I remove the persistency in each sentiment indicator by regressing that indicator on its past 10 lags and define the regression's residual as innovation. The number of lags is not strictly selected by information criteria, but is preferably chosen to ensure that the residuals are not significantly autocorrelated. Table 4.2 reports the correlations between the AR(1) residuals of TA index and the AR(1) residuals of other sentiment indicators.

The first two columns in Table 4.2 report the contemporaneous correlations between the innovation in the TA sentiment index and innovations in other sentiment indicators. I find strong contemporaneous correlations, implying that TA index tracks investor sentiment. The last two columns in Table 4.2 report the correlations between the lagged innovation in the TA index and the current innovations in other sentiment indicators. The lagged innovation in TA index is significantly correlated with the current innovations in all other sentiment indicators, except VIX. This suggests that TA sentiment has dual roles: monitoring investor sentiment and generating future sentiment. While the role of TA as sentiment generator has been repeatedly discussed in the literature, its role as a sentiment barometer has been largely ignored.

Table 4.2 Correlations of Innovations in Sentiment Indicators

This table reports the correlation between innovations in TA sentiment and innovations in other sentiment indices. I use the residuals from AR(10) regression as the innovations in sentiment indicators.

	Correlations with innovations in TA		Correlations with lagged innovations in TA	
	correlation	p-value	correlation	p-value
VIX	-0.55	0.000	-0.01	0.652
VOL	0.11	0.000	0.11	0.000
Put-Call Ratio	-0.36	0.000	-0.13	0.000
Individual Bull-Bear Spread	0.23	0.000	0.33	0.000
Institutional Bull-Bear Spread	0.23	0.000	0.29	0.000

4.2.2 Portfolio Construction

To substantiate whether TA sentiment affects asset prices, I follow Baker and Wurgler (2006) to construct portfolios based on ten firm characteristics that reflect the extent to which a stock is prone to investor sentiment. These characteristics include firm size (ME), firm age (Age), total risk (Sigma), earnings-book ratio (E/BE), dividend-book ratio (D/BE), fixed assets ratio (PPE/A), research and development ratio (RD/A), book-to-market ratio (BE/ME), external finance over assets (EF/A) and sales growth ratio (GS).

To construct my portfolios, I collect stock market data from CRSP for all common stocks (share codes 10 and 11) on NYSE, AMEX, and NASDAQ over the period from January 1962 to December 2008. Firm-level accounting data is obtained from Compustat. The year-end accounting data of year t-1 is matched to daily returns from July of year t to June of year t+1. The ten firm characteristics are used to sort stocks into deciles. All firm characteristics are winsorized at 99.5 percent and 0.5 percent annually. For the reason of consistency, breakpoints for the deciles are defined using NYSE firms only. The portfolios are rebalanced every year to allow stocks to shift from one portfolio to another. The High (H), Medium (M), and Low (L) portfolios are defined as the top three, middle four, and bottom three deciles, respectively. My long-short portfolios are constructed by longing sentiment-prone deciles and shorting sentiment-immune deciles. Detailed definitions of the firm characteristics and the long-short portfolios are provided below.

I first consider ME, Age, Sigma characteristics. ME is the price times shares outstanding in June every year. If there is more than one permanent code for a company, I sum up all the ME for the same company. Small stocks are disproportionally held by retail investors and are more difficult to value, indicating that small-cap firms are more prone to sentiment. In this context, I make the returns of ME-based long-short portfolio equal to the average return of Low (L) portfolio over High (H) portfolio. I denote this long-short portfolio as ME(L-H) hereinafter. Age is the number of months between a firm's first appearance on CRSP to the nearest month. Young firms have a short history and are typically more difficult to value and arbitrage. Therefore, I long the young stock portfolio and short the old stock portfolio, denoted as Age(L-H). Sigma is the annual standard deviation in monthly returns for the 12 months ending in June every year, and there should be no less than nine monthly returns available to estimate it. Since highly volatile stocks are more difficult to arbitrage, I construct the volatility-based long-short portfolio (or Sigma(H-L)) by longing more volatile stocks and shorting less volatile stocks.

I then consider profitability and dividend policy characteristics. E/BE is the earnings scaled by book equity. E is the income before extraordinary items (Item 18 in Compustat) add income statement deferred taxes (Item 50) less preferred dividends (Item 19). D/BE is the fiscal year-end dividends per share at the ex-date (Item 26) times shares outstanding (Item 25) scaled by book equity. BE is the shareholders' equity (Item 60) plus balance sheet deferred taxes (Item 35). Paying dividend enhances arbitrage profits and reduces holding costs (Pontiff, 1996). Following Baker and Wurgler (2006), the decile portfolios are constructed with both E/BE and D/BE. The E/BE long-short portfolio returns used in my regressions are the average return of non-profitable firms (E<0) minus that of profitable firms (E>0). I denote this portfolio as E/BE(<0->0). The D/BE long-short portfolio returns used in regressions are the average returns of non-dividend-paying firms (D=0) minus those of dividend-paying firms (D>0). I refer to this portfolio as D/BE(=0->0).

PPE/A and RD/A are related to the asset tangibility of a firm. PPE/A is Plant, property, and equipment (Item 7) divided by gross total assets (Item 6). RD/A is Research and development (Item 46) divided by gross total assets (Item 6). The coverage of R&D is sparse prior to 1972 because the disclosure of R&D was voluntary until 1974 under the Financial Accounting Standards Board. As firms with more intangible assets are more difficult to value and arbitrage, the long-short portfolios are constructed by longing firms with less tangible assets and shorting firms with more tangible assets. I denote these long-short portfolios as PPE/A(L-H) and RD/A(H-L).

The remaining three characteristics, namely BE/ME, EF/A, and GS, are defined as follows. BE/ME is the log of the ratio of book equity to market equity. EF/A is the external finance scaled by gross total assets. EF is the change in gross total assets (Item 6) minus the change in retained earnings (Item 36). When the change in retained earnings is not available, I use net income (Item 172) minus common dividends (Item 21) instead. Sales growth (GS) is the percentage change in net sales (Item 12). I first calculate the original sales growth ratio and then use GS to denote its decile. Baker and Wurgler (2006) argue that BE/ME, EF/A, and GS can be related to both growth and distress. The firms in the middle deciles (M) are usually stable, while the high (H) and low (L) deciles contain firms with strong growth opportunity or with severe financial distress. High BE/ME implies that the firm is in financial distress, while low BE/ME indicates the presence of strong growth opportunity. High values of EF/A or GS mean firms in distress, while low values indicate that firms have strong growth potential. To capture the multidimensional nature of these variables, I construct three long-short portfolios for each variable: when the three variables are considered as a generic pricing factor, the portfolios are denoted as BE/ME(H-L), EF/A(H-L), and GS(H-L); when the three variables represent firm growth opportunities, the portfolios are denoted as BE/ME(L-M), EF/A(H-M), and GS(H-M); when the three variables represent the level of financial distress, the long-short portfolios are denoted as BE/ME(H-M), EF/A(L-M), and GS(L-M) respectively.

All decile portfolios have a sample period from January 01, 1964 to December 31, 2008, except for the RD/A portfolio, in which the R&D data is generally available after 1972. In total, I obtain 9,466 daily returns of RD/A-based long-short portfolios. For all other decile portfolios and long-short portfolios, I obtain 11,329 daily observations.

4.3 Empirical Tests

In this section, I examine the pricing effect of my TA sentiment on the cross-sectional stock returns. I start with the contemporaneous regressions of cross-sectional stock returns on the change in the TA sentiment.

$$R_t = \alpha + \beta_1 \Delta TA_t + \gamma CV_t + \varepsilon_t, \tag{4.1}$$

where R_t is the return on a given long-short portfolio at time t, ΔTA_t is the change in TA sentiment from time $t-1$ to time t, and CV_t is a vector of control variables, including the Fama and French's (2015) five factors and Carhart's (1997) momentum factor.[15]

The Fama-French five factors include RMRF, SMB, HML RMW, and CMA. RMRF is the market return premium over the risk-free rate. SMB is the average return on the three small capitalization portfolios minus the average return on the three big capitalization portfolios, HML is the average return on the two value portfolios minus the average return on the two growth portfolios, RMW is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, and CMA is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios. The momentum factor (UMD) is the average return of the high prior return portfolio over the low prior return portfolio.

Any control factor analogy to the dependent variable in Equation (4.1) will be excluded from the list of control variables. To be specific, the SMB factor is excluded when the dependent variable is the returns of long-short portfolio ME(L-H). HML factor is removed

[15] The data are available on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 4.3 Contemporaneous Regressions of Portfolio Returns on TA Sentiment Changes

This table reports the results of the long-short portfolio average returns regressed on contemporaneous TA sentiment changes and a set of control variables.

$$R_t = \alpha + \beta_1 \Delta TA_t + \gamma CV_t + \varepsilon_t,$$

R_t is the daily return of the sixteen long-short portfolios constructed from the sentiment-prone variables. ΔTA_t is the difference between TA_t and TA_{t-1}. H, M, and L are respectively the top three, middle four, and bottom three deciles. CV_t is a vector of control variables, which includes the Fama and French five factors and the momentum factor (UMD). A factor is excluded from the list of control variables when it is the dependent variable in the regressions. The Newey and West (1987) robust t-statistics are in brackets. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		ΔTA_t	RMRF	SMB	HML	RMW	CMA	UMD	α
ME	L-H	2.03***	-0.30***		0.072**	-0.35***	-0.037	0.071***	0.041***
		(7.26)	(-15.09)		(2.17)	(-8.13)	(-0.95)	(2.95)	(6.05)
Age	L-H	0.61***	-0.10***	0.51***	-0.20***	-0.28***	-0.21***	-0.032**	0.042***
		(3.84)	(-8.60)	(33.42)	(-10.10)	(-14.74)	(-10.27)	(-2.44)	(10.78)
Sigma	H-L	0.48***	0.34***	0.54***	-0.15***	-0.28***	-0.14***	-0.020	0.030***
		(3.25)	(33.31)	(32.40)	(-10.48)	(-14.26)	(-7.06)	(-1.58)	(7.16)
E/BE	<0->0	0.26	0.031**	0.34***	-0.22***		0.12***	-0.045**	0.043***
		(1.17)	(2.12)	(12.76)	(-8.12)		(4.50)	(-2.01)	(6.86)
D/BE	=0->0	0.30	0.078***	0.42***	-0.33***		-0.036*	-0.032*	0.036***
		(1.63)	(5.67)	(20.04)	(-16.07)		(-1.72)	(-1.80)	(7.55)
PPE/A	L-H	0.93***	0.015	0.21***	-0.20***	-0.12***	-0.14***	-0.035**	0.0062
		(3.27)	(0.60)	(11.75)	(-8.21)	(-7.07)	(-6.79)	(-2.01)	(1.55)
RD/A	H-L	0.41***	0.11***	0.060***	-0.29***	-0.21***	0.056***	0.0050	0.012***
		(3.17)	(12.41)	(6.12)	(-20.59)	(-13.31)	(3.58)	(0.52)	(3.94)
BE/ME	H-L	0.46***	-0.26***	-0.067***		0.17***	0.40***	0.033*	0.038***
		(2.78)	(-21.46)	(-5.26)		(7.78)	(19.73)	(1.82)	(9.95)
EF/A	H-L	0.019	0.086***	0.052***	-0.085***	-0.084***	-0.26***	-0.030***	-0.023***
		(0.20)	(12.14)	(7.57)	(-9.20)	(-9.59)	(-23.78)	(-5.51)	(-11.96)
GS	H-L	0.11	0.10***	0.069***	-0.088***	0.046***	-0.26***	-0.013*	-0.020***
		(1.21)	(14.86)	(8.58)	(-8.21)	(3.96)	(-23.53)	(-1.91)	(-9.38)
BE/ME	L-M	0.076	0.13***	0.040***		-0.22***	-0.33***	-0.0066	-0.0046*
		(0.58)	(13.21)	(3.85)		(-11.75)	(-19.65)	(-0.53)	(-1.68)
EF/A	H-M	0.15*	0.063***	0.13***	-0.093***	-0.12***	-0.18***	-0.044***	-0.0037*
		(1.76)	(10.72)	(15.49)	(-11.90)	(-12.36)	(-16.97)	(-7.81)	(-1.91)
GS	H-M	0.066	0.097***	0.16***	-0.14***	-0.14***	-0.19***	-0.034***	-0.0023
		(0.73)	(16.30)	(19.13)	(-15.11)	(-13.27)	(-15.86)	(-5.31)	(-1.15)
BE/ME	H-M	0.54***	-0.13***	-0.027**		-0.047***	0.070***	0.026***	0.033***
		(5.39)	(-18.72)	(-2.50)		(-4.13)	(6.38)	(2.75)	(12.63)
EF/A	L-M	0.13*	-0.023***	0.073***	-0.0080	-0.037***	0.077***	-0.013***	0.019***
		(1.74)	(-4.58)	(12.06)	(-0.83)	(-5.16)	(8.20)	(-2.83)	(9.56)
GS	L-M	-0.045	-0.0035	0.094***	-0.055***	-0.19***	0.070***	-0.021***	0.018***
		(-0.54)	(-0.70)	(12.05)	(-5.86)	(-17.68)	(6.47)	(-3.15)	(7.59)

when the dependent variable is the returns of any one of the three long-short portfolios constructed with BE/ME. RMW factor is omitted if the dependent variable is the return of long-short portfolio E/BE(L-H) or D/BE(L-H). I report Newey-West standard errors (Newey and West, 1987) that are robust to heteroscedasticity and serial correlation.

Table 4.3 reports the results of contemporaneous regressions for the sixteen long-short portfolios. The coefficients of the change in TA sentiment are positive and statistically significant (at the 10% level or better) for 9 out of 16 long-short portfolios. For the remaining 7 long-short portfolios, the coefficients of the change in TA sentiment are insignificant, and 6 of them are positive. These results suggest that when TA sentiment increases, the sentiment-prone and difficult to arbitrage stocks tend to earn higher returns than the sentiment-immune and easy to arbitrage stocks, consistent with the view that TA sentiment is a sentiment indicator. However, this finding should be taken with caution, due to endogeneity concerns.

The FF five factors and the momentum factor all have strong explanatory power on contemporaneous returns conditional on the effect of investor sentiment. The abnormal alphas are much smaller than the corresponding dependent variables but the alphas are still significant after controlling for the commonly-used pricing factors and my TA sentiment.

To alleviate endogeneity concerns, I use the following predictive regressions of daily returns from the long-short portfolios on TA sentiment and other control variables:

$$R_t = \alpha + \sum \beta_i TA_{t-i} + \gamma CV_t + \varepsilon_t, \tag{4.2}$$

The key variables of my interest are TA_{t-i}, i.e., the lagged TA sentiment indicators. According to the lack of synchronization among arbitragers, sophisticated investors may delay arbitrage and ride the mispricing. Thus, I expect the long-short portfolio returns to increase in the short term and reverse later. Since the exact time at which sophisticated investors can coordinate their attack on mispricing is not known with uncertainty, how long does it take for the returns of a long-short portfolio to revert back is an open empirical question. One way to decide the number of lags (i) of the TA sentiment indicators is to run the Likelihood Ratio test to compare the model fitness. At the significance level of 5%, 11 out of 16 portfolios have better model fitness with only two lagged TA sentiment. For robustness purposes, I also consider alternative values for i in my regressions.

Table 4.4 shows the regression results. Panel A reports the results of the models with only one TA sentiment lag ($i = 1$) with or without control variables. Although I do not know how long the short-term momentum would persist, I expect to observe the momentum effect one day following a TA sentiment increase. Panel A shows that 12 out of 16 of the coefficients of TA_{t-1} are positive and significant at 10% level or better. The magnitudes of the TA_{t-1} coefficients decrease in most cases after controlling for the Fama-French five factors and the momentum factor, but 11 out of 16 of the coefficients remain positive and significant. The coefficients of TA_{t-1} in the PPE/A and RD/A portfolio regressions become insignificant after controlling for Fama-French five factors and the momentum factor. This finding is consistent with Baker and Wurgler (2006), who also show that sentiment does not predict the future returns of PPE/A and RD/A long-short portfolios. Also similar to Baker and Wurgler (2006), I find inconclusive results for the regressions involving BE/ME(H-L), EF/A(H-L) and GS(H-L) long-short portfolios.

Panel B in Table 4.4 reports the results of models with two TA sentiment lags. The second lag would allow me to examine whether the momentum effect continues or the returns reverse two days after a TA sentiment increase. I find that consistent with Panel A, the first-order TA lag positively predicts returns of the majority of long-short portfolios, indicating a short-term momentum effect. The coefficients of TA_{t-2} are basically negative, suggesting the returns on sentiment-prone stocks begin to drop on the second day following sentiment increase. Similar to Panel A, Panel B also provides inconclusive evidence on the ability of TA sentiment to explain the future returns of BE/ME(H-L), BE/ME(H-M), EF/A(H-L), and

Table 4.4 Predictive Regressions of Portfolio Returns

This table reports the coefficients for lagged TA sentiment of regressions of long-short portfolio returns on lagged TA sentiment and a vector of control variables.

$$R_{t,1} - R_{t,2} = \alpha + \sum \beta_i TA_{t-i} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the long-short portfolios constructed from the sentiment-prone variables. H, M, and L are respectively the top three, middle four, and bottom three deciles. CV_t is a vector of control variables, which includes the Fama and French five factors and the momentum factor (UMD). A factor is excluded from the list of control variables when it is the dependent variable in the regressions. Panel A reports the results of the regressions with the previous period TA as the only independent variables, i.e., $i = 1$. Panel B reports results of regressions with two TA lags as the independent variables, i.e., $i = 2$. The Newey and West (1987) robust t-statistics are in brackets. The sample period is from 1964/01/01 to 2008/12/31. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		Panel A		Panel B			
		No Control Variables	With Control Variables	No Control Variables		With Control Variables	
		β_1	β_1	β_1	β_2	β_1	β_2
ME	L-H	0.15***	0.15***	2.48***	-2.34***	2.84***	-2.70***
		(8.77)	(8.23)	(13.87)	(-12.98)	(15.62)	(-14.85)
Age	L-H	0.14***	0.076***	2.42***	-2.29***	0.85***	-0.77***
		(8.23)	(6.92)	(15.11)	(-14.13)	(7.83)	(-7.09)
Sigma	H-L	0.11***	0.037***	3.01***	-2.90***	0.51***	-0.47***
		(4.92)	(3.19)	(15.58)	(-14.95)	(3.93)	(-3.66)
E/BE	<0->0	0.14***	0.11***	1.50***	-1.36***	0.48***	-0.38**
		(7.63)	(6.19)	(8.32)	(-7.45)	(2.72)	(-2.13)
D/BE	=0->0	0.13***	0.081***	1.98***	-1.86***	0.50***	-0.42***
		(6.83)	(5.72)	(11.98)	(-11.11)	(3.25)	(-2.75)
PPE/A	L-H	0.039***	0.011	1.48***	-1.45***	0.59***	-0.58***
		(2.71)	(0.92)	(12.11)	(-11.77)	(5.16)	(-5.09)
RD/A	H-L	0.0093	-0.0027	0.84***	-0.84***	0.20**	-0.20**
		(0.73)	(-0.32)	(7.11)	(-7.02)	(2.32)	(-2.37)
BE/ME	H-L	0.032*	0.054***	-0.64***	0.67***	0.42***	-0.37***
		(1.96)	(4.81)	(-4.48)	(4.67)	(3.98)	(-3.49)
EF/A	H-L	-0.0068	-0.019***	0.61***	-0.62***	0.044	-0.063
		(-0.78)	(-3.82)	(7.63)	(-7.66)	(0.72)	(-1.03)
GS	H-L	-0.022**	-0.031***	0.60***	-0.62***	0.051	-0.082
		(-2.52)	(-5.45)	(6.89)	(-7.13)	(0.82)	(-1.33)
BE/ME	L-M	0.011	-0.0058	0.85***	-0.84***	0.14*	-0.15*
		(0.90)	(-0.69)	(8.22)	(-8.04)	(1.65)	(-1.73)
EF/A	H-M	0.042***	0.021***	1.00***	-0.96***	0.29***	-0.27***
		(4.47)	(3.87)	(12.42)	(-11.77)	(4.37)	(-4.06)
GS	H-M	0.038***	0.012**	1.07***	-1.03***	0.15**	-0.13**
		(3.54)	(2.14)	(11.76)	(-11.26)	(2.16)	(-2.00)
BE/ME	H-M	0.043***	0.049***	0.21**	-0.17*	0.57***	-0.52***
		(5.66)	(6.80)	(2.44)	(-1.95)	(7.25)	(-6.71)
EF/A	L-M	0.049***	0.040***	0.38***	-0.33***	0.24***	-0.20***
		(9.08)	(7.92)	(6.29)	(-5.46)	(4.13)	(-3.46)
GS	L-M	0.061***	0.043***	0.47***	-0.41***	0.096	-0.053
		(7.88)	(6.76)	(6.02)	(-5.22)	(1.41)	(-0.77)

GS(H-L). With the exception of these four portfolios and GS(L-M), including control variables does not alter the sign or significance of β_1 and β_2. When BE/ME, EF/A, and GS are used to capture growth and distress, β_1 and β_2 are statistically significant as hypothesized in most cases.

I consider three lags of TA sentiment and find that the coefficients of the first-order TA lag are in general positive, while the coefficients of the second and the third lags are in general negative. Alternatively, in Table E.7 I include the first lag of TA sentiment, and the average TA sentiment between $t-2$ and $t-26$. While the coefficients of the first-order TA lag remain positive, the coefficients of the average of the past TA sentiment are negative. These results suggest that, on average, an increase in TA sentiment predicts a momentum on the following day and a reversal afterwards. The finding that TA is a contrarian predictor for future cross-sectional returns suggests that my TA sentiment index is indeed a sentiment indicator.

I conduct several additional tests to examine the robustness of my results. The results of these tests are reported in Appendix E.2.

The first set of tests examine whether the observed return patterns reflect changes in firms' fundamentals. I do this by including macroeconomic variables in the set of the control variables in Equations (4.1) and (4.2). Since I consider daily momentums and reversals, I include the following macroeconomic control variables with available data at daily frequency: default spread, TED spread, macroeconomic activities index (ADS), and economic policy uncertainty (EPU). Default spread is the difference between Moody's AAA and Baa bond yields and TED spread is the difference between the yield on 3-month LIBOR and the yield on 3-month US Treasury bills. When examining the effect of sentiment on returns, Da et al. (2014) employ two macroeconomics variables ADS and EPU as control variables. ADS is constructed by Aruoba et al. (2009) with a battery of seasonally adjusted macroeconomic variables of mixed frequencies to measure daily macroeconomic activities. Baker et al.

(2016) construct EPU by counting the number of US newspaper articles with terms related to economic policies. As reported in Table E.8, the sign and significance of coefficients of TA sentiment do not alter after including the macroeconomic variables as additional controls in Equations (4.1) and (4.2).

To rule out the rational explanation for the predictability of TA sentiment, I also follow Baker and Wurgler (2006) and add sentiment into a conditional CAPM model:

$$R_t = \alpha + \sum \beta_i TA_{t-i} + (d + \sum \lambda_i TA_{t-i}) RMRF_t + \varepsilon_t, \tag{4.3}$$

where R_t is the portfolio return premium at time t, and $RMRF_t$ is the market return premium.

If the rational story holds, TA sentiment index would vary with systematic risks (beta loadings) of the sentiment-based portfolio return premium. If the effect of TA lags on return arises from the time-varying beta-loadings of market return premium, the sign of λ_i would be the same as the sign of β_i in Table 4.4 and remain significant; otherwise, the behavioural story holds.

Table 4.5 presents the results of conditional CAPM model regressions. Check the results against the two latent systematic risk explanations respectively. One explanation is that the predictive pattern between TA sentiment and cross-sectional return is due to the effect of TA sentiment on the beta loading of market return premium. If the rational story holds, TA sentiment index will vary with systematic risks (beta loadings) of the sentiment-based portfolio return premium, and the sign of λ_i is the same as the sign of β_i in Regression (4.2); otherwise, the behavioural story holds.

Panel A of Table 4.5 shows that the coefficients λ_1 are significant for ten out of sixteen regressions, but in most cases, the signs of coefficients λ_1 do not match the signs of the respective β_1 in Table 4.4. Because the dependent variables for each regression in Table 4.5 are the return premium of sentiment-prone stocks over sentiment-immune stocks, I expect

Table 4.5 Conditional Market Beta Loadings

This table reports the coefficients for lagged TA sentiment and the coefficients of interaction terms of TA sentiment and market return premium (RMRF). The regressions are noted as

$$R_t = \alpha + \sum \beta_i TA_{t-i} + (d + \sum \lambda_i TA_{t-i}) RMRF_t + \varepsilon_t.$$

Panel A reports results of model with only one-term lagged TA sentiment, where $i = 1$. Panel B reports the results of model with two TA sentiment lags, where $i = 2$. The first two column indicates how dependent variable R_t is formed. A superscript 'a' ('b') indicates that a statistical significant coefficient of the interaction term of TA sentiment and RMRF matches (does not match) the sign of return predictability of TA sentiment from Table 4.4. The Newey and West robust t-statistics are in brackets. ***, ** and * indicates the statistical significance at 1%, 5% and 10% level, respectively.

		Panel A			Panel B				
		b	β_1	λ_1	b	β_1	β_2	λ_1	λ_2
ME	L-H	-0.26***	0.16***	-0.012	-0.27***	3.06***	-2.91***	-0.75	0.73
		(-24.15)	(8.86)	(-0.39)	(-31.41)	(16.52)	(-15.71)	(-1.44)	(1.39)
Age	L-H	-0.067***	0.14***	-0.067*b	-0.076***	2.60***	-2.47***	-0.37	0.29
		(-5.56)	(8.18)	(-1.93)	(-6.82)	(16.54)	(-15.53)	(-0.52)	(0.42)
Sigma	H-L	0.34***	0.11***	-0.058*b	0.33***	2.35***	-2.25***	-0.48	0.41
		(36.42)	(5.92)	(-1.88)	(36.61)	(14.23)	(-13.53)	(-0.92)	(0.80)
E/BE	<0->0	0.021***	0.14***	-0.033	0.014*	1.49***	-1.35***	-0.45	0.42
		(2.65)	(7.70)	(-1.11)	(1.82)	(8.46)	(-7.58)	(-1.11)	(1.02)
D/BE	=0->0	0.11***	0.12***	-0.024	0.10***	1.79***	-1.67***	-0.46	0.43
		(11.36)	(7.12)	(-0.64)	(10.62)	(10.94)	(-10.11)	(-0.87)	(0.81)
PPE/A	L-H	0.085***	0.036***	0.062	0.079***	1.32***	-1.29***	-0.24	0.30
		(11.46)	(2.60)	(1.36)	(10.06)	(11.54)	(-11.17)	(-0.91)	(1.16)
RD/A	H-L	0.18***	0.0066	0.064***a	0.18***	0.55***	-0.54***	-0.13	0.19
		(37.37)	(0.60)	(2.59)	(34.71)	(5.30)	(-5.25)	(-0.84)	(1.26)
BE/ME	H-L	-0.31***	0.038***	0.092***a	-0.31***	-0.020	0.058	0.042	0.050
		(-36.75)	(2.99)	(3.27)	(-43.01)	(-0.17)	(0.50)	(0.10)	(0.12)
EF/A	H-L	0.14***	-0.010	-0.025	0.14***	0.33***	-0.34***	-0.17*b	0.14
		(41.77)	(-1.42)	(-1.55)	(39.97)	(4.71)	(-4.83)	(-1.65)	(1.38)
GS	H-L	0.15***	-0.026***	-0.024	0.15***	0.30***	-0.33***	-0.12	0.096
		(38.03)	(-3.45)	(-1.31)	(41.32)	(4.22)	(-4.59)	(-0.80)	(0.63)
BE/ME	L-M	0.19***	0.0072	-0.050**b	0.18***	0.48***	-0.47***	-0.094	0.043
		(27.17)	(0.70)	(-1.99)	(31.38)	(4.98)	(-4.89)	(-0.27)	(0.12)
EF/A	H-M	0.10***	0.040***	-0.058***b	0.10***	0.81***	-0.77***	-0.29*b	0.23
		(25.01)	(5.11)	(-3.75)	(25.00)	(10.60)	(-10.00)	(-1.65)	(1.31)
GS	H-M	0.14***	0.035***	-0.053***b	0.14***	0.80***	-0.76***	-0.25	0.20
		(31.70)	(4.07)	(-2.62)	(33.79)	(9.55)	(-9.11)	(-1.08)	(0.84)
BE/ME	H-M	-0.12***	0.046***	0.042***a	-0.12***	0.46***	-0.42***	-0.051	0.092
		(-36.76)	(6.50)	(4.27)	(-41.50)	(6.15)	(-5.58)	(-0.50)	(0.90)
EF/A	L-M	-0.040***	0.050***	-0.033***b	-0.042***	0.48***	-0.43***	-0.12	0.087
		(-11.84)	(9.18)	(-4.18)	(-17.95)	(8.16)	(-7.27)	(-1.01)	(0.72)
GS	L-M	-0.0086**	0.061***	-0.029***b	-0.011***	0.50***	-0.44***	-0.13	0.10
		(-2.38)	(7.97)	(-2.65)	(-2.84)	(6.58)	(-5.75)	(-0.97)	(0.73)

positive coefficients of the first-order TA sentiment lag. The signs of β_1 are generally positive as hypothesized. In Panel A the signs of coefficients λ_1 matches the signs of β_1 in Table 4.4 only for three out of sixteen regressions; the coefficient λ_1 is statistically positive for the RD/A(H-L), BE/ME(H-L) and BE/ME(H-M) portfolios. My findings of significant positive λ_1 for BE/ME(H-M) is consistent with Baker and Wurgler (2006), who also find significant coefficient of interactions terms for BE/ME(H-M). The signs of β_1 are still notably positive as expected for all the portfolios that show strong sentiment conditional effect in the previous regressions.

Look into Panel B of Table 4.5. The signs of λ_1 and λ_2 are no longer significant in most cases except for the EF/A(H-L) portfolio and EF/A(H-M) portfolio, while in those two regressions the sign of statistically significant λ_1 does not match the sign of β_1 in Table 4.4. Both the sign and magnitude of the coefficients of TA lags are strongly consistent with that in Table 4.3. The predictive ability of TA sentiment does not change after allowing for time-variation in the conditional market betas. Generally speaking, the first systematic risk explanation does not hold and does not undermine the explanatory power of behavioural story. In Table 4.5, the sign of significant λ_1 matches the sign of the coefficients of the first-order TA lag in Table 4.4 in only in 3 out of the 16 regressions, suggesting that the behavioural story holds for 13 out of the 16 regressions. I also find that the sign and significance of coefficients of TA lags, β_i, are consistent with those in Table 4.4, implying that the predictive ability of TA sentiment does not change after allowing for time-variation in conditional market betas.

Another systematic risk explanation considers the market beta loadings fixed but argues the market return premium varies with TA sentiment, and therefore the cross-sectional return changes in proportion. If this story holds, then the coefficient for market return premium should be consistent for all the sixteen portfolios constructed similarly based on variables representing the sentiment-prone level of a stock. However, the coefficients of market return premium in Table 4.3 vary in signs across the regressions for the sixteen portfolios. In the

CAMP model, the coefficients d in Regression Equation (4.3) for market return premium vary in signs for the sixteen portfolios as well. In addition, I run some simple tests and find out that TA sentiment does not perform well in predicting the overall market returns. The correlation of market return premium and TA sentiment lag is insignificant. With or without control variables, the coefficient of TA sentiment is not significant when regressed on overall market returns. To sum, neither systematic risk explanations hold for the predictive power of TA sentiment index. The bulk of the results show that the predictability of TA sentiment on future returns is not a reflection of systematic risk compensation.

The second set of tests investigate the sensitivity of my results to the way in which TA sentiment is constructed. The regression results are tabulated in Appendix E2.3. I construct a TA sentiment with historical data of Dow Jones Industrial Average Index and produce similar results in Table E.12. Furthermore, instead of using an equal-weighted average of the technical analysis forecasts, I compute a performance-weighted average of the 2,127 technical forecasts as TA sentiment index, for which performance of each trading rule is measured by its returns in the past year, and obtain consistent results. The performance-weighted TA sentiment captures the idea that better performing strategies are more likely to be used. The regression results using performance-weighted TA sentiment are reported in Table E.14.

The third set of tests investigate the robustness of my findings to alternative long-short portfolio return calculations and to addressing the Stambaugh bias and multi-collinearity issues in the regressions. Explicitly, I construct the long-short portfolios by longing the most sentiment-prone decile portfolio and shorting the least sentiment-prone decile portfolio and find that my results still hold. I also calculate the value-weighted return premium to isolate the size effect on the portfolio return premium and show that the predictive power of TA sentiment does not change, as shown in TableE.16. Finally, I address a potential multi-collinearity issue (due to the high persistency of TA similar to other sentiment indicators) by orthogonalizing TA_{t-2} to TA_{t-1} when both TA_{t-1} and TA_{t-2} are included in the regressions.

I replace TA_{t-2} with recursive residuals of a rolling regression to avoid the look-ahead bias. The results show that one-day lagged TA sentiment predicts higher returns while the orthogonalized second lag of TA sentiment has a significant negative link with future returns, consistent with the results in Table E.11.

Furthermore, I investigate whether the observed momentum-reversal pattern in the cross-sectional returns following a TA sentiment increase reflects liquidity by adding a market-wide liquidity measure, the detrended daily trading volume of S&P 500 index (VOL), into the control variables. I find that the sign and the significance of the lagged TA coefficients remain similar, inconsistent with the liquidity explanation. Similar results are obtained when the average bid-ask spread of a sentiment-prone portfolio minus that of a sentiment-immune portfolio, instead of the detrended VOL, is used a liquidity measure. The results after controlling for liquidity effect are reported in Table E.9 of Appendix E2.2.

I also examine whether TA sentiment has incremental value beyond the alternative sentiment indicators, such as VIX. I find that the effect of my sentiment measure remains significant after including VIX as a control variable in my regressions. See Table E.10in Appendix E2.2.

The final set of tests is to add macroeconomic variables into the control variables. Given that the near term momentums and reversals occur within a few days when macroeconomic conditions are similar, macroeconomic conditions are unlikely to drive my results,. Yet, I still add four daily-frequency macroeconomic control variables, namely default spread, TED spread, macroeconomic activities index (ADS) and economic policy uncertainty (EPU)[16], into the regressions. Default spread and TED spread are commonly accepted macroeconomic variables. I borrow ADS and EPU from Da et al. (2014), who uses them as control variables

[16]Default spread and TED spread are from Bloomberg. Default spread is the differential between Moody's AAA and Baa yield, starting from 1986/01/02. TED spread is the difference between the interest rates on interbank loans and on short-term U.S. government T-bills, starting from 1984/12/06. ADS is available at http://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index, starting from 1960/03/01. EPU is available at http://www.policyuncertainty.com/us_daily.html, starting from 1985/01/01.

when trying to validate the daily search volume of negative words as a sentiment indicator. ADS is constructed in Aruoba et al. (2009) with a battery of seasonally adjusted macroeconomic variables of mixed frequencies, including weekly initial jobless claims, monthly payroll employment, monthly industrial production, monthly personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP. High ADS means good macroeconomic conditions. Baker et al. (2016) construct EPU by counting the number of US newspaper articles with at least one term from each of the three categories of terms 1) economic or economy 2) uncertain or uncertainty 3) deficit, regulation, legislation, congress, Federal Reserve or White House. EPU is a crucial control variable, as some argue that official intervention might be a reason for the profitability of technical analysis. In an unreported table, both the sign and magnitude of the coefficients for TA sentiment terms are strongly consistent after accounting for the four macroeconomic variables based on the results in Table E.8.

Apart from the tests on the relationship between TA indicator and cross-sectional stock returns, I propose another way to validate TA indicator as an investor sentiment measure. I show the predictability of TA indicator on sentiment-induced future crash risk to prove TA indicator captures investor sentiment in Appendix E2.1. Because of the lack of synchronisation among arbitragers, the sentiment-induced mispricing persists in the asset price. When the bubbles are big enough and finally collapse, the coordinated arbitrage actions will trigger a sharp deceleration in the asset price. Therefore, a good investor sentiment indicator would not only predict the return momentum but also perform well in forecasting the future crash risk. I expect my TA sentiment to predict future crash risk in the cross-section. More specifically, I expect more sentiment-prone stocks to have higher crash risk than less sentiment-prone stocks following a TA sentiment increase. The documented evidence suggests that arbitragers who ride mispricing encounter a big chance of dramatic drops in their portfolio returns if they are unable to "beat the gun" (i.e., before the joint attack on mispricing is triggered).

4.4 Simple TA Trading Strategies

This new TA sentiment index can be used to design trend-following trading strategies and quantify the effect of sentiment on return. In this section, I will first employ TA sentiment index to time the sixteen long-short portfolios and test the profitability and marketing power of my TA trading strategies. Then I check the profit of applying TA timing rule on decile portfolios constructed with the ten characteristics, to have a better understanding of the sources of profitability. I also calculate the break-even transaction costs to demonstrate my TA trading strategies are practical and tradable.

4.4.1 Implementation on Cross-sectional Long-short Portfolios

One critical assumption behind the delayed arbitrage of sophisticated investors is that riding mispricing is on average profitable. While I do not know exactly which trading strategies are used by arbitrageurs, I trade on signals inferred from my TA sentiment indicator. I then apply my TA timing rule to the sixteen long-short portfolios, which long the most sentiment-prone deciles and short the least sentiment-prone deciles. In what follows, I refer to these long-short portfolios as the original long-short portfolios to distinguish them from the portfolios generated from the implementation of the TA timing rule.

The TA timing rule is straightforward: a 'buy' ('sell') signal is generated when a TA sentiment at the end of the current trading day is higher (lower) than the moving average of TA sentiment over previous five days.[17] When I apply the timing rule to the sixteen original long-short portfolios, I long or continue to hold the original long-short portfolio the next day when a 'buy' signal is generated today, and short the original long-short portfolio the next day when a 'sell' signal is generated. In this way, I get sixteen TA trading strategies. For example, the TA trading strategy for the Age-sorted portfolio is to buy young and sell old firms when

[17] I also use moving average over alternative window period in my robustness checks.

the TA sentiment gives a 'buy' signal, and to buy old and sell young firms when the TA sentiment generates a 'sell' signal. Essentially, my TA time strategies are trend-following strategies designed to take advantage of delayed arbitrage. I do not consider a contrarian strategy to exploit return reversals, as the inability to observe coordinated events makes it difficult to time reversals.

Panel A in Table 4.6 reports the average returns and risk-adjusted returns (Sharpe ratio and the Alphas from regressions with the Fama-French five factors and the momentum factor) of original long-short portfolios. Most of these portfolios have significantly positive average returns and risk-adjusted returns. Approximate one-third of these TA-sentiment-timing strategies have significantly negative average returns and risk-adjusted returns. Unlike the results in Panel A, both average returns and risk-adjusted returns of my TA trading strategies in Panel B are positive and salient for almost all portfolios. The only exceptions are GS(10-1), which has significant albeit small negative average returns and BE/ME(10-1) and GS(10-1), which have insignificant alphas. The average performances range from -1.74% to 36.42% and the Sharpe ratios range from -0.25 to 2.76. Adjusting for the Fama-French five factors and the momentum factor affects average returns only marginally. The low profitability of BE/ME(10-1), EF/A(10-1), and GS(10-1) is not surprising because both the long leg and the short leg of the three portfolios are sentiment-prone.

Table 4.6 Profitability of TA Trading Strategies

This table reports the summary statistics of the original long-short portfolio returns, the TA timing returns, and the *TAP* returns. The original portfolios are constructed by longing the most sentiment-prone deciles and shorting the least sentiment-prone deciles. TA timing rule represents holding the original portfolio when current TA sentiment is no less than the average TA sentiment over prior five trading days and shorting the original portfolio otherwise. *TAP* is the abnormal returns on the sentiment timing strategy over original portfolio returns. *AvgRet* is the average return. *SRatio* is the Sharpe ratio. *Alpha* is the abnormal return of the portfolio after adjusting for Fama and French five factors and the momentum factor. *BETC* in Panel B is the break-even transaction costs of TA trading strategies. *Success* in Panel C is the percentage of non-negative *TAP* returns. All the returns are annualised and in percentages. The sample period is between 01/1964 and 12/2008. The asterisks $***$, $**$ and $*$ indicates the t-test significance at 1%, 5% and 10% level, respectively.

		Panel A Original Portfolio			Panel B TA Trading Strategy				Panel C *TAP*		
		Avg Ret	SRatio	Alpha	Avg Ret	SRatio	Alpha	BETC	Avg Ret	Alpha	Success
ME	1-10	18.7***	1.4	21.5***	36.42***	2.76	35.6***	61.15	17.72***	14.1***	0.78
Age	1-10	7.19***	0.73	10.9***	24.69***	2.52	24.7***	41.45	17.5***	13.7***	0.78
Sigma	10-1	12.83***	0.97	13.1***	28.57***	2.18	31.5***	47.96	15.74***	18.4***	0.77
E/BE	1-10	9.71***	1.37	9.40***	9.51***	1.34	8.93***	15.96	-0.21	-0.45	0.77
D/BE	1-10	9.08***	1.08	10.6***	19.13***	2.3	20.1***	32.12	10.05***	9.52***	0.78
PPE/A	1-10	-2.43**	-0.3	-0.90	8.18***	1.01	8.44***	13.74	10.61***	9.36***	0.79
RD/A	10-1	5.35***	0.49	10.3***	8.32***	0.76	9.32***	13.97	2.96	-0.98	0.8
BE/ME	10-1	17.1***	1.68	14.8***	2.85*	0.28	2.06	4.79	-14.24***	-12.7***	0.75
EF/A	10-1	-12.65***	-1.72	-9.39***	3.16***	0.43	3.64***	5.31	15.81***	13.0***	0.79
GS	10-1	-10.9***	-1.59	-9.60***	-1.74*	-0.25	-0.95	-2.92	9.17***	8.62***	0.78
BE/ME	1-5	-2.41**	-0.31	2.03**	4.89***	0.63	5.45***	8.22	7.31***	3.42**	0.77
EF/A	10-5	-4.35***	-0.59	-1.08	12.28***	1.68	13.0***	20.62	16.63***	14.1***	0.79
GS	10-5	-3.83***	-0.49	-0.77	9.28***	1.2	10.2***	15.58	13.11***	10.9***	0.78
BE/ME	10-5	14.68***	2.26	14.5***	7.75***	1.19	7.59***	13.01	-6.94***	-6.92***	0.75
EF/A	1-5	8.3***	1.56	8.32***	9.12***	1.71	9.36***	15.31	0.82	1.06	0.77
GS	1-5	7.08***	1.08	8.82***	11.02***	1.69	11.1***	18.49	3.94***	2.33	0.77

One critical issue is whether my TA trading strategies can survive the transaction costs. I calculate break-even trading costs (BETC) that make the average returns of my TA timing portfolio zero. BETC depends on both the profitability and the trading frequency of a strategy. High BETC arises from high profitability or low trading frequency of a strategy. The higher the BETC is, the more likely a trading strategy will survive the transaction costs. The last column of Panel B shows that 4 out of the 16 TA timing portfolios have BETCs higher than the benchmark transaction cost of 25 basis points (see, Lynch and Balduzzi, 2000). The highest BETC of 61.15 basis points is observed in the case of ME (1-10) portfolio. Note that sophisticated investors, such as hedge funds, usually have lower transaction costs. Furthermore, using a longer moving average window to generate trading signals will reduce the trading frequency and transaction costs. Indeed, 9 (12) out of the 16 TA timing portfolios have BETC above 25 basis points when a 30 (60) day moving average window is used to generate trading signals. While I acknowledge that determining an appropriate transaction cost is not an easy issue, my results show that transaction costs reduce but do not eliminate the profitability of my trading strategies.[18]

To demonstrate the incremental value of applying my trading strategy, I also compute TAP_t, the return difference between each TA trading strategy and its corresponding original portfolio. Panel C in Table 4.6 shows applying TA trading strategy generates significantly positive returns over the original long-short portfolios in 11 out of the 16 cases. The size of TAP_t is remarkable, averaging 12% per annum. *TAP* is particularly large for ME(1-10), AGE(1-10), Sigma(10-1), EF/A(10-1) and EF/A(10-5), with values exceeding 15% per annum. Adjusting *TAP* for risk factors yields significantly positive alphas in 11 out of the 16 TA timing portfolios, with an average alpha of 6.1% after accounting for the Fama-French five factors and the momentum factor. I also report the success rate of a TA trading strategy,

[18] I can also apply my timing rule on individual decile portfolios as in Han et al. (2013). Returns (BETC) on the TA trading strategies are much higher (higher) for the most sentiment-prone deciles than that of the long-short portfolio constructed with the same firm characteristic.

defined as the percentage of trading days with non-negative *TAP*s. I find that the success rate ranges from 75% to 80%, indicating that the TA trading strategies perform well most of the time.

What happens if after applying the TA trading strategy to the original long-short portfolios based on one-day prior TA sentiment index level at date t, I continue to hold the same TA timing portfolio for the following 24 days? That is, I long the original portfolio for the next 25 days if current TA trading signal is positive, and short the original portfolio for the next 25 days if current TA trading is negative. Hence I ignore the trading signals from TA trading strategy between day 2 and day 25. In untabulated results, I show that this new strategy generates substantial positive returns on day one and these returns decline afterwards and fluctuate randomly around a certain level (mainly around zero or below the average returns of the original long-short portfolios). Such a pattern echoes the reversal effect found in my predictive regression analysis in Table 4.4. These findings also corroborate with results from Vector Autoregression models (VAR) of TA sentiment and the returns of the original long-short portfolios. The simple impulse response functions from VAR analysis show that after a positive sentiment shock, the returns on the original portfolios increase sharply on the first day and then declines gradually in the following days. This suggests that the increase in portfolio returns following shocks in the TA sentiment tends to die out gradually.

I also show that the profitability of my TA trading strategy is robust to using performance-weighted TA sentiment index, constructing TA sentiment by applying technical analysis to the Dow Jones Industrial Average Index, and applying TA timing rule on value-weighted returns of the original portfolios. The results are documented in Appendix E2.3.

Since my TA sentiment is constructed from applying TA to a market index, the TA trading strategy is a market timing strategy and a stock-picking strategy that it selects stocks on the basis of their exposure to investor sentiment. To see whether my TA sentiment index has any ability to time the market, I follow Han et al. (2013) and estimate the following regression models:

$$TAP_t = \alpha + \beta_m RMRF_t + \beta_{m^2} RMRF_t^2 + \varepsilon_t \tag{4.4}$$

$$TAP_T = \alpha + \beta_m RMRF_t + \gamma_m RMRF_t D_{rmrf} + \varepsilon_t \tag{4.5}$$

where $D_{rmrf} = 1$ when the market return premium is above 0 and $D_{rmrf} = 0$ otherwise and the remaining variables are as defined above.

The regression Equation (4.4) is based on the methodology in Treynor and Mazuy (1966), and the regression Equation (4.5) employs the market timing test in Henriksson and Merton (1981). A significantly positive β_{m^2} in Equation (4.4) or γ_m in Equation (4.5) indicates successful market timing ability, and the regression alphas represent the abnormal returns after controlling for market timing ability of TA sentiment.

Table 4.7 shows that β_{m^2} (Panel A) and γ_m (Panel B) are significantly positive for most of *TAP*s, suggesting that my timing strategy generally helps time the market. However, it is important to emphasise that my trading strategy exploits the cross-sectional profitability after timing the market and it perhaps, for this reason, I observe a very small R-square in the market timing regressions as above. The significantly positive abnormal alpha in Panel A implies that the market timing explanation could only partially explain the profitability of TA Trading Strategy. Market timing explanation does not fully eliminate the abnormal alpha returns of TA trading strategy.

To further understand the plausible sources of the profitability of my trading strategies, I also explore the decile portfolios for each strategy. I expect the profits of my strategies to be stronger among the sentiment-prone stocks than the sentiment-immune stocks.

Table 4.7 Market Timing Tests for TA Trading Strategy Profit

This table reports results of market timing regressions of the long-short portfolio TAPs . Panel A shows the results of Treynor and Mazuy (1966) quadratic regressions

$$TAP_t = \alpha + \beta_m RMRF_t + \beta_{m^2} RMRF_t^2 + \varepsilon_t,$$

Panel B presents the results of Henriksson and Merton (1981) regressions

$$TAP_T = \alpha + \beta_m RMRF_t + \gamma_m RMRF_t D_{rmrf} + \varepsilon_t.$$

The alphas are annualised and in percentages. The asterisks $***$, $**$ and $*$ indicates significance at 1%, 5% and 10% level, respectively. The Newey and West robust t-statistics are in parenthesis. The sample period is from 1964/01/01 to 2008/12/31.

		Panel A. TM Regression				Panel B. HM Regression			
		α	β_m	β_{m^2}	R^2	α	β_m	γ_m	R^2
ME	1-10	5.07	-0.24***	5.82***	8.74	-22.63***	-0.52***	0.50***	6.86
		(1.27)	(-11.47)	(5.30)		(-2.86)	(-7.00)	(5.32)	
Age	1-10	10.97***	-0.17***	3.08***	6.03	-4.09	-0.31***	0.27***	5.08
		(3.27)	(-9.97)	(3.25)		(-0.72)	(-6.12)	(3.93)	
Sigma	10-1	12.42***	-0.21***	1.79**	3.11	-2.56	-0.33***	0.23***	3.18
		(3.12)	(-10.04)	(2.48)		(-0.40)	(-6.13)	(3.21)	
E/BE	1-10	-0.36	-0.04***	0.13	0.34	-4.47*	-0.06**	0.05	0.43
		(-0.19)	(-2.76)	(0.39)		(-1.65)	(-2.54)	(1.64)	
D/BE	1-10	5.93**	-0.14***	2.02***	5.06	-5.61	-0.25***	0.20***	4.68
		(2.21)	(-10.92)	(2.89)		(-1.25)	(-6.33)	(3.68)	
PPE/A	1-10	9.92***	-0.06***	0.41	0.83	7.77*	-0.09**	0.04	0.81
		(4.00)	(-5.90)	(0.53)		(1.82)	(-2.51)	(0.70)	
RD/A	10-1	0.75	-0.09***	1.00**	1.07	-2.57	-0.13***	0.07	0.93
		(0.22)	(-5.51)	(2.19)		(-0.48)	(-3.41)	(1.25)	
BE/ME	10-1	-14.54***	0.03	0.07	0.06	-16.31***	0.02	0.02	0.07
		(-5.52)	(1.64)	(0.14)		(-3.97)	(0.50)	(0.53)	
EF/A	10-1	14.56***	-0.06***	0.65	1.01	12.23***	-0.09***	0.05	0.91
		(7.53)	(-6.46)	(1.23)		(3.38)	(-2.93)	(1.08)	
GS	10-1	8.41***	-0.03***	0.38	0.25	8.43**	-0.04	0.01	0.19
		(4.46)	(-3.05)	(0.64)		(2.33)	(-1.13)	(0.24)	
BE/ME	1-5	7.37***	-0.06***	0.09	0.65	3.95	-0.08***	0.04	0.69
		(3.62)	(-5.55)	(0.39)		(1.38)	(-4.26)	(1.50)	
EF/A	10-5	14.75***	-0.09***	0.97***	2.22	7.65**	-0.15***	0.11***	2.21
		(7.25)	(-9.02)	(3.29)		(2.54)	(-6.61)	(3.58)	
GS	10-5	10.99***	-0.09***	1.06***	1.93	4.35	-0.15***	0.11***	1.85
		(5.10)	(-9.47)	(2.84)		(1.22)	(-5.59)	(2.83)	
BE/ME	10-5	-7.18***	-0.03**	0.16	0.34	-12.36***	-0.07**	0.07**	0.50
		(-4.09)	(-2.35)	(0.35)		(-4.53)	(-2.33)	(2.05)	
EF/A	1-5	0.19	-0.03***	0.32	0.50	-4.58**	-0.06***	0.07***	0.68
		(0.14)	(-3.88)	(1.08)		(-2.19)	(-4.02)	(2.89)	
GS	1-5	2.59	-0.06***	0.69**	1.43	-4.08*	-0.11***	0.10***	1.57
		(1.40)	(-5.16)	(2.55)		(-1.82)	(-5.98)	(4.43)	

Consistent with my conjecture, I find that the TA trading strategies built on sentiment-prone decile portfolios notably outperform their benchmark portfolios. Compare the *TAP*s in Panel A and B. Both the average returns and risk-adjusted returns of *TAP*s in Panel A are higher than the data presented in Panel B.

I compare my timing strategies with the momentum strategy. Both the momentum strategy and my trading strategies are trend-following strategies. The momentum strategy has an annualised return of 12%, which is substantially lower than the returns generated by my TA trading strategies. In the regressions of TA trading profits from decile portfolios, the alphas are prominently positive, and the coefficients of the momentum factor are all negative, implying that my timing strategies and momentum capture different aspects of the market. I also calculate the annual returns of TA trading strategy and momentum trading strategy (S&P 500 Index Return) and compare them in Figure E.1 (Figure E.2) in Appendix E2.4.

Recall that Table 4.4 shows that conditional on the effect of TA_{t-1}, two-term lagged TA indicator is negatively associated with future returns. To better illustrate the reversal effect of investor sentiment, I also look into the profitability of holding the same portfolio on a trading signal over the future 25 days with Figure 4.3.

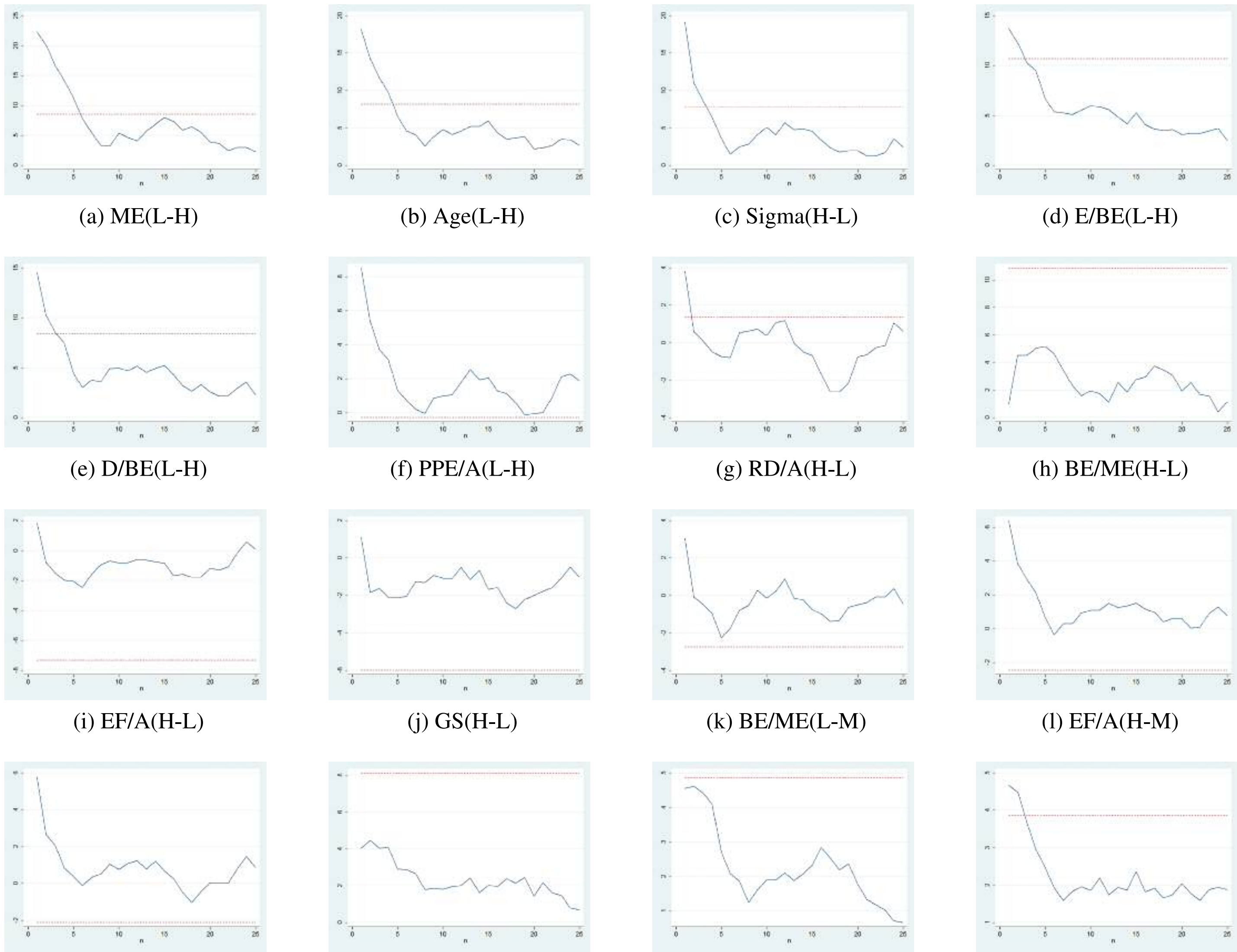
Figure 4.3 compares the overtime return of holding the portfolio with the benchmark when I do not time the market, which is the average returns of the original portfolio. If current sentiment is high, then I expect the following short-run return high and I expect the return of holding this portfolio shall reverse after an uncertain period.[19] On the starting day I apply TA timing rule based on one-day prior TA sentiment index level, and then I ignore the following trading signals continue holding the same TA timing portfolio for the next 24 days. Put differently: the strategy is to long the original portfolio for the next 25 days if current TA trading signal is positive, and to short the original portfolio for the next 25 days if current

[19] I could not determine when the reversal effect starts to come into effect, so I just let the data talk. It is not possible to show the timing of reversal. Otherwise, the backward induction will lead to a dilemma that mispricing could be corrected if everyone could time the market correctly.

TA trading is negative. I choose 25-day window period to observe whether the impact of a trading signal for the following one month.

In Figure 4.3, generally speaking, the return for holding the sentiment timing portfolio is the highest on day one, and then the daily return for holding the portfolio reduces sharply for at least the first five days, and afterwards the return fluctuates around a certain level. Such a pattern of TA sentiment timing strategies return coming off first-day highs indicates that the reversal effect of high TA sentiment takes longer time to offset the momentum effect of high TA sentiment. Consider the first four graphs. After a sentiment shock, for example, following the high sentiment day, my trading strategies outperform by riding the bubble. Then the return falls and continues to drop below the average level, the below average level indicates that the reversal is not purely due to the mean-reverting pattern of sentiment, but at least partially caused by the overreaction in the price.

It is also noteworthy that applying TA sentiment timing on BE/ME(H-L), BE/ME(H-M) and EF/A(L-M) portfolio does not generate better return compared with the benchmark return. This is consistent the negative or insignificant alpha for those portfolios in Table 10. TA sentiment timing strategy does not perform well on BE/ME(H-L) due to the cross-sectional U-shape pattern of decile returns of BE/ME sorted portfolios. Except for those three portfolios, the first-day returns of TA sentiment timing strategies are all greater than corresponding benchmark returns, which again confirms that trading signals based on TA sentiment help predict future return.



(a) ME(L-H) (b) Age(L-H) (c) Sigma(H-L) (d) E/BE(L-H)

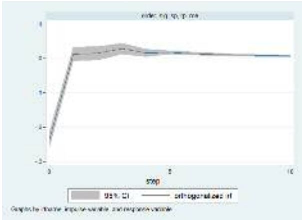
(e) D/BE(L-H) (f) PPE/A(L-H) (g) RD/A(H-L) (h) BE/ME(H-L)

(i) EF/A(H-L) (j) GS(H-L) (k) BE/ME(L-M) (l) EF/A(H-M)

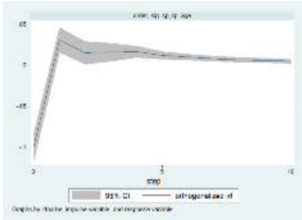
(m) GS(H-M) (n) BE/ME(H-M) (o) EF/A(L-M) (p) GS(L-M)

Profit of holding a portfolio based on current TA trading signal over 25 following days The solid line is the return for holding a portfolio based on TA trading signal. The dashed line is the original portfolio averaged returns, which serves as a benchmark for the profitability of TA trading strategies. The sample period is from 1964 to 2008.

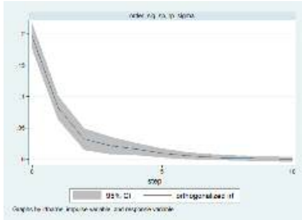
Fig. 4.3 TA Trading Strategy Profit over Time



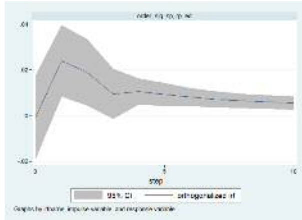
(a) ME(L-H)



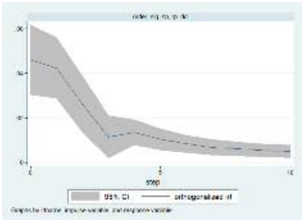
(b) Age(L-H)



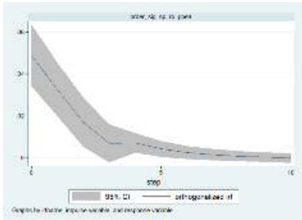
(c) Sigma(H-L)



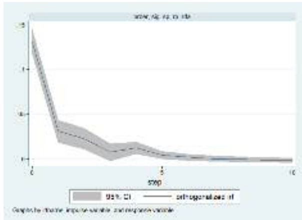
(d) E/BE(L-H)



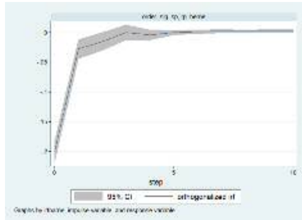
(e) D/BE(L-H)



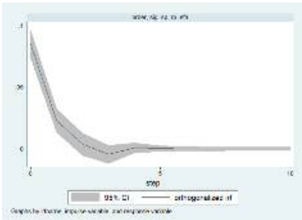
(f) PPE/A(L-H)



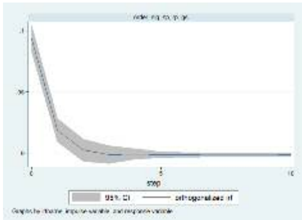
(g) RD/A(H-L)



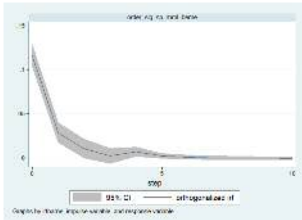
(h) BE/ME(H-L)



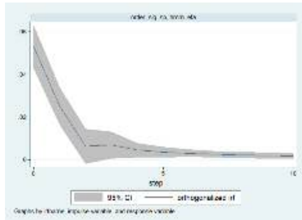
(i) EF/A(H-L)



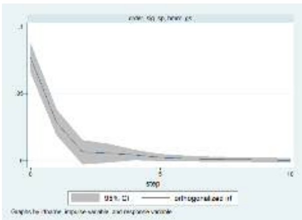
(j) GS(H-L)



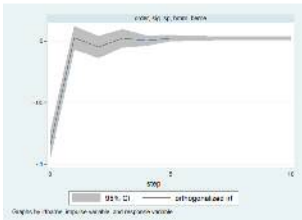
(k) BE/ME(L-M)



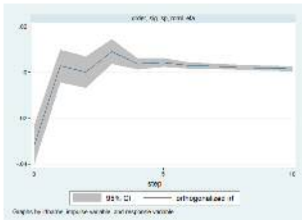
(l) EF/A(H-M)



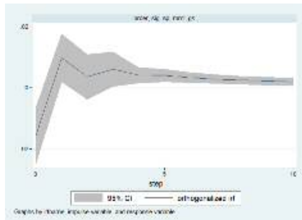
(m) GS(H-M)



(n) BE/ME(H-M)



(o) EF/A(L-M)



(p) GS(L-M)

Impulse Response Graphs of Long-Short Portfolio Returns to TA Sentiment Shock Each impulse–response graph shows the effect of a one-standard-deviation TA sentiment shock on the daily cross-sectional return premium over a 10-day period. The sample period is from 1964 to 2008. The cross-sectional long-short portfolio returns in each panel are calculated as the return premium of sentiment-prone stocks over sentiment-immune stocks indicated by the panel title. The grey area is the 95% confidence bands.

Fig. 4.4 Impulse Response of Long-Short Portfolio Returns to TA Sentiment

I also run the Vector Autoregression model (VAR) to investigate the simple impulse response functions (IRF) of the original portfolio returns to a positive sentiment shock. VAR model is an approach to analyse the joint dynamics and causal relations among a set of time-series variables. To be more specific, each variable is dependent on its own lags and the lags of every other variables in the vector of variables included in a VAR model. The order of variables affect the impulse response results. In this chapter, I have sixteen VAR models; each model contains two variables, the TA sentiment and the cross-sectional portfolio return. The ordering of variables in VAR model should be imposed based on the economic relations of the variables. I follow the rule that each variable is contemporaneously uninfluenced by the shock to the equation above it, and therefore the TA sentiment is placed at the first order. TA sentiment is allowed to affect the cross-sectional return contemporaneously. I run a battery of lag-order selection tests. The likelihood ratio test, the final prediction error and Akaike's information criterion all recommend four lags, and therefore I set the lag-order at four for all sixteen VAR models. I also employ small-sample corrections to the large-sample estimation statistics estimated in the VAR models. With the VAR model estimation, I build the impulse response function to trace out the effect of shock in TA sentiment. Figure 4.4 reports the impulse response of one standard-deviation shock in TA sentiment on the original portfolio returns for a 10-day period.

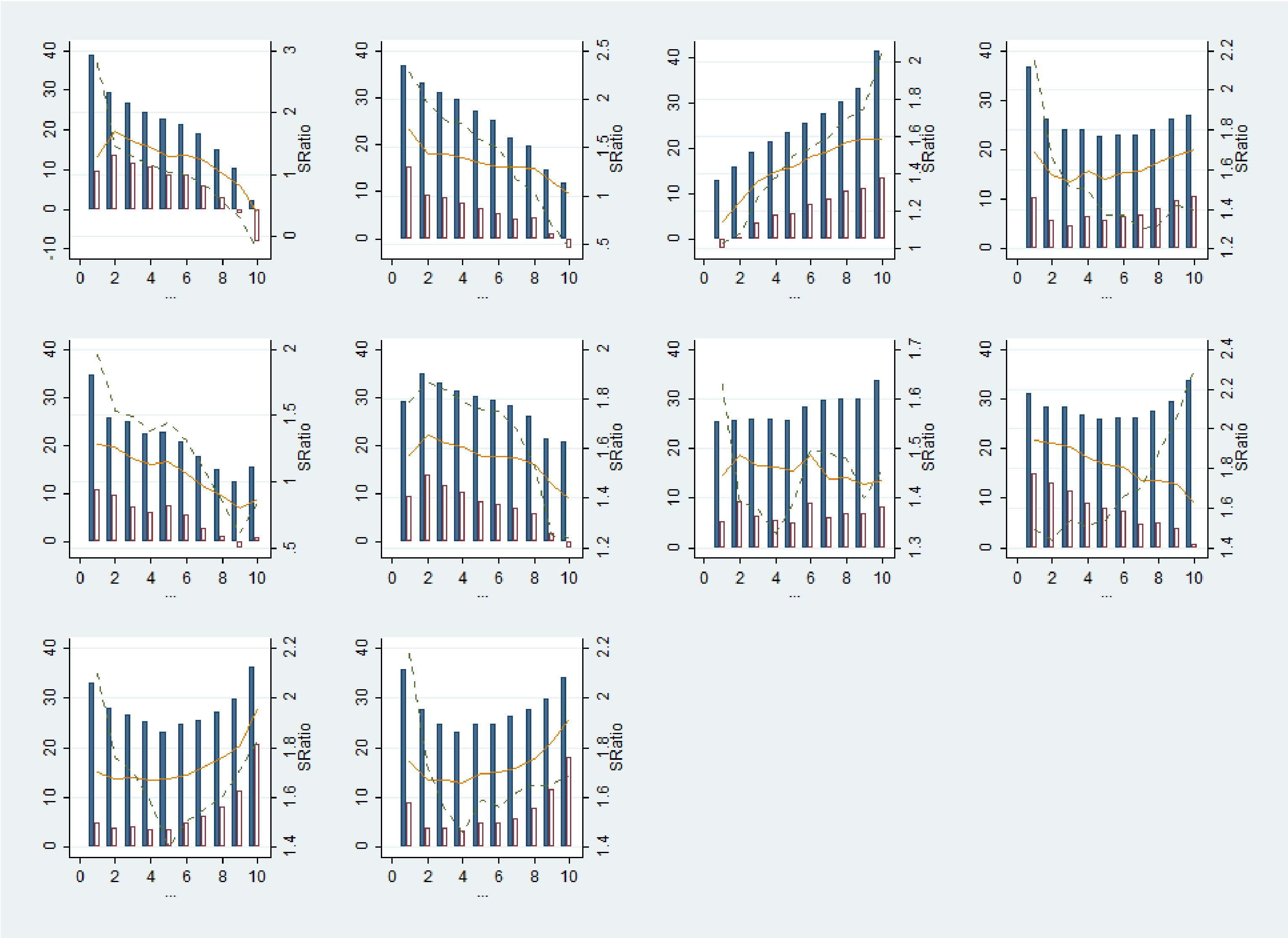
In Figure 4.4, the results show that the responses of the original portfolio returns to one unit of TA sentiment shock. The grey area is the 95% confidence bands. The response is generally significant if the upper and lower bounds of the grey area carry the same sign. For most of the sixteen cases, when there is a positive sentiment shock, the original portfolio returns experience a sharp increase on the first day and then keep declining gradually for the following days remarkably for almost all cases except the RD/A and BE/ME(H-L) portfolio. The positive increase of portfolio return caused by TA sentiment shock generally dies after more than five days. This shows that the momentum effect of sentiment shock are stronger than the reversal effect at the beginning, and the reversal effect takes place over a longer horizon. That also helps explain why I take advantage of the momentum effect to time the market and make profits. I also obtain a similar conclusion in Figure 4.3.

I also look into the time-series variation of the profit of TA trading strategies. I calculate the annual average returns of TA trading strategies RTA_t and draw figures to show the trend of the annual performances of applying TA timing rules on all the sixteen long-short portfolios from 1964 to 2008. The profitability of TA trading strategies is generally higher after 1990. I also regress RTA_t on time t and notice a significant and dominant rising trend. Unlike the declining size effect or the declining value effect, the performance of TA trading strategy is weaker for the beginning period but stronger for the recent periods. I revisit the predictive regressions of cross-sectional returns using different subsample periods. Intriguingly, I find that TA sentiment has stronger predictive power on returns for the subsample period after 1990 than for the subsample period before 1990.

The enhancing predictive power of technical analysis over time is consistent with the growing profitability of TA trading strategies over time. This finding seems to be inconsistent with Qi and Wu (2006), who argue that the improved market efficiency and increased liquidity make the profit of applying technical trading rules weaker during the recent periods. Such a tendency that the effect of technical analysis is becoming stronger after 1980 could hardly be explained by theoretical models on technical analysis such as informational diffusion model and liquidity model. Those theories see technical analysis as a method of processing fundamental information, and better computing skills and increased liquidity shorten the process of pricing reaching to equilibrium. However, this thesis argues that technical analysis is a method of processing the non-fundamental information, and arbitragers who face synchronisation risk may choose to ride the bubble and drive the price further away from the fundamental. My TA sentiment index captures the uninformed demand of biased and irrational investors. With the development of technology, the transaction cost reduces, and the computing skills improvement, it is becoming easier for investors to apply technical analysis to monitor sentiment and cheaper for them to ride the bubble. One could say that in the context of synchronisation risk models the arbitrageurs can better apply technical analysis to monitor sentiment and ride the bubble with the progressively cheaper computing power, lower transaction costs and increased liquidity in the stock market for the past two decades.

4.4.2 Implementation on Decile Portfolios

To further understand the potential sources of the profitability of my trading strategies, I also explore the decile portfolios for each strategy as well. The profitability of my strategies relies on whether there are detectable trends in the cross-section of the stock market. If TA sentiment is an adequate measure of sentiment, the profits of TA trading strategies tend to show up more strongly for the sentiment-prone stocks than for the sentiment-immune stocks. In this part, all the deciles are constructed with the ten characteristics that represent sentiment-prone level as used in the cross-sectional portfolio. For each decile, the TA timing rule is to long the decile portfolio during high TA period and to short this decile portfolio during low TA period. Mathematically, the decile sentiment timing return is denoted as $RTA_{X,j,t} = R_{X,j,t}D_{t-1)}$, where $R_{X,j,t}$ is the original return of the jth decile portfolio sorted by X characteristics at time t, and j is the number of decile rank, and X is one of the ten firm characteristics representing sentiment-prone level. D_{t-1} has the same definition as in the previous section. The difference between the TA timing return and the original buy-and-hold decile return is denoted as $TAP_{X,j,t} = RTA_{X,j,t} - R_{X,j,t}$.



Decile Profitability and Abnormal Return of Sentiment Timing Portfolio, 1964-2008 When today's sentiment are no less than average of the previous five trading days' sentiment I define it as a high sentiment day; otherwise define it as a low sentiment day. For each decile, the solid bars are the average returns of TA trading strategies (*RTA*); the clear bars are average *TAP* returns. The solid line is the abnormal returns of *TAP* adjusted for FF five factors and momentum factor. The dashed line is the Sharpe Ratio of TA trading strategy, and its corresponding y-axis is on the right side. All the returns are annualised equal-weighted average and are in percentage. The y-axis on the left side is for the returns. The sample period is from 1964 to 2008.

Fig. 4.5 Statistics of Decile Portfolio Sentiment Timing Performance

Figure 4.5 graphically displays all the essential statistics of TA trading strategies implemented on decile portfolios. The solid bar is the annualised average of $R_{X,j}$ for each decile portfolio; the clear bar is the $TAP_{X,j,t}$; the solid line is the abnormal return of $RTA_{X,j,t}$ adjusted for FF Five factors and momentum factor; the dashed line is the Sharpe Ratio of $RTA_{X,j,t}$, and its corresponding y-axis is on the right side.

Figure 4.5 shows that the TA timing returns show a monotonic decreasing pattern across ME or Age deciles and a monotonic increasing pattern across Sigma deciles. The graphs in Figure 4.5 show that Sharpe Ratios share the same pattern with the TA timing returns in the cross-section. That is because the Sharpe Ratio are principally driven by the noticeable rise in returns and the slightly increase in standard deviations of returns after employing the TA timing rule. The cross-decile patterns of TA timing returns and Sharpe Ratios indicate that the profitability of TA trading strategies monotonically increases with the decile sentiment-prone level. Moreover, the abnormal returns, i.e. the alphas of regressing *TAP*s on FF five factors and the momentum factor, are also increasing with the sentiment-prone level. Figure 4.5 roughly indicates that the most profitable trading strategy should be timing with the most sentiment-prone deciles.

Table 4.8 provides the summary statistics of the 13 most sentiment-sensitive deciles in Panel A and that of 10 least sentiment-sensitive deciles in Panel B. In Panel A of Table 4.8, the TA timing returns of those sentiment-sensitive deciles are favourable and basically over 8% per annum. Generally speaking, the sentiment-prone decile portfolios in Panel A have more notable positive *TAP*s than the sentiment-immune decile portfolios in Panel B. It shows TA timing rule works better for sentiment-prone deciles. Take ME top decile as an example, applying TA timing rule on large stock portfolio make the return worse off.

Table 4.8 Summary Statistics of Timing Decile Portfolios

Table 4.8 reports summary statistics of the original return, TA timing return and return difference *TAP* for all the most sentiment-prone deciles in Panel A and for all the most sentiment-immune deciles in Panel B. The first two column show the choice of decile portfolios as original portfolios. The first column shows the characteristics used to form the decile portfolio. The second column reports the decile rank. TA sentiment timing rule is to hold the original portfolio when current TA sentiment is no lesser than the average TA sentiment over prior five trading days and to short the original portfolio otherwise. *TAP* is the return disparity of sentiment timing returns over original portfolio returns. Last column is the success ratio (Success), which is the percentage of non-negative *TAP* returns. All the average return are annualised and in percentages. ** and * indicates the t-test significance at 1% and 5% level, respectively.

		Original Portfolio Return				Sentiment Timing Return				TAP			
SP	Decile	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	SD	Skew	SRatio	Avg Ret	SD	Skew	Success
Panel A													
ME	1	29.26**	12.02	-0.8	1.97	38.75**	11.92	0.88	2.79	9.49**	18.69	1.82	0.75
Age	1	21.28**	13.83	-0.66	1.14	36.62**	13.7	0.63	2.27	15.34**	21.5	1.43	0.76
Sigma	10	28.04**	17.64	-0.51	1.28	41.56**	17.53	0.43	2.06	13.52**	27.5	1.04	0.75
E/BE	1	26.15**	14.52	-0.58	1.42	36.58**	14.43	0.56	2.15	10.43**	22.52	1.26	0.75
D/BE	1	23.87**	15	-0.59	1.22	34.79**	14.92	0.48	1.96	10.93**	23.52	1.16	0.75
PPE/A	1	19.74**	13.18	-0.54	1.08	29.05**	13.11	0.41	1.79	9.31**	20.63	1.03	0.75
RD/A	10	25.65**	19.46	-0.44	1.03	33.83**	19.41	0.33	1.46	8.18	29.99	0.87	0.79
BE/ME	1	33.16**	12.32	-0.74	2.24	33.91**	12.31	0.65	2.31	0.75	18.73	1.59	0.75
BE/ME	10	16.07**	17.22	-0.36	0.61	31.06**	17.14	0.26	1.49	14.99**	27.08	0.7	0.75
EF/A	1	28.16**	13.17	-0.75	1.72	33.12**	13.13	0.5	2.1	4.96	20.59	1.34	0.75
EF/A	10	15.51**	16.96	-0.44	0.59	36.28**	16.84	0.42	1.83	20.77**	26.58	0.97	0.76
GS	1	26.99**	13.99	-0.63	1.53	35.8**	13.91	0.54	2.18	8.81**	21.58	1.31	0.75
GS	10	16.08**	17	-0.46	0.62	34.06**	16.9	0.41	1.69	17.98**	26.68	0.97	0.76
Panel B													
ME	10	10.56**	16.83	-0.32	0.3	2.33	16.84	0.21	-0.19	-8.23*	25.95	0.54	0.75
Age	10	14.09**	13.89	-0.87	0.62	11.93**	13.9	0.64	0.46	-2.16	21.57	1.6	0.75
Sigma	1	15.21**	7.23	-0.6	1.34	12.99**	7.25	0.3	1.03	-2.22	11.22	0.95	0.74
E/BE	10	16.44**	15.45	-0.58	0.71	27.07**	15.39	0.37	1.4	10.63**	24.37	1.01	0.76
D/BE	10	14.79**	12.07	-0.59	0.77	15.66**	12.06	0.45	0.84	0.87	18.71	1.12	0.75
PPE/A	10	22.17**	12.4	-0.58	1.34	20.87**	12.41	0.21	1.24	-1.3	19.26	0.83	0.75
RD/A	1	20.29**	12.31	-0.95	1.2	25.51**	12.27	0.54	1.63	5.21*	19.31	1.57	0.79
BE/ME	5	18.12**	13.37	-0.73	0.94	26.01**	13.31	0.45	1.54	7.89*	20.78	1.3	0.76
EF/A	5	19.65**	12.69	-0.74	1.11	23.22**	12.67	0.48	1.4	3.58	19.77	1.31	0.75
GS	5	19.95**	12.18	-0.69	1.18	24.84**	12.15	0.5	1.59	4.89*	18.9	1.31	0.75

With regard to the standard deviation of returns, the standard deviation slightly reduces when implementing TA timing rule on sentiment-prone deciles, but it barely changes when applying TA timing rule on sentiment-immune deciles. The notable increase in return and slightly decrease in standard deviation makes the Sharpe Ratio increase remarkably after applying TA timing rule on sentiment-prone deciles. This magnitude of Sharpe Ratio is comparable with Han et al. (2013), who employ Moving Average Timing Strategy on a similar Sigma sorted decile portfolios. I also find that TA timing rule does not improve the Sharpe Ratio for the sentiment-immune deciles. This cross-sectional pattern again shows that it is a sentiment measure that contributes to the predictability of technical analysis forecasts.

I also conduct the robustness tests on the performance of TA timing rule applied on decile stocks. I calculate the abnormal alphas for each decile controlled for market return premium or controlled for FF Five factors and momentum factor. Table 4.9 reports the risk-adjusted *TAP* returns for most sentiment-sensitive decile portfolios in Panel A and that of least sentiment sensitive decile portfolios in Panel B.

Look into Table 4.9. Among the 13 sentiment-sensitive deciles, 10 of them have salient and positive CAPM abnormal returns, ranging from 9.92% per annum to 22.06% per annum. Similarly, those 10 sentiment-sensitive deciles also have significant and positive FF model risk-adjusted returns, ranging from 10.28% per annum to 21.56% per annum. The TA timing rule is not effective on the RD/A top decile, BE/ME top decile and EF/A bottom decile, which is consistent with my findings in Section 4.3.1 and consistent with Baker and Wurgler (2006). One plausible reason is that RD/A and PPE/A may not capture investor sentiment-prone level in the cross-section very well. The statistical high and novel abnormal return shows that TA sentiment performs well for those high sentiment-prone deciles.

Consider Panel B of Table 4.9, I find TA timing rule perform poorly for those sentiment-immune deciles. It conjectures that the performance TA sentiment index relies not only on itself but also on the sentiment-sensitivity level of the original portfolio. The statistical insignificance results in Panel B could help understanding why TA sentiment does not perform so well for some of the previous sixteen portfolios that obtain cross-sectional premium.

For most deciles, the market betas have strongly negative coefficients. It is also intriguing that the most potent risk factor in explaining *TAP* is RMW (Robust minus Weak) factor when calculating the abnormal return in the FF model for all the deciles. The coefficients of RMW are prominently negative for almost all the deciles. It indicates that my timing strategies are effective in mitigating the risk measured by RMW. Another outstanding explanatory factor for *TAP* is the momentum factor (UMD), but even so the coefficients of UMD are only significant for the sentiment-prone deciles.

When runing the regressions to obtain alphas, the coefficient for momentum factor are all remarkably negative, which indicates that my timing strategies and momentum capture the different aspects of the market. My abnormal returns of sentiment-prone decile portfolios are still significantly large controlling for the momentum factor. Such magnitude of abnormal returns cannot be explained away by a known asset pricing model or the momentum factor. In Figure E.1, I also compare my timing strategies with momentum anomaly. Both momentum anomaly and my trading strategies are all results of trend-following. Momentum anomaly gets an annualised return of 12%, which is substantially less than the returns of TA trading strategies (*RTA*). The correlation of momentum return and decile *TAP*s are high.

I a

Table 4.9 CAPM and Fama-French Alphas of Decile Portfolios

Table 4.9 reports the CAPM and Fama-French Five Factor adjusted alphas of the most sentiment-prone deciles in Panel A and that of the most sentiment-immune deciles in Panel B. The first column shows the characteristics used to form the decile portfolio. The second column reports the decile rank. The alphas are annualised and in percentages. ** and * indicates statistical significance at 1% and 5% level, respectively. The Newey-West robust t-statistics are reported in parenthesis. The sample period is from 1964/01/01 to 2008/12/31.

Panel A								Panel B							
		CAPM			FF model					CAPM			FF model		
SP	Decile	α	β_m	R^2	α	β_m	R^2	SP	Decile	α	β_m	R^2	α	β_m	R^2
ME	1	10.75**	-.286**	5.5	10.59**	-.256**	6.02	ME	10	-8.19*	-0.01	-0.01	-8.8**	0.023	0.38
		(2.82)	(-8.48)		(2.65)	(-6.02)				(-2.43)	(-.41)		(-2.61)	(0.81)	
Age	1	16.54**	-.27**	3.72	16.58**	-.249**	4.78	Age	10	-1.77	-.087**	0.38	-1.2	-.081**	0.67
		(4.18)	(-7.29)		(4.24)	(-6.1)				(-.56)	(-3.33)		(-.36)	(-2.65)	
Sigma	10	14.9**	-.314**	3.06	14.7**	-.28**	3.96	Sigma	1	-1.79	-.097**	1.74	-0.82	-.114**	2.16
		(3.06)	(-7.36)		(3.05)	(-5.96)				(-.88)	(-4.82)		(-.39)	(-4.65)	
E/BE	1	11.6**	-.267**	3.31	11.57**	-.248**	4.19	E/BE	10	11.64**	-.229**	2.08	11.03**	-.182**	2.67
		(2.79)	(-7.28)		(2.83)	(-6.08)				(2.92)	(-5.29)		(2.67)	(-4.03)	
D/BE	1	12.1**	-.266**	3.02	11.86**	-.236**	3.8	D/BE	10	1.36	-.11**	0.81	1.3	-.096**	0.93
		(2.89)	(-6.74)		(2.84)	(-5.45)				(0.49)	(-4.13)		(0.45)	(-3.37)	
PPE/A	1	10.31**	-.227**	2.85	11**	-.218**	3.52	PPE/A	10	-0.6	-.16**	1.61	0.5	-.173**	1.99
		(2.81)	(-6.15)		(2.92)	(-5.3)				(-.2)	(-5.26)		(0.16)	(-5.03)	
RD/A	10	9.45	-.275**	2.19	8.54	-.222**	2.9	RD/A	1	6.05	-.181**	2.3	7.02	-.188**	2.84
		(1.69)	(-5.52)		(1.51)	(-4.29)				(1.67)	(-4.96)		(1.85)	(-4.63)	
BE/ME	1	16.14**	-.261**	2.19	16.07**	-.225**	2.86	BE/ME	5	8.77*	-.199**	2.15	9.93**	-.202**	2.7
		(3.67)	(-6.39)		(3.67)	(-5.41)				(2.51)	(-4.88)		(2.76)	(-4.8)	
BE/ME	10	1.78	-.233**	3.65	3.17	-.26**	4.55	EF/A	5	4.42	-.192**	2.22	5.33	-.185**	2.87
		(0.49)	(-7.78)		(0.89)	(-7.94)				(1.36)	(-5.32)		(1.58)	(-4.75)	
EF/A	1	5.96	-.226**	2.82	6.75	-.222**	3.69	GS	5	5.73	-.189**	2.36	6.66*	-.188**	2.94
		(1.59)	(-6.46)		(1.81)	(-5.75)				(1.78)	(-5.44)		(1.99)	(-4.78)	
EF/A	10	22.06**	-.291**	2.82	21.56**	-.249**	3.61								
		(4.88)	(-6.68)		(4.77)	(-5.22)									
GS	1	9.92*	-.251**	3.18	10.28**	-.24**	4.14								
		(2.48)	(-7.35)		(2.62)	(-6.44)									
GS	10	19.22**	-.281**	2.6	18.72**	-.237**	3.37								
		(4.31)	(-6.62)		(4.17)	(-5.04)									

4.4.3 Tradability of TA Trading Strategies

To address the tradability of TA trading strategies, I argue that the practitioners could apply my TA timing rule on the ETF funds that traces the return of small-cap stocks and large-cap stocks, so that the transaction cost would be much lower. When TA sentiment is high, investors could long the small-cap ETFs and short the large-cap ETFs. One could even apply the TA timing rule merely on the small-cap ETFs, which are more sensitive to sentiment; that is to long the small-cap ETFs when TA sentiment is high and to short the small-cap ETF when TA sentiment is low.

Applying TA timing rule on the cross-sectional return premium generate more conservative results on profitability relative to applying TA timing rule on decile portfolios. Recall that in Figure 4.5 the decile return of sentiment-immune stocks are also high. The actual transaction cost for applying TA timing rule on decile portfolios is lower than that for applying TA timing rule on long-short portfolios. Given that the short-selling is costlier than merely opening and closing long positions, a more cost-effective investment strategy is to avoid the short-selling transactions by investing money into the risk-free assets. Although the absolute value of average return during low sentiment periods are generally a little higher than the risk-free rate, considering the short selling constraints and the transaction cost, the most practical strategy is to only take long position after a high-sentiment day and invest money into the risk-free asset after a low-sentiment day.

I also follow Han et al. (2013) framework and use BETC to check whether my TA sentiment timing strategy is practical without taking a stand of actual transaction costs. Break-even trading cost is the trading cost that makes the average returns of my TA trading strategies become zero. The higher BETC a trading strategy has, the more practical this trading strategy is. Break-even trading cost depends on both the profitability and the trading frequency of a strategy. Higher profitability and lower trading frequency will make the BETC higher.

To see whether my TA trading strategies can survive the transaction costs, I first check the fraction of trading days, the average consecutive holding days, and the break-even transaction costs. Since TA trading strategy is based on daily signals of TA sentiment index, it is essential to see how often the transactions are required. The frequency of trading depends on how frequent the trading signal D_t changes. Trading signal D_t is defined by comparing TA_t with its smoothing average of a specified prior period. If the signs of D_t does not change frequently, that is to say, there is no need for frequent transactions. In this way, the trading costs will be lower, and the investor only need to make transactions on the first and last day for a continuous high/low sentiment period and hold the portfolio for the rest days. Therefore, it is understandable that when the signal is determined using a smoothing average over a longer horizon, the trading frequency will be smaller and the holding days extend. Take 1-day horizon as an example, the trading signal is actually obtained by comparing TA_t with TA_{t-1}: one is supposed to buy if today TA is higher than yesterday and to sell if it is lower. The smoothing average is more volatile when calculated over the 1-day horizon and therefore the transactions will happen more often.

Table 4.10 Trading Frequency and Holding Time

This table reports the trading frequency and average holding days for TA trading strategies with different signal-generating horizons. Horizon is the length of window period employed to calculate smoothing average, which will serve as a benchmark for current TA index. The timing rule is to buy when current TA is higher than this smoothing average and to sell when it is lower. The first column of each panel shows the total number of days when transactions are required, the second column is the fraction of trading days, and the third column is the average conservative holding days. The sample period starts from 1964/01/01 and ends at 2008/12/31.

Horizon	Trading days	Trading frequency	Holding time
1-day smoothing average	3039	0.27	3.73
5-day smoothing average	1339	0.12	8.46
30-day smoothing average	617	0.05	18.36
60-day smoothing average	491	0.04	23.07
120-day smoothing average	429	0.04	26.41
250-day smoothing average	321	0.03	35.29

Table 4.10 reports the number of transactions, the fraction of trading days and the average

holding days for TA signals based on different window periods. The number of trading days decreases remarkably when the calculation horizon of the benchmark smoothing average moves from one day to five days. Then the number of trading days decreases at a decreasing speed when the smoothing average horizon increases. The trading frequency is calculated using trading days divide the total number of observations over my 45-year sample period. When TA trading signal is defined using the 5-day smoothing average, over the entire 11329-day sample period I need to make 1339 transactions, which is less than half of the trading days if trading signal D is defined using 1-day smoothing average. The trading frequency drops from 27% to 4% when the horizon increases from 1-day to 60-day. The trading frequency of my TA timing rule is similar to that of the MA trading strategies examined by Han et al. (2013), which drop from around 20% for 10-day horizon MA strategy to 3% for 200-day horizon MA strategy.

I also investigate the sensitivity of my results to the choice of the length of the moving average window used to generate my trading signals. I consider a buying signal if TA is higher than the past average of 1, 5, 10, 30, 60, 120 and 250 days. I find substantial trading profits remain in all cases, although profitability tends to decline with the increase in the length of the moving average window.

Table 4.11 reports the profitability and the break-even transaction costs of applying TA timing rule on the sixteen sentiment-based long-short portfolios with TA signals generated with different TA sentiment and with different horizons. In addressing the robustness of the superior performance of TA sentiment, I change the definition of high/low sentiment period. I still obtain strong returns for TA timing rule when defining the dummy D by comparing today's sentiment level with smoothing average of different window periods. In Panel A, the TA trading strategy returns of sixteen long-short portfolios are higher when the trading signals are generated using 1-day or 5-day smoothing average as a benchmark. The profitability of BE/ME(H-L), EF/A(H-L), and GS(H-L) are not strongly positive, and this is

Table 4.11 Profits and BETCs with Alternative Horizons for TA Timing Signals

This table reports the profitability and the break-even transaction costs of applying TA timing rule on the sixteen sentiment-based long-short portfolios with TA signals generated with different TA sentiment and with different horizons. Panel A reports the annualised profitability in percentage and Panel B reports the BETC in basis points. BETC is the transaction costs that would make profit of TA trading strategies equal to zero. The second row denotes the horizon of smoothing average used to calculate trading signals. Horizon is the length of window period employed to calculate smoothing average, which will serve as a benchmark for current TA sentiment to generate trading signal. The sample period is from 1964/01/01 to 2008/12/31.

		Panel A. Return of TA Trading Strategy							Panel B. BETC of TA Trading Strategy						
		1-day	5-day	10-day	30-day	60-day	120-day	250-day	1-day	5-day	10-day	30-day	60-day	120-day	250-day
ME	1-10	33.46	36.42	33.94	27.93	27.72	27.77	25.08	24.75	61.15	78.81	101.76	126.9	145.53	175.64
Age	1-10	24.7	24.69	22.22	18.74	18.97	18.9	17.86	18.27	41.45	51.6	68.26	86.85	99.02	125.09
Sigma	10-1	34.04	28.57	22.24	17.01	19.37	19.26	20.15	25.18	47.96	51.65	61.99	88.67	100.92	141.13
E/BE	1-10	6.93	9.51	9.4	8.39	9.32	9.26	9.49	5.13	15.96	21.83	30.56	42.67	48.52	66.46
D/BE	1-10	21.93	19.13	15.84	13.17	14.33	15.46	15.86	16.22	32.11	36.77	47.98	65.62	80.98	111.09
PPE/A	1-10	10.71	8.18	5.51	6.08	5.58	4.39	4.85	7.92	13.73	12.79	22.17	25.57	23.02	33.94
RD/A	10-1	13.78	8.32	4.58	2.29	4.83	5.65	7.39	10.19	13.97	10.63	8.33	22.1	29.6	51.77
BE/ME	10-1	-2.79	2.85	4.97	5.84	5.49	5.73	3.82	NA	4.79	11.54	21.29	25.13	30.03	26.76
EF/A	10-1	6.21	3.16	0.23	0.36	-0.92	-0.76	-0.54	4.6	5.31	0.53	1.31	NA	NA	NA
GS	10-1	1.8	-1.74	-3.17	-2.97	-3.55	-2.85	-2.43	1.33	NA	NA	NA	NA	NA	NA
BE/ME	1-5	8.19	4.89	2.13	1.33	2.56	2.72	4.91	6.06	8.21	4.96	4.84	11.71	14.27	34.36
EF/A	10-5	14.28	12.28	9.48	7.93	7.35	8.2	8.97	10.56	20.62	22.02	28.89	33.65	42.97	62.84
GS	10-5	12.51	9.28	6.85	5.32	5.84	6.7	8.04	9.25	15.58	15.9	19.39	26.72	35.11	56.28
BE/ME	10-5	5.4	7.75	7.11	7.17	8.05	8.45	8.73	3.99	13	16.5	26.13	36.84	44.3	61.12
EF/A	1-5	8.06	9.12	9.25	7.57	8.27	8.96	9.51	5.96	15.31	21.49	27.58	37.87	46.96	66.61
GS	1-5	10.71	11.02	10.02	8.3	9.39	9.55	10.46	7.92	18.49	23.27	30.22	42.97	50.03	73.28

because those three portfolios are constructed using most sentiment-prone deciles instead of longing sentiment-prone deciles and shorting sentiment-immune deciles. Apart from those three portfolios, other portfolios all have sizable and positive returns when using the TA timing.

The TA timing returns change slightly when using longer than 30 day window period. In Table 4.11, Panel A shows that TA timing rule performs best with using the 5-day window period to calculate moving average as benchmark TA. The 5-day window period is a better choice, because going too far back into the historical TA sentiment may undervalue the trend of current TA. Whereas choosing a much shorter period as the window period will lose the information of TA sentiment level for prior period.

In general, the large scale of my TA timing returns (relative to the performance of other trading strategies in the literature) and the modest amount of transactions indicate my TA trading strategies are likely to survive the transaction costs. In Panel B, it is noteworthy that an increase in the horizon length for calculating trading signals associates with a monotonic increase in BETCs. This is principally because of the sharp decrease of trading frequency when horizon increases. The BETCs for those portfolios with positive returns are reasonably large due to the limited transactions one may need to execute. When using a smoothing average of a longer horizon to determine trading signals, the trading frequency decline sharply, and the break-even transaction costs increase notably. For example, the break-even transaction costs of the ME long-short portfolio would be 49.5 basis points when using 1-day horizon to get trading signal, and it would dramatically increase to 351.29 basis points when using 250-day horizon to get the trading signals. The BETCs for 5-day horizon trading signals are reasonably high, ranging from 9.58 to 122.3 basis points for portfolios with positive TA timing returns. I conclude that my TA trading strategies would still be profitable after accounting for the transaction cost.

With regard to the BETCs for the decile portfolios sorted by the ten firm characteristics that represent sentiment-prone level, the BETCs show the same pattern with that of decile TA timing returns. Because the trading frequency for all deciles is the same, the pattern of BETCs across deciles depends on the decile TA timing returns. In this case, the more sentiment-prone deciles have higher BETCs and the sentiment-immune deciles have lower BETCs. For any portfolio sorted by the ten characteristics, *RTA* returns for the most sentiment-prone decile are higher than the *RTA* returns of the corresponding long-short portfolios constructed with the same firm characteristic; therefore, the BETCs of the most sentiment-prone decile are also much higher than that of the long-short portfolio built on the same characteristic.

I conduct a series of robustness checks for the profitability of my TA sentiment timing strategies. See Appendix E2.4. See Table E.13. DJIA-based TA sentiment indicator performs no worse in my TA trading strategy than the TA sentiment indicator derived from the trend of S&P 500 index. Table E.15 show that returns of trading on signals generated by performance-weighted TA sentiment are generally more significant but slightly less in terms of magnitude than the returns of trading on equal-weighted TA sentiment. To mitigate the effect of size on sentiment index, I also apply TA timing rule on value-weighted returns of the original portfolios (descriptive summary statistics are reported in Table E.17). The profitability of applying TA timing rule on value-weighted returns is strongly consistent with that on equal-weighted returns (even slightly higher); using value-weighted return does not reduce the profitability of TA trading strategies. I also use performance-weighted TA sentiment index. My main conclusions remain the same.

I also examine the profitability and BETC of TA trading strategies with TA sentiment index based on historical data of DJIA index rather than S&P 500 index. The results on profitability of my sentiment-based trading strategies are highly robust. My conclusions do not change.

4.5 Conclusion

Chapter 4 attempts to bridge the long-standing gap between academic researchers and financial market traders regarding the merits of TA. Like many practitioners, I argue that TA is a barometer of investor sentiment. I apply a spectrum of technical analysis to a market index (such as S&P 500) to build a novel market sentiment indicator. I show that this new TA sentiment indicator correlates strongly with other commonly used sentiment indicators. I also test the cross-sectional pricing effect of my TA sentiment.

Baker and Wurgler (2006) argue that stocks differ in their exposure to market-wide sentiment and hence sentiment affects the cross-section of stock returns. Furthermore, when rational arbitrageurs have a synchronisation problem (Abreu and Brunnermeier, 2002; 2003), they delay arbitrage and ride mispricing until the coordinated arbitrage is triggered. Therefore, I expect that following a TA sentiment increase, the returns of more sentiment-prone stocks, relative to those of sentiment-immune stocks: (a) are contemporaneously high due to limits to arbitrage; (b) continue to be high in the near-term due to delayed arbitrage; (c) reverse over the longer term when sentiment decays and coordinated arbitrage occurs; (d) have high crash risk in subsequent periods due to coordinated attacks.

I provide empirical evidence consistent with all of these predictions based on U.S. data for 1964 to 2008. Finally, I examine whether it is profitable to delay arbitrage by devising a simple timing rule that captures the momentum effect of TA sentiment. I demonstrate that riding the TA sentiment can result in substantial profits. Unlike previous literature that tests the profitability of TA with single stocks or the overall market, I show that applying TA to a market index while trading in the cross-section generates substantial profits.

Chapter 5

Volatility Timing, Sentiment, and the Short-term Profitability of VIX-Based Cross-Sectional Trading Strategies

5.1 Introduction

The Chicago Board Options Exchange's implied volatility index (VIX) is a measure of market expectation of stock return volatility implied from the supply and demand of S&P index options over the next 30 calendar days. Financial practitioners commonly use VIX-based trading strategies for hedging, speculative, and market timing purposes (see, e.g., Nagel, 2012). VIX is also widely perceived as an "investor fear gauge" (Da et al., 2014; Kaplanski and Levy, 2010; Whaley, 2000, 2009), with low VIX indicating high overall market sentiment, and vice versa. Consistent with this view, VIX notably elevated in the NBER recession and was considerably low during the anecdotal bubble period in US market.

Several studies view VIX as a measure of expected volatility in a mean-variance framework where investors are assumed to have constant risk aversion (e.g. Clements and Silvennoinen, 2013; Fleming et al., 2003; Merton, 1980). They argue that because of the positive mean-variance relationship, an increase in VIX should be associated with higher future return. Other studies deem VIX as an 'investor fear gauge' and use it to predict future returns. For example, Giot (2005), Banerjee et al. (2007) and Bekaert and Hoerova (2014) document strong negative associations between contemporaneous returns and incremental VIX and between long-term future returns (e.g., 30-day/ 60-day/ monthly return) and the VIX level. Similarly, Giot (2005) shows that during very high/low VIX period, VIX positively predicts future 60-day returns on S&P 100. Banerjee et al. (2007) also present that VIX is positively related to the next 30-day future returns in the cross-section of the stock market. This strand of studies almost exclusively uses low-frequency return data to test whether VIX predicts the long-run reversals arising from mispricing correction.

Unlike previous studies, which commonly focus on the in-sample ability of VIX to predict the long-term (one month or longer) return reversals, this study investigates the profitability of VIX-based strategies arising from the short-run (next day) momentum in the cross-section of stock returns. Specifically, I test whether VIX can be used as a sentiment indicator to design trading strategies that can exploit the short-term return momentum. My study is motivated by Abreu and Brunnermeier's (2002) theory of delayed arbitrage, in which rational arbitrageurs are assumed to correct mispricing only when a significant mass of arbitrageurs come together to trade against noise trader sentiment. However, since arbitrageurs may not know when their peers recognise mispricing, they may choose to ride the sentiment until a synchronized attack takes place. The delayed arbitrage leads to short-term momentum in stock returns after an increase in sentiment. My empirical tests show a significant negative association between lagged VIX and return is stronger during high sentiment periods and among sentiment-prone stocks. Therefore, carefully designed trading strategies that use VIX as a sentiment proxy has the potential to exploit the short-term return momentum caused by the delayed arbitrage. The choice of VIX as the sentiment indicator in my trading strategies is justified on two grounds. First, VIX is obtained primarily from the trading activity of sophisticated investors on S&P options. Its ability to reflect the sophisticated investors' estimation of the overall market sentiment, makes VIX an ideal candidate to test the delayed arbitrate theory. Second, VIX is one of the most prevalently accepted daily sentiment indicators, allowing us to examine the profitability of the sentiment-based trading strategies over short time intervals.

In this study, I design trading strategies that involve holding sentiment-prone stocks when VIX is low and holding sentiment-immune stocks when VIX is substantially high; where substantially high (low) VIX is defined as VIX increases of 10% or more (less than 10%) relative to its moving average over the previous 25 days[1]. I use firm characteristics, namely size, firm age, return volatility, earning-to-book ratio, dividend-to-book ratio, fixed asset ratio, research and development ratio, book-to-market ratio, external finance over asset and sales growth ratio, to determine the extent to which a stock is exposed to changes in investor sentiment. Baker and Wurgler (2006) argue that firms are more prone to sentiment when they are small, young, volatile, non-profitable, non-dividend-paying, have high financial distress and a great growth opportunity. In this study, I argue that when investor sentiment is high (VIX is low), the contemporaneous returns of sentiment-prone stocks are also likely to be high due to limits to arbitrage. If the theory of delayed arbitrage holds, the prices of the already overpriced sentiment-prone stocks will increase further in the short term. Thus, longing sentiment-prone stocks when sentiment is high reflects my attempt to exploit the short-term cross-sectional momentum profits associated with these stocks.

I find that my VIX-based trading strategies generate considerable excess returns over the unconditional long-short portfolio, which always longs sentiment-prone portfolios and shorts sentiment-immune portfolios. Specifically, I find that the annualised returns of my VIX trading strategies range from 22.05% to 42.38%, and the corresponding benchmark

[1] I also used 0%, 5%, 15% and 20% as the threshold, with my trading strategies still yielding strong and significant profits.

long-short portfolios have returns ranging from -3.15% to 28.01%. I also show that the annualised excess returns of the VIX-based trading strategies over their corresponding benchmark portfolios range from 11.66% to 25.55%. The most profitable trading strategy involves shifting investments between the smallest and the largest stocks deciles, and the least profitable trading strategy is the one that shifts investments between the bottom and the middle book-to-market portfolios. Further analysis indicates that the Sharpe ratios increase significantly after applying VIX-based trading strategies in 14 out of 16 cases. Shifting investments based on size has the highest Sharpe ratio of 2.70, and shifting investments between the bottom and the middle book-to-market portfolios has the lowest Sharpe ratio of 1.13.

Furthermore, I regress the excess returns of my trading strategies and those of the benchmark portfolios on the well-known risk factors. I find that the risk-adjusted excess returns (alphas) are slightly smaller than their unadjusted excess returns counterparts, whist remaining remain positive and statistically significant. This finding shows that the common risk factors cannot fully explain the abnormal profitability of my trading strategies. Additional analysis presents that my trading strategy remains profitable after considering effects of macroeconomic factors such as term spread, default spread, TED spread and the liquidity factor.

Finally, I calculate the break-even transaction cost to see whether my trading strategy could survive the transaction costs. The break-even transaction costs of my strategies are roughly higher than 50 basis points. In literature, transaction costs are usually set lower than 50 basis points. For example, Lynch and Balduzzi (2000) set the transaction costs at 25 basis points to calculate the profit. Frazzini et al. (2012) measure the real-world trading costs for asset pricing anomalies such as size and value trading strategies, with the trading costs calculated to be no higher than 25 basis points. My high break-even transaction costs indicate that my trading strategies are still profitable after taking the transaction costs into account.

This study contributes to the literature by providing a new behavioural explanation that influences the profitability of the volatility timing strategies in the cross-section of stock returns. Prior studies use VIX as a proxy for expected volatility, market volatility, market liquidity, or macroeconomic expectation. Most of these studies effectively explain the long-term positive VIX-return relation, whilst rarely discussing the potentially negative association between VIX and the next-day return. Unlike prior literature, I regard VIX as a market-wide sentiment indicator and then design trading strategies to exploit its cross-sectional effect on stock returns in the spirit of Baker and Wurgler (2006). This cross-sectional effect, combined with Abreu and Brunnermeier's (2003) delayed arbitrage theory, provides the rationale behind the success of my VIX timing strategies.

The closest study to ours is that conducted by Copeland and Copeland (1999), who also design trading strategies that involve shifting investments across stock portfolios based on changes in VIX. This chapter is distinct from Copeland and Copeland (1999) in two ways. First, I explain the profitability of the VIX-timing strategy using a sentiment story, with my hypothesis derived from the theoretical work on the effect of sentiment on stock returns and delayed arbitrage (Abreu and Brunnermier, 2002; Delong et al., 1990). Copeland and Copeland (1999) view VIX as a proxy for future discount rate, i.e., higher VIX means higher future discount rates and falling prices. However, this argument is not consistent with the broadly documented reversal effect of VIX on stock return. My study uses the investor sentiment channel to reconcile between the momentum and reversal effects of VIX. Second, my study applies VIX-based strategies in a broader spectrum of cross-sectional stock returns, showing that the VIX-based trading strategies are profitable. The finding that VIX-based strategies can generate significant abnormal returns may help explain the prevalent applications of such strategies in the financial industry.

The rest of this chapter proceeds as follows. Section 5.2 describes the data. Section 5.3

reports the profitability of my VIX-based trading strategy. Section 5.4 concludes.

5.2 Related Literature

Existing empirical studies commonly show that investor sentiment and future returns are inversely related. The contrarian predictive power of investor sentiment on future return are usually tested with low frequency data, as most of the commonly used investor sentiment measures, including mutual fund flow, consumer confidence index, closed-end fund discount, Baker Wurgler index, are only available at monthly frequency (e.g., Baker and Wurgler, 2006, 2007; Lee et al., 1991; Lemmon and Portniaguina, 2006; Neal and Wheatley, 1998). Most prior studies investigate the extent to which these monthly sentiment indicators predict the monthly, quarterly, or longer-term future returns. These studies often argue that bullish investor sentiment pushes current price above fundamentals and the correction of mispricing results in lower future returns.

However, the delayed arbitrage model of Abreu and Brunnermeier (2002) implies that the negative relation between investor sentiment and future return may not hold in the short run. This is because in a market where arbitrageurs do not know their sequence in notifying the mispricing, sophisticated investors choose to beat the gun and ride the trend. The lack of coordination among arbitrageurs may, in turn, lead to a persistent mispricing particularly in the short run. Ample empirical studies also indicate that sophisticated arbitrageurs actively ride the bubbles and contribute to the bubble (e.g., Berger and Turtle, 2015; Brunnermeier and Nagel, 2004; DeVault et al., 2014; Griffin et al., 2011; Xiong and Yu, 2011). Therefore, I argue that investor sentiment may have a momentum effect on short-run future returns. The momentum effect of investor sentiment on future returns does not conflicts with the well-documented reversal effect of investor sentiment. To quote Yu (2011), who studies the reversal effect of investor sentiment, “the synchronization problem among arbitrageurs may create limits to arbitrage or even amplify the mispricing". In this case, the reversal effect of investor sentiment could be more pronounced due to the delayed arbitrage. My study compliments the previous literature by investigating at the momentum effect of sentiment on the short-run future returns.

While several studies have already examined the predictive power of VIX on future returns, these VIX studies usually view VIX as a proxy for expected future volatility or liquidity rather than as a sentiment measure. For example, Banerjee et al. (2007) propose a theory in which the positive association between VIX and stock return is attributed to the possibility that VIX proxies for market volatility. Consistent with this view, Jackwerth and Rubinstein (1996), Coval and Shumway (2001), and Bakshi and Kapadia (2003) show that market volatility has a negative price and high levels of volatility translate to high price risk premiums when investors are averse to volatility risk. Thus, high VIX indicates high market volatility and therefore low current price and high future return. VIX is also often regarded as a liquidity measure. In Nagel (2012), VIX is deemed as a liquidity measure that strongly predicts the returns from liquidity evaporation. High VIX indicates low funding liquidity and hence higher future returns. However, while the theories proposed by Banerjee et al. (2007) and Nagel (2012) explain the positive long-term VIX-return relation, i.e., the reversal effect, they do not work well in explaining the negative short-run VIX-return relation, i.e. the return momentum. To reconcile the reversal with the momentum effects of VIX on return, I consider VIX as a measure of investor sentiment.

In this study, I argue that VIX is not only an indicator of a limit of arbitrage but also a measure of investor sentiment. Tu et al. (2016) argue that VIX can predict absolute mispricing because of the limit to arbitrage. Specifically, they argue that high VIX implies high expected volatility and therefore stronger limits to arbitrage, which in turn amplifies mispricing. However, VIX can also be view as a sentiment measure. If limit to arbitrage is assumed to be constant, VIX is expected to be negatively related to the contemporaneous mispricing, resulting in higher return momentum when arbitrage is delayed. Unlike Tu et al. (2016), I use VIX-based strategies to exploit mispricing.Viewing VIX as a sentiment indicator reconciles the long-term return reversals with the short-term return momentum following increases in VIX.

Existing studies find that the long-term return reversals following sentiment increases is controversial in the aggregate market level, but strong in the cross-section. Baker and Wurgler (2007) argue that stocks that are more prone to speculative demand and more difficult to arbitrage are more prone to sentiment. Some stocks, such as young and small stocks, are more prone to sentiment while others are tend to be sentiment-immune. Hence, sentiment may play a more prominent role in predicting the return disparity between sentiment-prone stocks and sentiment immune stocks than predicting aggregate market returns. Stambaugh et al. (2012) argue that stocks with more constraints to arbitrage are more sensitive to investor sentiment. Ljungqvist and Qian (2016) argue that, because of the synchronization problem (Abreu and Brunnermeier, 2002), sophisticated investors may deliberately target stocks with sever short-sell constraints, limiting the scope of coordinated short-selling actions. Campbell et al. (2011) also find that distressed stocks underperform more severely following increases in VIX. This evidence suggests that the short-term return momentum caused by delayed arbitrage may also be stronger in the cross-section. Specifically, I hypothesize that sentiment-prone stocks will exhibit stronger momentum effect as they are more prone to sophisticated arbitrageurs and more difficult to arbitrage during the bubble periods.

Several studies use VIX to time the market. Some of these studies apply the mean-variance theory to design VIX-based volatility timing strategies (Clements and Silvennoinen, 2013; Fleming et al., 2001, 2003; Johannes et al., 2002). A strand of studies demonstrate the profitability of trading strategies that benefit from the return momentum induced by the news-based sentiment (Huynh and Smith, 2017; Sun et al., 2016; Uhl, 2017). Copeland and Copeland (1999) propose to shift asset allocation in the cross-section based on VIX. Their motivation for this trading strategy is that VIX represent future discount rate and therefore influence price in discount cash flow model; however, this explanation does not strongly illustrate why VIX has asymmetric predictability on future return in the cross-section. I see VIX as sentiment indicator and based on the asymmetric effect of investor sentiment in the cross-section stock market, I design a wider spectrum of trading strategies by building portfolios based on different sentiment sensitive level measures. To the best of my knowledge, few paper view VIX as sentiment and test trading strategies that capture the VIX-induced return momentum in the cross-section stock market, and this paper contributes to the existing literature by filling this gap.

5.3 Research Design and Data Sources

I construct decile portfolios based on firm characteristics that relate to exposure to irrational investors' speculative demand and arbitrage constraints. Baker and Wurgler (2006) argue that sentiment-prone firms tend to be small, young, volatile, non-dividend-paying, non-profitable, informationally opaque, financially distressed, and have strong growth opportunity. Therefore, the firm size (ME), age (Age), return volatility (Sigma), earning ratio (E/BE), dividend ratio (D/BE), tangible and intangible asset ratio (PPE/A and RD/A), book-to-market ratio (BE/ME), external finance ratio (EF/A), and sales growth (GS) are the ten characteristics I employ to gauge the extent of stocks' sensitivity to investor sentiment.[2]

Baker and Wurgler (2006) argue that stocks that are prone to speculative demand are also difficult to arbitrage. Take Age as an example. The lack of an earnings history combined with the presence of apparently unlimited growth opportunities for young firms makes young firms difficult to value. Unsophisticated investors consequently generate a wide range of valuations for these firms depending on their sentiment. This lack of consensus among

[2] Details on these characteristics variables are provided in the Appendix B.

unsophisticated investors increases the volatility of returns, which in turn deters rational investors from trading fully against mispricing.

Similar to Baker and Wurgler (2006), I construct sixteen long-short portfolios. Each of these long-short portfolios longs the most sentiment-prone decile portfolio and shorts the most sentiment-immune decile portfolio. I consider the bottom (top) deciles of ME, Age, E/BE, D/BE, and PPE/A as the most sentiment-prone (sentiment-immune) and the top (bottom) deciles of Sigma and RD/A as the most sentiment-prone (sentiment-immune). Three of the firm characteristics included in my analysis, namely BE/ME, EF/A, and GS have a multi-dimensional nature, as they reflect both growth and distress. Take BE/ME as an example. High book-to-market ratio represents severe distress, whereas a low value of the same ratio indicates extreme growth potential. Stocks with either of these extreme BE/ME ratios are more difficult for investors to price accurately. Stocks with financial distress are highly appealing to speculative demand, so firms with high BE/ME, low EF/A, and low GS are sentiment-prone. Firms with strong growth potential are also hard for investors to value, so returns of firms with low BE/ME, high EF/A, and high GS are more prone to investor sentiment. The middle deciles are considered most sentiment-immune for those three characteristics. Hence, the long-short portfolio could be top-minus-middle and bottom-minus-middle decile for BE/ME, EF/A, and GS. In addition, BE/ME (EF/A, GS) itself could be seen as generic pricing factor, and therefore the top BE/ME (bottom EF/A, GS) decile is expected to be more sensitive to VIX than the bottom BE/ME (top EF/A, GS) decile.

Firm-level accounting data is retrieved from Compustat. The monthly stock returns are downloaded from CRSP. My sample includes all common stocks (share codes in 10 and 11) between January 1988 and December 2016 on NYSE, AMEX, and NASDAQ (with stock exchange code in 1 2 3). All the firm characteristic variables are winsorized at 99.5 and 0.5% annually. The breakpoints for deciles are defined only using NYSE firms. I match the year-end accounting data of year t-1 to monthly returns from July t to June t+1. I obtain

VIX data over the period from 1990/01/01 to 2016/04/30 from WRDS. I also obtain the historical data on the implied volatility conveyed from S&P 100 index, NASDAQ index, and DJIA index. The momentum factor (UMD), defined the average return of high prior return portfolio over low prior return portfolio, and the Fama-French five factors, i.e., the market return premium over risk-free rate (RMRF), the average return on the three small-cap portfolios minus the average return on the three big-cap portfolios (SMB), the average return on the two value portfolios minus the average return on the two growth portfolios (HML), the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios (RMW), and the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios (CMA), are downloaded from Kenneth French website[3].

5.4 Empirical Results

In this section, I start with the in-sample predictive regressions of VIX on the next-day cross-sectional returns. I then report the performances of the simple VIX-based trading strategies, both raw and risk-adjusted, and compare them with those of the benchmark portfolios.

5.4.1 Predictive Regressions

To substantiate the predictive power of VIX on the next-day stock returns in the cross-section, I regress portfolio returns on the one-day lagged VIX and other contemporaneous risk factors. The regression is specified as follows:

$$R_{X,t} = \alpha + \beta_1 VIX_{t-1} + \gamma CV_t + \upsilon_t, \tag{5.1}$$

[3]The data are available on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I thank Kenneth R. French for providing the data.

where $R_{X,t}$ is the portfolio returns X at time t, and the portfolio X can be one of the following: 1) a long-short portfolio that longs sentiment-prone stocks and shorts sentiment-immune decile portfolio (P-I); 2) a sentiment-prone decile portfolio (P); 3) a sentiment immune decile portfolio (I). VIX_{t-1} is the standardised VIX level at time $t-1$, and CV_t is a vector of control variables, including the Fama-French (2015) five factors and the Carhart (1997) momentum factor (UMD). A control factor is omitted from the regression when it is analogy to the dependent variable. For example, SMB factor is ruled out if the dependent variable is the daily returns of long-short portfolio ME(1-10). HML factor is excluded when the dependent variable is the daily returns of the long-short portfolios constructed from BE/ME. RMV is excluded the regression of E/BE and D/BE portfolios.

Table 5.1 reports the coefficients of the lagged VIX in the regressions with different data samples and portfolio returns as dependent variable and the Newey-West standard errors (Newey and West, 1987) that are robust to heteroscedasticity and serial correlation.[4] Panel A reports the regression results for the entire sample period, and Panel B and Panel C present the results for the high sentiment period (i.e., standardised lagged VIX is lower than -0.5 and low sentiment period (i.e., standardised lagged VIX is greater than 0.5), respectively. I divide the sample into high and low sentiment periods to test whether the ability of VIX to predict returns depends on investor sentiment. As previous studies show that the predictability of VIX is strong when VIX is at the extreme (either substantially high or substantially low), I set the threshold as 0.5.[5]

The coefficients of the one-day lagged VIX in Panel A of Table 5.1 are negative and statistically significant (at the 10% or better) in 6 out of 16 long-short portfolios and insignificant in the rest portfolios. This finding is consistent with the delayed arbitrage theory, which

[4] I set a maximum lag of 15 when calculating Newey-West robust standard errors for the coefficients.

[5] I choose 0.5 as the threshold to define extreme high/low VIX sub-samples because it results in a large sample size in both sub-samples. This choice is likely to make my results more conservative. I also consider 1 as the threshold, and I find more dominant regression results. The trading rules is to hold sentiment-immune stocks following a substantial rise in VIX. As a consequence of larger threshold, I make less transactions and the break-even transaction costs is more striking.

predicts high returns following a rise in sentiment, i.e., a negative relationship between the relative returns of sentiment-prone stocks over sentiment-immune stocks and the one-day lagged VIX. Columns (2) and (3) of Panel A present the results of regressing the returns on sentiment-prone decile and sentiment-immune decile on lagged VIX, respectively. The results suggest that lagged VIX has a much stronger predictive power on sentiment-prone stocks than sentiment-immune stocks. In Column (3), apart from the top ME decile portfolio regression, none of the sixteen regressions exhibits a significant correlation between lagged VIX and future returns. For the top ME decile return regression, the coefficient of VIX is even significantly positive. One plausible explanation for this positive coefficient is "flight-to-quality" (see also Baker and Wurgler (2007)), i.e., investors seek safer portfolios in low sentiment period.

Panel B of Table 5.1 presents the regression results for the high sentiment sub-sample. I find that both the magnitude and the significance of the coefficients of the lagged VIX increase during the high sentiment period. VIX is a significant negative predictor of the one-day forward return for 11 out of the 16 long-short portfolios. Similarly, I find that the ability of VIX to predict the returns of the sentiment-prone deciles also increases when sentiment is high. Column (3) of Panel B shows that when sentiment is sufficiently high, even the returns of some of the sentiment-immune deciles exhibit a significant negative association with the lagged VIX.

Panel C of Table 5.1 shows that when sentiment is low, VIX has little predictability of the next-day returns, regardless of whether the returns of the sentiment-prone deciles or those of the sentiment-immune deciles are used as the dependent variables in the regression. Specifically, I find the lagged VIX to be a significant return predictor for only 5 out of the 16 long-short portfolios. The reduced predictability of VIX in low sentiment period is consistent with Stambaugh et al. (2012), who argue that investor sentiment is more likely to have a more considerable influence on stock prices during periods of high sentiment, as short sale constraints are generally more binding during these periods.

Recall that Tu et al. (2016) explain the predictive power of VIX on returns through the limit to arbitrage channel. They claim that VIX is a measure of expected volatility and high VIX imposes stronger limits to arbitrage. Hence, mispricing may be amplified if sentiment remains stable. On the other hand, high VIX means low sentiment, if limits arbitrage is assumed constant, I expect VIX negatively relates with contemporaneous mispricing. This chapter focuses on the sentiment channel though, not the limits to arbitrage channel. This chapter extends this strand of literature by documenting a strong negative association between VIX and the next day return. This finding is consistent with the delayed arbitrage argument, whereas the mean-variance theory and the liquidity evaporation theory do not work well in explaining this empirical finding.

To check the robustness of my results, I add more control variables into the regression. First, even though the liquidity evaporation explanation explains the positive relationship between VIX and return and I find the negative short-run relationship, I build a liquidity measure and add it as a control variable in the robustness test. My liquidity control variable is the difference of the average bid-ask spread between the corresponding long and short portfolios used in each regression. I find that sentiment-prone decile portfolios have higher bid-ask spread relative to sentiment-immune stocks. Table E.19 show that though the bid-ask spread difference plays a significant role in return disparity, the coefficients of one-day lagged VIX on returns remain significantly negative. By controlling for liquidity risk factor, I could at least say that the liquidity evaporation does not fully explain or does not subsume the momentum effect of VIX.

Table 5.1 Regressions of Portfolio Returns on Lagged VIX

Table 5.1 reports the coefficients of lagged VIX in regressions of sentiment-based long-short portfolio returns on one-day lagged VIX and control variables in the whole sample and sub-samples.

$$R_{X,t} = \alpha + \beta_1 VIX_{t-1} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the portfolio X, where X could be a sentiment-prone decile (P), a sentiment-immune decile (I) or the long-short portfolio of sentiment-prone decile over sentiment-immune decile (P-I). The control variables include the FF 5 factors and the momentum factor (UMD). Any control factor will be excluded from the regression when it is the cross-sectional return premium being forecasted. The first two columns indicate the decile rank of sentiment-prone and sentiment-immune portfolios. The first row indicates the selection criteria for choosing the data samples. The second row indicates the choice of X. The Newey and West (1987) robust t-statistics are in brackets. ***, ** and * indicates the statistical significance at 1%, 5% and 10% level, respectively. The sample period is from 1990/01/01 to 2016/04/30.

Table 5.1 Regressions of Portfolio Returns on Lagged VIX

			Panel A. All Samples			Panel B VIX<-0.5			Panel C VIX>0.5		
	P	I	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$
ME	1	10	-0.045***	-0.037**	0.008**	-0.181***	-0.158***	0.023*	-0.054	-0.046	0.008
			(-2.688)	(-2.406)	(2.323)	(-3.231)	(-3.168)	(1.684)	(-1.547)	(-1.489)	(0.822)
Age	1	10	-0.007	-0.014	-0.007	-0.078*	-0.090**	-0.012	0.007	-0.014	-0.021
			(-0.708)	(-1.372)	(-1.284)	(-1.760)	(-2.535)	(-0.485)	(0.361)	(-0.641)	(-1.508)
Sigma	10	1	-0.011	-0.015	-0.004	-0.162***	-0.133**	0.029	-0.004	-0.022	-0.018
			(-0.899)	(-1.173)	(-0.805)	(-2.850)	(-2.570)	(1.306)	(-0.166)	(-0.792)	(-1.414)
E/BE	1	10	-0.016*	-0.021*	-0.005	-0.075*	-0.145***	-0.070***	-0.024	-0.031	-0.007
			(-1.769)	(-1.821)	(-0.875)	(-1.881)	(-3.604)	(-2.673)	(-1.410)	(-1.330)	(-0.492)
D/BE	1	10	-0.024***	-0.016*	0.008	-0.105***	-0.099***	0.005	-0.029*	-0.025	0.004
			(-3.045)	(-1.905)	(0.887)	(-2.875)	(-3.221)	(0.226)	(-1.678)	(-1.448)	(0.170)
PPE/A	1	10	0.001	-0.009	-0.010	0.022	-0.031	-0.053	0.018	-0.001	-0.019
			(0.050)	(-1.347)	(-0.906)	(0.380)	(-0.973)	(-1.064)	(0.805)	(-0.059)	(-0.776)
RD/A	10	1	0.014**	0.005	-0.009	-0.086*	-0.120**	-0.035*	-0.007	-0.015	-0.007
			(1.979)	(0.522)	(-1.452)	(-1.875)	(-2.483)	(-1.721)	(-0.498)	(-0.676)	(-0.533)

Table 5.1 Regressions of Portfolio Returns on Lagged VIX (Continued)

	P	I	Panel A. All Samples			Panel B VIX<-0.5			Panel C VIX>0.5		
			$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$	$R_{P-I,t}$	$R_{P,t}$	$R_{I,t}$
BE/ME	10	1	-0.037***	-0.033**	0.003	0.008	-0.098**	-0.106***	-0.068**	-0.055	0.013
			(-2.745)	(-2.001)	(0.438)	(0.186)	(-2.147)	(-2.943)	(-2.450)	(-1.620)	(0.872)
EF/A	1	10	-0.011	-0.016*	-0.005	-0.011	-0.098***	-0.086**	-0.040***	-0.034*	0.006
			(-1.601)	(-1.791)	(-0.482)	(-0.348)	(-2.858)	(-2.314)	(-3.071)	(-1.789)	(0.317)
GS	1	10	-0.009	-0.015	-0.006	-0.022	-0.109***	-0.087**	-0.016	-0.023	-0.007
			(-1.546)	(-1.307)	(-0.686)	(-0.640)	(-2.746)	(-2.494)	(-1.530)	(-1.040)	(-0.364)
BE/ME	1	5	0.005	0.003	-0.003	-0.097***	-0.106***	-0.019	0.018	0.013	-0.010
			(0.739)	(0.438)	(-0.406)	(-2.853)	(-2.943)	(-0.866)	(1.445)	(0.872)	(-0.632)
EF/A	10	5	-0.005	-0.005	0.000	-0.070**	-0.086**	-0.033*	0.012	0.006	-0.011
			(-0.574)	(-0.482)	(-0.073)	(-1.971)	(-2.314)	(-1.662)	(0.806)	(0.317)	(-0.840)
GS	10	5	-0.004	-0.006	-0.004	-0.081**	-0.087**	-0.012	0.004	-0.007	-0.021
			(-0.554)	(-0.686)	(-0.581)	(-2.280)	(-2.494)	(-0.569)	(0.304)	(-0.364)	(-1.415)
BE/ME	10	5	-0.032**	-0.033**	-0.003	-0.088**	-0.098**	-0.019	-0.050*	-0.055	-0.010
			(-2.193)	(-2.001)	(-0.406)	(-2.081)	(-2.147)	(-0.866)	(-1.688)	(-1.620)	(-0.632)
EF/A	1	5	-0.016**	-0.016*	0.000	-0.081***	-0.098***	-0.033*	-0.028**	-0.034*	-0.011
			(-2.378)	(-1.791)	(-0.073)	(-2.616)	(-2.858)	(-1.662)	(-2.003)	(-1.789)	(-0.840)
GS	1	5	-0.013	-0.015	-0.004	-0.103***	-0.109***	-0.012	-0.012	-0.023	-0.021
			(-1.399)	(-1.307)	(-0.581)	(-2.739)	(-2.746)	(-0.569)	(-0.724)	(-1.040)	(-1.415)

5.4.2 Two-Way Sorts

I divide my sample into high and low VIX periods by the trading signals implied by the historical and current levels of VIX. To gain an initial insight into the ability of VIX to predict returns, I conduct two–way sorts of decile portfolio returns. First, I sort stock returns into ten deciles based on a firm characteristic that is associated with the extent to which the stock is prone to market-wide investor sentiment. Then, I sort the returns in each decile conditional on whether the return is following a high sentiment day or a low sentiment day. In this case, day t is classified as a low sentiment day; if VIX at time $t-1$ is at least 10% higher than the average VIX between $t-26$ and $t-2$, otherwise day t is classified as a high or normal sentiment day. Figure 1 shows the two-way sorts of returns for the period from Jan 1990 to Dec 2016.

Generally, the results in Figure 5.1 suggest that low VIX predicts higher next-day returns for sentiment-prone stock deciles and high VIX predicts higher next-day returns for sentiment-immune stocks. Figure 5.1 indicates that when sentiment is high, sentiment-prone deciles, such as young firms, are likely to have larger persistent overpricing due to delayed arbitrage. Similarly, when sentiment is low, young firms tend to be more undervalued by irrational investors, as it takes time for arbitrageurs to take synchronized actions to eliminate the underpricing.

Figure 5.1 also shows that the return difference between the solid bar and the white bar is lower for high ME, high Age, low Sigma, high E/BE, and high D/BE decile portfolios, in line with the conjecture that these portfolios are less sensitive to sentiment. However, I do not find any conclusive pattern in the return difference between the high sentiment period and the low sentiment period in the cross-section of the PPE/A and RD/A deciles, implying that the sentiment-prone level is not well reflected by PPE/A and RD/A. This evidence is consistent with the findings of Baker and Wurgler (2006) and Chung et al. (2012).

Two-way sorts one-day forward portfolio average returns, 1994:01-2016:12. I place the daily return observations into bins according to the decile rank that a characteristic takes. The subtitles show the sentiment-sensitivity measure used to sort deciles. Then I sort return by VIX level on the previous day. If current VIX is at least 10% higher than its prior 25-day average, I define it a high VIX day. The solid bars are the annualised equal-weighted average returns following low VIX (high sentiment) days; the clear bars are average returns following high VIX (low sentiment) days.

Fig. 5.1 Two-Way Sorts: One-Day Forward Returns Sorted on VIX Levels and Sentiment-Exposure

Furthermore, Figure 5.1 shows that sentiment-immune stocks outperform sentiment-prone stocks after high VIX. For example, I find that the returns of ME decile increase almost monotonically following high VIX. I also observe a general pattern of negative average return following the high VIX period across all the sentiment-prone deciles, except for PPE/A and RD/A. Figure 5.1 also shows that high VIX predicts future returns for sentiment-prone stocks. In other words, sentiment-prone stocks tend to have negative returns following periods of low sentiment. Finally, a closer look at the graphs of returns pertaining BE/ME, EF/A, and GS. The white bars all show an inverted U-shape pattern. The lowest differences between the solid bars and the white bars are in the middle BE/ME, middle EF/A, and middle GS deciles. This finding confirms that firms in the middle deciles are less sensitive to sentiment changes than those in the bottom and top deciles of BE/ME, EF/A, and GS, consistent with the multi-dimensional nature of these three variables.

5.5 VIX-Based Trading Strategies

The rule of my trading strategies is to hold sentiment-immune stocks when VIX increases by at least 10% more than the average of its prior 25-day historical level and to hold sentiment-prone stocks otherwise.[6] These VIX-based timing strategies aim at capturing the momentum effect of sentiment on the cross-section of stock returns. I use the relative returns of sentiment-prone decile portfolio over sentiment-immune decile portfolio (P-I) as the benchmark portfolio returns. The excess return of my trading strategies over benchmark portfolio is denoted as RVIX.

[6]Note that my trading strategy does not require short-selling. In addition, I argue that one could also apply my VIX-based trading strategy on the ETF funds that traces the return of small-cap stocks and large-cap stocks, so that the transaction cost would be much lower. To be specific, the trading strategy would be to hold the small-cap ETF when VIX is low and to shift the asset allocation to large-cap ETF when VIX is substantially high.

Table 5.2 Summary Statistics of the Profitability of VIX-Based Trading Strategy

This table reports average returns (Avg Ret), the standard deviation (Std Dev), skewness (Skew) and the Sharpe ratio (SRatio) for benchmark portfolios, VIX timing strategy, and the RVIX returns, where RVIX is the excess returns of VIX strategy return over the benchmark long-short portfolio return. The first number in second column represents the rank of a sentiment-prone decile and the second number represents the rank of a sentiment-immune decile. The first three columns indicate the construction of benchmark portfolio and the VIX Timing strategy. The benchmark portfolio is to long the sentiment-prone decile (P) and short the sentiment-immune decile (I), and that the timing strategy is to hold the sentiment-prone decile after low VIX and hold the sentiment-immune decile after high VIX. VIX-based trading strategy is to buy and hold the sentiment-immune decile following a high VIX trading day and to buy and hold the sentiment-prone decile otherwise. A high VIX trading day is defined as current VIX is at least 10% higher than its prior 25-day average. Last column, the success ratio (Success), is the percentage of non-negative RVIX return. All the average returns are annualised and are in percentages. ***and ** indicates the t-test significance at 1% and 5% level, respectively. The sample period is from 1990/01/01 to 2016/04/30.

			Panel A. Benchmark Portfolio Return				Panel B. VIX Strategy Return				Panel C. RVIX			
	P	I	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	Success
ME	1	10	23.11***	13.95	-0.53	1.66	42.38***	15.7	0.17	2.7	19.26***	23.58	0.97	0.54
Age	1	10	10.90***	11.21	-0.2	0.97	28.35***	16.99	-0.27	1.67	17.42***	17.75	0.27	0.55
Sigma	10	1	18.85***	15.55	-0.2	1.21	38.25***	18.2	-0.32	2.1	19.45***	10.44	-0.1	0.58
E/BE	1	10	13.37***	7.91	-0.03	1.69	33.41***	17.9	-0.37	1.87	20.05***	18.65	-0.18	0.57
D/BE	1	10	11.58***	8.84	-0.26	1.31	30.83***	16.95	-0.33	1.82	19.26***	16.39	-0.04	0.56
PPE/A	1	10	-3.15	10.12	-0.12	-0.31	22.38***	15.98	-0.2	1.4	25.55***	19.91	-0.11	0.57
RD/A	10	1	9.23***	12.58	-0.05	0.73	31.43***	20.34	-0.34	1.54	22.20***	15.74	-0.36	0.6
BE/ME	10	1	17.60***	12.04	-0.24	1.46	40.49***	17.59	-0.14	2.3	22.92***	24.08	0.18	0.58
EF/A	1	10	11.84***	8.55	-0.24	1.38	29.67***	17.79	-0.4	1.67	17.82***	22.49	-0.14	0.58
GS	1	10	12.39***	7.56	-0.17	1.64	31.82***	18.35	-0.37	1.73	19.45***	22.09	-0.13	0.57
BE/ME	1	5	10.42***	13.41	-0.02	0.78	22.05***	19.51	-0.32	1.13	11.66***	9.16	-0.29	0.58
EF/A	10	5	8.61***	13.6	-0.24	0.63	23.02***	18.82	-0.34	1.22	14.44***	8.11	-0.28	0.58
GS	10	5	8.08***	13.88	-0.22	0.58	22.73***	18.8	-0.32	1.21	14.66***	7.92	-0.14	0.59
BE/ME	10	5	28.01***	9.2	0.2	3.04	41.31***	16.15	-0.23	2.56	13.35***	10.68	0.14	0.57
EF/A	1	5	20.46***	9.24	-0.53	2.21	32.93***	16.03	-0.42	2.05	12.49***	8.4	-0.03	0.58
GS	1	5	20.47***	10.81	-0.42	1.89	35.11***	16.56	-0.39	2.12	14.66***	8.41	0.12	0.59

Table 5.2 summarises the buy-and-hold long-short portfolio returns (i.e., the return of the benchmark portfolio), the returns of VIX-based trading strategy, the excess returns of my trading strategy over benchmark long-short portfolio, and the success rate of my trading strategy, defined as the percentage of trading days in RVIX is zero or higher. That is, when my VIX timing strategy performs at least as good as the benchmark portfolio. Panels A and B in Table 5.2 reports average returns, the standard deviation, the skewness, and the Sharpe ratio of the sixteen original portfolio returns. The results suggest that my VIX-based trading strategies generate higher average returns and Sharpe ratios than the benchmark portfolios. The annualised returns of benchmark portfolios in Panel A range from -3.15% (PPE/A long-short portfolio) to 23.11% (ME long-short portfolio), and the annualised returns of VIX-based trading strategies range from 22.05% to 42.38%. Although the standard deviations in Panel B is slightly higher than those standard deviation in Panel A, the Sharpe ratios of the VIX-based strategies are higher than those of the benchmark portfolios. In Panel B, the annualised returns of shifting investments between top and bottom ME-sorted deciles and BE/ME-sorted deciles are 42.38% and 40.49%, respectively. The remarkable profitability associated with shifting investments between size and value portfolios is consistent with the findings of Copeland and Copeland (1999). With the exception of ME-sorted portfolios, the skewness statistics of the long-short portfolio returns in Panel A are higher than those of the VIX-based trading strategies in Panel B, suggesting that my trading strategies incur lower crash risk than the benchmark strategy.

Panel C in Table 5.2 shows that the average returns of the VIX-based strategies are notably higher than those of benchmark portfolios. Even the least profitable portfolio generates a nontrivial excess return of 11.66% after adopting the VIX-based trading strategy. The success rate of my VIX trading strategies ranges from 0.54 to 0.60 for the 16 cases, indicating that more often than not the VIX-based trading strategies generate larger returns than the benchmark portfolios.

Table 5.3 Abnormal Alphas of RVIX

RVIX is the excess returns of the VIX-based trading strategy over the buy-and-hold long-short portfolio return. In Panel A, I regress RVIX on the daily market excess return. Panel B reports the results of RVIX regressed on FF3 factors and the momentum factor. Panel C reports the results of RVIX regressed on FF5 factors and the momentum factor. Panel D reports the results of RVIX regressed on Stambaugh and Yuan (2017) four mispricing factors. Any risk factor will be excluded from the regression when it is the portfolio being estimated. The alphas are annualised and are in percentages. The Newey and West robust t-statistics are in parentheses. *** and ** indicates significance at 1% and 5% level, respectively. The sample period is from 1990/01/01 to 2016/04/30.

			Panel A CAPM		Panel B FF3 Umd		Panel C FF5 Umd		Panel D Mispricing4	
	P	I	α	R^2	α	R^2	α	R^2	α	R^2
ME	1	10	10.03***	85.35	10.07***	85.35	10.35***	87.04	10.89***	85.56
			(5.48)		(5.48)		(5.68)		(5.50)	
Age	1	10	11.11***	70.30	10.07***	74.07	5.88***	81.62	6.40***	74.66
			(5.34)		(5.59)		(3.68)		(3.07)	
Sigma	10	1	17.49***	19.53	16.65***	24.79	14.55***	30.44	13.86***	29.73
			(8.56)		(8.51)		(7.48)		(6.88)	
E/BE	1	10	12.94***	80.75	11.90***	85.95	12.97***	86.46	11.59***	85.13
			(6.91)		(8.19)		(9.18)		(7.35)	
D/BE	1	10	13.45***	69.98	11.92***	76.28	11.90***	77.71	10.13***	76.06
			(7.21)		(7.23)		(7.17)		(5.55)	
PPE/A	1	10	19.46***	52.24	17.41***	62.24	15.53***	64.12	17.38***	59.37
			(6.34)		(6.79)		(5.78)		(6.07)	
RD/A	10	1	17.00***	60.73	14.50***	80.47	13.95***	82.49	14.92***	75.27
			(7.81)		(9.66)		(9.62)		(8.51)	
BE/ME	10	1	14.26***	72.15	12.99***	81.24	18.42***	85.22	17.68***	83.73
			(4.71)		(5.49)		(8.47)		(7.30)	
EF/A	1	10	9.98***	67.64	9.14***	81.01	14.11***	84.54	14.18***	83.25
			(2.84)		(3.59)		(6.32)		(5.71)	
GS	1	10	11.43***	73.47	10.47***	85.31	14.54***	87.98	14.79***	87.27
			(3.79)		(4.95)		(8.14)		(7.44)	
BE/ME	1	5	8.89***	51.18	8.39***	61.02	7.02***	67.55	6.53***	63.34
			(7.43)		(8.27)		(7.01)		(5.75)	
EF/A	10	5	12.01***	50.06	10.99***	63.02	10.02***	65.29	9.34***	62.61
			(10.19)		(11.04)		(10.19)		(8.54)	
GS	10	5	12.42***	44.63	11.39***	57.46	10.53***	59.86	9.97***	57.74
			(10.44)		(10.80)		(10.48)		(9.26)	
BE/ME	10	5	9.59***	69.11	9.04***	77.72	8.46***	78.83	8.01***	76.89
			(8.04)		(8.60)		(8.61)		(7.45)	
EF/A	1	5	9.49***	71.05	8.69***	82.02	8.47***	82.58	8.15***	80.59
			(9.95)		(12.63)		(12.85)		(10.86)	
GS	1	5	11.86***	61.85	10.96***	71.28	10.35***	73.41	10.30***	70.05
			(11.17)		(12.02)		(11.87)		(10.69)	

The summary statistics suggest that my VIX-based trading strategies outperform their benchmarks. However, it is not clear whether the excess returns of my VIX strategies (RVIX) represent compensation for risk. Thus, I adjust RVIX for risk using four different models. Table 5.3 reports the risk-adjusted RVIX (i.e., the alphas) and the adjusted R-square associated with the four models. Panel A presents the results of the CAPM model, Panel B reports the results from the FF three factors plus the momentum (SMB, HML, RMRF, UMD), Panel C shows the results from the FF five factors plus momentum (SMB, HML, RMRF, CMA, RMW, UMD), and Panel D shows the results of the four mispricing factors model of Stambaugh and Yuan (2016) (RMRF, MSMB, MGMT, PERF).[7] In Stambaugh and Yuan (2017) mispricing model, MGMT is a composite factor constructed by combining the rankings of six anomaly variables that represent quantities that firms' management can affect directly, PERF is a composite factor based on five anomaly variables that relate to performance, but are less directly controlled by management, and MSMB is the return between the small-cap and large-cap leg sorted on the two composite mispricing measures used to construct MGMT and PERF.

The alphas in Table 5.3 are generally smaller than the excess returns in Table 5.2, suggesting that the superior performance of my VIX trading strategies is at least partly driven by risk. The salient coefficients of risk factors and high R-square also indicate that returns of VIX-based trading strategy are associated with risk factors. However, all alphas in Table 5.3 are positive and highly significant (at 1% or better), implying that adjusting for risk mitigates but does not fully eliminate the profitability of my VIX strategies. Can the profitability of my VIX-based trading strategy be attributed to market timing? Following Han et al. (2013), I use two approaches to test whether the superior performance of my VIX strategies stems from their ability to detect periods of low market return premium. The first approach is the

[7]The Stambaugh and Yuan daily mispricing factors available on Prof. Yu Yuan's personal website http://www.saif.sjtu.edu.cn/facultylist/yyuan/.

quadratic regression of Treynor and Mazuy (1966)

$$RVIX_t = \alpha + \beta_m RMRF_t + \beta_{m^2} RMRF_t{}^2 + \upsilon_t. \tag{5.2}$$

A significantly positive coefficient β_{m^2} would indicate successful market timing ability. The second approach is the regression of Henriksson and Merton (1981)

$$RVIX_t = \alpha + \beta_m RMRF_t + \gamma_m RMRF_t D_{rmrf} + \upsilon_t, \tag{5.3}$$

where D_{rmrf} is a dummy variable with a value of unity when the market return premium is positive, and zero otherwise. A significantly positive coefficient γ_m would indicate that the profitability of my trading strategies is due to their ability to predict booming periods. The alpha in each regression shows to the abnormal returns after controlling for market timing ability of my VIX-based trading strategy.

Table 5.4 reports the market timing regression results. Panel A reports the results of the quadratic regression (Equation 5.2). The coefficients of squared market return premium, β_{m^2}, are not statistically significant, except for the ME sorted portfolio. The regression alphas are largely significantly positive, except for the ME sorted portfolio. Panel B reports the results of Equation 5.3. The coefficients γ_m are roughly insignificant, whereas the intercepts (α) are positive and significant. For some regressions such as the PPE/A and RD/A sorted portfolio regressions, the intercepts are even greater than the dependent variable, inconsistent with the market timing explanation. The prominent positive γ_m and the salient negative alphas are only observed in the case of ME-sorted portfolios, indicating that the market timing explanation exclusively applies to these portfolios.

Table 5.4 Market Timing Tests On VIX Based Trading Strategy

This table reports results of market timing regressions of RVIX, the excess returns of VIX-based trading strategy over benchmark portfolio return. Panel A shows the results of Treynor and Mazuy (1966) quadratic regressions, and Panel B show the results of Henriksson and Merton (1981) regressions. The alphas are annualised and are in percentages. *** and ** indicates statistical significance at 1% and 5% level, respectively. The Newey and West robust t-statistics are in parenthesis. The sample period is from 1990/01/01 to 2016/04/30.

			Panel A. TM Regression				Panel B. HM Regression			
	P	I	α	β_m	β_{m^2}	R^2	α	β_m	γ_m	R^2
ME	1	10	1.60	1.22***	2.62***	85.86	-10.98***	1.11***	0.22***	85.72
			(0.66)	(34.82)	(3.63)		(-2.66)	(30.27)	(4.63)	
Age	1	10	9.92***	0.83***	0.37	70.32	10.98***	0.83***	0.00	70.3
			(3.79)	(25.20)	(0.54)		(2.68)	(24.68)	(0.03)	
Sigma	10	1	17.13***	0.26***	0.11	19.52	18.06***	0.26***	-0.01	19.52
			(7.85)	(10.10)	(0.20)		(4.97)	(7.16)	(-0.14)	
E/BE	1	10	13.66***	0.94***	-0.22	80.75	16.79***	0.95***	-0.04	80.77
			(7.04)	(43.66)	(-0.70)		(6.23)	(38.57)	(-1.50)	
D/BE	1	10	13.51***	0.76***	-0.02	69.97	12.75***	0.76***	0.01	69.98
			(7.33)	(26.24)	(-0.03)		(3.97)	(21.36)	(0.19)	
PPE/A	1	10	23.35***	0.80***	-1.21	52.38	33.55***	0.87***	-0.15***	52.46
			(5.56)	(17.10)	(-1.37)		(7.37)	(18.83)	(-3.31)	
RD/A	10	1	20.94***	0.68***	-1.22**	60.97	28.80***	0.74***	-0.12***	60.99
			(9.08)	(19.11)	(-2.39)		(7.49)	(18.36)	(-2.88)	
BE/ME	10	1	14.87***	1.14***	-0.19	72.15	18.53***	1.16***	-0.04	72.16
			(4.42)	(40.03)	(-0.26)		(3.73)	(33.49)	(-0.85)	
EF/A	1	10	12.83***	1.03***	-0.89	67.7	23.69***	1.10***	-0.14***	67.81
			(3.04)	(47.60)	(-0.97)		(4.51)	(37.08)	(-2.72)	
GS	1	10	13.02***	1.06***	-0.49	73.48	20.85***	1.10***	-0.10**	73.55
			(3.76)	(61.26)	(-0.75)		(4.84)	(51.84)	(-2.42)	
BE/ME	1	5	10.77***	0.37***	-0.59	51.34	14.54***	0.39***	-0.06**	51.35
			(7.43)	(19.06)	(-1.59)		(5.80)	(19.74)	(-2.15)	
EF/A	10	5	13.28***	0.32***	-0.40	50.15	15.28***	0.34***	-0.03	50.12
			(9.09)	(20.19)	(-1.01)		(6.32)	(18.12)	(-1.24)	
GS	10	5	14.13***	0.29***	-0.53	44.8	16.57***	0.32***	-0.04	44.75
			(9.63)	(18.20)	(-1.35)		(6.78)	(16.27)	(-1.56)	
BE/ME	10	5	8.78***	0.50***	0.25	69.13	7.22***	0.48***	0.02	69.13
			(7.53)	(35.63)	(1.25)		(4.24)	(29.78)	(1.34)	
EF/A	1	5	9.36***	0.40***	0.04	71.05	10.01***	0.40***	-0.01	71.05
			(8.77)	(42.75)	(0.17)		(6.08)	(31.70)	(-0.31)	
GS	1	5	11.51***	0.37***	0.11	61.86	11.25***	0.37***	0.01	61.85
			(10.06)	(25.69)	(0.38)		(6.16)	(20.62)	(0.31)	

5.5.1 Robustness Checks

I document a battery of additional tests to examine the robustness of my VIX-based cross-sectional trading strategies in Appendix E.3. I first examine whether the profitability of my VIX-based trading strategies is robust to alternative definitions of what a "substantially high" VIX means. Recall that in the previous tables, VIX is defined as substantially high when current VIX is 10% higher than its prior 25-day average, where the 25-day window represents the number of trading days in a month there are 25 trading days in month. I also consider alternative horizons of prior 1-day, 5-day, 10-day, 60-day, 120-day and 250-day average. Panel A of Table 5 shows that the profitability of my VIX-based trading strategies is not very sensitive to the choice of VIX definition horizon. The return differential between any two different horizons is less than 5%, with the returns being higher for the 10-day and 25-day horizons and lower for either shorter or longer horizon. I also use 0%, 5%, 15% and 20% as alternative thresholds for my definition of substantially high VIX. Table E.24 shows that the excess returns are positive and salient across all these thresholds.

I then test whether transaction costs can eliminate the profitability of my trading strategies in Panel B of Table 5.5. Following Han et al. (2013), I calculate Break-even trading cost (BETC) to check whether my VIX-based trading strategies survives the transaction costs without taking a stand on actual transaction costs. Break-even trading cost is the trading cost that makes the average actual returns of my VIX-based trading strategies become zero. The higher BETC of a trading strategy, the more likely that this trading strategy is profitable after the transaction costs. Panel B of Table 5 reveals that all estimated BETCs are larger than 50 basis points. This demonstrates that the transaction costs must be unrealistically high to eliminate the profitability of my VIX-based trading strategies.

Table 5.5 Returns and BETCs on Different VIX Trading Signal Horizons

This table reports the returns and break-even transaction costs of VIX-based trading strategies if I choose alternative horizons to compare the VIX with its past average. For instance, I define a high VIX day if current VIX is at least 10% higher than its prior 10-day average. In this table, I show the results when using 1-day, 5-day, 10-day, 25-day, 60-day, 120-day and 250-day horizons. Panel A reports the returns of my VIX-based trading strategies when using different horizon average to define high VIX, and the returns are in percentages. Panel B reports the corresponding break-even transaction costs and the costs are in basis points. The sample period is from 1990/01/01 to 2016/04/30.

Panel A. Profitability on different trading signal horizons									
	P	I	1-day	5-day	10-day	25-day	60-day	120-day	250-day
ME	1	10	38	41.81	42.51	43.21	42.44	40	37.91
Age	1	10	26.24	29.05	29.25	28.95	30.08	28.21	26.15
Sigma	10	1	36.34	38.43	38.67	38.13	39.34	37.44	35.62
E/BE	1	10	31.81	34.03	34.11	33.69	33.78	32.89	30.8
D/BE	1	10	29.38	31.04	30.91	31.34	31.76	30.46	29
PPE/A	1	10	22.93	23.26	23.08	22.51	22.64	23.56	23.61
RD/A	10	1	32.58	33.29	32.58	31.57	32.04	31.62	30.38
BE/ME	10	1	39.54	40.36	40.11	40.77	38.9	38.53	37.54
EF/A	1	10	30.97	29.52	29.66	29.81	28.68	28.84	29.1
GS	1	10	31.88	31.97	32.45	32.05	31.59	31.65	30.75
BE/ME	1	5	22.27	23.02	23.02	22.16	23.26	23.5	22.68
EF/A	10	5	21.32	22.99	23.37	23	23.96	23.3	22.55
GS	10	5	20.78	22.01	21.98	22.68	23.49	22.64	21.95
BE/ME	10	5	40.58	42.14	41.9	41.7	40.93	40.8	38.99
EF/A	1	5	32.53	32.74	33.27	33.05	32.88	32.37	31.88
GS	1	5	33.22	34.54	34.98	35.28	35.63	34.84	33.25
Panel B. BETC on different trading signal horizons									
	P	I	1-day	5-day	10-day	25-day	60-day	120-day	250-day
ME	1	10	116.53	124.14	124.57	143.25	177.3	205.27	220.78
Age	1	10	80.47	86.25	85.72	95.97	125.67	144.78	152.31
Sigma	10	1	111.45	114.12	113.32	126.41	164.37	192.12	207.45
E/BE	1	10	97.56	101.04	99.97	111.69	141.15	168.77	179.38
D/BE	1	10	90.09	92.16	90.57	103.92	132.7	156.34	168.9
PPE/A	1	10	70.3	69.07	67.65	74.63	94.6	120.92	137.48
RD/A	10	1	99.92	98.87	95.49	104.67	133.86	162.29	176.92
BE/ME	10	1	121.26	119.84	117.56	135.18	162.53	197.72	218.62
EF/A	1	10	94.98	87.64	86.93	98.84	119.84	147.98	169.44
GS	1	10	97.77	94.94	95.11	106.26	131.98	162.43	179.06
BE/ME	1	5	68.29	68.34	67.45	73.47	97.18	120.62	132.07
EF/A	10	5	65.37	68.26	68.49	76.26	100.1	119.58	131.33
GS	10	5	63.73	65.37	64.41	75.2	98.13	116.2	127.83
BE/ME	10	5	124.43	125.13	122.78	138.26	171	209.37	227.04
EF/A	1	5	99.74	97.22	97.5	109.58	137.36	166.13	185.67
GS	1	5	101.86	102.56	102.53	116.98	148.85	178.82	193.64

Some studies choose to set the transaction costs at a conservative rate of 25 basis points (see, Lynch and Balduzzi, 2000) , other studies choose to calculate the realized transaction costs (Frazzini et al., 2012). For instance, Frazzini et al. (2012) find the trading costs is 11.21 basis points for large-cap stocks and 21.27 basis points for small-cap stocks. In my case, the lowest BETC for trading on size portfolio is 116.53 basis points calculated with 1-day VIX benchmark, and even the lowest BETC for size portfolio is sufficiently higher than the 21.27 bps realistic transaction costs in Frazzini et al. (2012).

I also find that the BETCs increase almost monotonically with the length of the horizon used in the definition of VIX strategies in Panel B of Table 5. When longer horizons are used as benchmarks, the average VIX tend to be more stable and consequently the investor will have consecutive high or low VIX days without trading. Take the 25-day window period as an example, the BETCs range from 73.47 to 143.25 basis points, which is much larger than 50 basis points. This is because BETCs depend on both the profitability and the trading frequency. In other words, for any given profitability, a low trading frequency leads to a high BETC. My trading strategies have such reasonably high BETCs which rely not only on the high returns but also on the low transaction frequency. Take 25-day window period size portfolio trading strategy as an example, the actual number of actual transactions is 1356 out of 11329 trading days, which means in this sample period the average portfolio holding time length is more than 8 trading days.

Furthermore, to understand whether macroeconomic factors and other risk factors explain the superior performance of my VIX-based trading strategies, I also adjust the excess returns for the daily difference between the yield on interbank loans and 3-month treasuries (TED spread), and the difference between the yield on 10-year and 3-month treasuries (term spread, or TS) in Table E.18. I find economically large and statistically significant alphas when these factors are included in the regressions. I also calculate the bid-ask spread for all the sixteen long-short portfolios, i.e., the average bid-ask spread of high sentiment-prone portfolio minus that of low sentiment-prone portfolio, and include it as a control variable into the respective regression. Based on the results in Table E.19, the effect of TA sentiment on returns is unaffected after controlling for cross-sectional variations in the bid-ask spread. Interestingly, the difference between Moody's AAA and Baa bond yields (Default Spread, or DS) could explain the excess return very well. I find only 8 out of 16 trading strategies still have significant and large positive abnormal return after controlling for Default Spread.

Moreover, I test the robustness of returns of each VIX-based trading strategies by changing the benchmark portfolio from its corresponding long-short portfolio to the overall market index returns. I find that my trading strategies reasonably outperform the S&P 500 Index Return. Figure E.3 examines the persistence of the performance of my VIX-based trading strategies. Figure E.3 shows that the annual average returns of each trading strategy is consistently higher than the S&P500 index return every calendar year in my sample. I also investigate whether the profitability of my trading strategies is sensitive to choice of alternative implied volatility indexes. I show that strategies that based on trading signal from other indexes, such as the CBOE S&P 100 Volatility Index (VXO), the CBOE NASDAQ Volatility Index (VXN), and the CBOE DJIA Volatility Index (VXD), generate significant profits. The results are respectively shown in Table E.20, Table E.21 and Table E.22.

Additionally, I design two additional sets of VIX-based trading strategies. The trading rule for the first set involves holding sentiment-prone stocks and shorting sentiment-immune stocks when VIX is low and shorting sentiment-prone stocks and longing sentiment-immune stocks when VIX is higher than its prior moving average. Table E.25 shows that this trading rule generates significant positive excess returns and high Sharpe ratios, albeit the magnitudes of the excess returns are smaller than those reported in my baseline results. The second set of trading strategies is implemented on the decile portfolios. In this set, the trading rule involves holding sentiment-prone decile when VIX is low and shorting the sentiment-prone decile when VIX is substantially high. See Table E.26 for test results. I show that this trading rule also generates higher returns and higher Sharpe ratios than the benchmark strategy of buy-and-hold sentiment-prone decile portfolios. Thus, the performance of both sets of trading strategies indicate that VIX index has a value in timing the market. However, the baseline set of trading strategies, which requires shifting asset allocations conditional on VIX, is more practical than these two alternative sets of trading strategies. This is because these alternative ones require short-selling, which can be costly and limited for some investors. For example, mutual funds are typically prohibited from short-selling.

Finally, VIX is an index conveyed from S&P 500 stock index options, where S&P 500 index members are practically the largest stocks in US stock market. In this case, I argue that VIX is a very conservative measure of the overall market sentiment. Also, due to the fact that size-based portfolio returns are highly correlated with other characteristics based portfolio returns, one may question the profitability of VIX on timing those portfolios are mainly due to the size effect. To mitigate the effect of size, I also examine the profitability of VIX-based timing strategy on value-weighted cross-sectional returns in Table E.23. It turns out that when applying VIX timing rules on value-weighted returns, the profitability is slightly smaller than applying it on equal-weighted returns. Still, the raw and risk-adjusted returns of VIX-based trading strategy remain significantly positive in most cases.

5.6 Conclusion

Chapter 5 explores the cross-sectional profitability of VIX-based trading strategies. My trading strategies involve holding sentiment-prone stocks when VIX is low and holding sentiment-immune stocks when VIX is high. The motivation of my trading strategies is the short-run negative VIX-return relation arises from the delayed arbitrage theory (Abreu and Brunnermeier, 2002). In this chapter, VIX is deemed as a daily measure of investor sentiment, and due to the lack of coordinated actions among arbitrageurs, the mispricing caused by investor sentiment may even amplify, which leads to a short-run negative VIX-return relationship. Interpreting VIX-return relation from behavioural perspective enables us to interpret the negative short-run relation as the return momentum caused by delayed arbitrage and interpret the positive long-run relation as the correction of mispricing. Unlike most existing literature that focus on interpreting the positive VIX-return relation, I argue that delayed arbitrage leads to high returns for sentiment-prone stocks following a decline in VIX (high sentiment), and that flight-to-quality leads to the better performance of sentiment-immune stocks over sentiment-prone stocks following an increase in VIX (low sentiment).

Consistent with my explanation, I find that VIX strongly and negatively associates with one-day forward stock return in the in-sample predictive regressions. This finding is robust with or without controlling for other well-documented risk factors. I conduct various robustness tests to further demonstrate that seeing VIX as investor sentiment could better explain the return momentum and reversal. For instance, I find the effect of VIX is stronger during the high sentiment period, which is consistent with the argument that sentiment plays a less important role due to the short-sell constraints in low sentiment period.

Following on the short-run negative VIX-return pattern, I devise trading strategies to capture the return momentum attributed by investor sentiment. I not only cover the value and size rotation based on VIX, but also explore the profitability of VIX timing over a large spectrum of cross-sectional portfolios based on the extent to which a stock is exposed to market-wide investor sentiment. I find that my VIX-based trading strategies generate significant excess returns and higher Sharpe ratios. The excess returns of my trading strategies cannot be fully explained by Fama-French five factors, momentum factors, liquidity, and other macroeconomic variables. In addition to their strong profitability, my trading strategies do not require short-selling. The strong and consistent profitability of applying VIX-based trading strategy on different cross-sectional sentiment-based portfolios also supports the investor sentiment perspective explanation on VIX-return relation.

To sum up, I contribute to existing literature by combine the delayed arbitrage theory and flight-to-quality to explain the pattern between sentiment-based cross-sectional stock returns and VIX. I show strong empirical evidence supporting the short-run return momentum caused by VIX. From the behavioural finance point of view, I use the negative VIX-return connection to design highly profitable and practical trading strategies which is to shift asset allocation to sentiment-prone stocks when VIX is low and to sentiment-immune stocks when VIX is high.

Chapter 6

Conclusion

This thesis focuses on the effect of investor sentiment on cross-sectional stock returns. It is essential to study investor sentiment as it has been widely applied to examine a variety of financial issues and anomalies. Yet, I find a few gaps in existing literature about investor sentiment. This thesis mainly contributes to fill in two research gaps. The first gap is that no theory has demonstrated the effect of investor sentiment in the cross-section, while empirical tests mostly are on the cross-sectional level. The second gap is that most studies explore the predictability of investor sentiment on return reversal while few examine the existence of sentiment-induced momentum. Inspired by the delayed arbitrage theory, this thesis argues that delayed arbitrage leads to the persistence of mispricing caused by investor sentiment, and therefore one can test the momentum effect of investor sentiment in the short-run with higher frequency data.

There is no consensus as to the effect of investor sentiment in literature. Previous literature finds the effect of investor sentiment on the aggregate stock market controversial but finds demonstrated evidence in the cross-sectional stock market. One explanation for those two seemingly conflicting findings is that the sentiment-prone level of stocks varies in the cross-section. The first essay theoretically demonstrates that the effect of investor sentiment is stronger on the cross-section than on the aggregate market because assets have different levels of sentiment sensitivity.

The extended model inspires me to decompose investor sentiment into long- and short-term components and test their effects in the empirical part of the first essay. In the empirical parts, I sort the stocks based on the sentiment-prone level in the cross-section and regress the cross-sectional return premium of sentiment-prone stocks over sentiment-immune stocks on the decomposed short-run incremental sentiment and long-run previous sentiment level. The empirical tests in Chapter 3 document a negative relationship between the long-run sentiment component and subsequent stock returns and positive association between the short-run sentiment component and contemporaneous stock returns. I further investigate the explanatory power of decomposed investor sentiment for the cross-sectional decile portfolio returns and further confirm the opposite effect of long-run and short-run investor sentiment. By decomposing investor sentiment, I integrate the literature that only focuses on the positive contemporaneous relationship between sentiment shock and stock returns with the studies that find negative predictability of lagged sentiment on asset returns. The decomposition of investor sentiment achieves substantial improvement in explaining stock returns both at the cross-sectional level and at the portfolio level.

The multiple risky-assets noise trader risk model enables the future research to mathematically demonstrate how investors trade stocks during periods with varying sentiment level. The theoretical derivation could also be extended to the research on the relationship between investor sentiment and comovement in return (or comovement in liquidity).

The main contribution of the second essay is connecting technical analysis with investor sentiment. I propose that technical analysis is a means of capturing investor sentiment. To examine this argument, I construct a TA sentiment index from the forecasts of applying 2,127 technical trading on the overall market index S&P 500. I show that this TA index predicts the momentum and reversal of the cross-sectional stock returns and future crash risk just as a sentiment indicator would do. A rise in the TA sentiment accompanies high contemporaneous returns and predicts higher near-term returns, lower subsequent returns and higher crash risk in the cross-section. These results are broadly consistent with the explanation that the lack of synchronization induces rational arbitrageurs to ride the mispricing before it's corrected. A simple trading strategy based on TA sentiment index earns substantial risk-adjusted returns. I find that both the predictability and the profitability of this TA index are stronger among the widely-acknowledged sentiment-prone stocks than among the sentiment-immune stocks.

It is of essence to test the argument that connect technical analysis with investor sentiment. This is the first attempt to explain the usefulness of technical analysis from a behavioral finance perspective and design a series of empirical tests to formally examine this point of view. Technical analysis is widely used in the industry, however, the logic beneath its prevailing application does not gain enough attention in academia. With the development of behavioral finance, it is of essence to help economists and investors to understand technical analysis better from a new perspective. This research also has a practical value in terms of the measurement of investor sentiment. The investor sentiment indicator at high frequency is not easy to measure in the real market. By establishing the connection between technical analysis and investor sentiment, this essay provides a new of measuring investor sentiment for any asset market both at individual asset level and at the overall market level at different frequency.

The future research in the direction is closely related to the challenges in the research area about investor sentiment. One challenge in investigating investor sentiment is that it is not directly observable. It is difficult to find a good test ground for identify the effect of investor sentiment empirically. The same issue occurs when it comes to the measurement of investor sentiment. Though I have brought up a new investor sentiment indicator based on technical trading rules and verified this TA indicator by showing its ability to predict the return momentum, reversal and future crash risk as a sentiment indicator would do, more identification tests are in need to demonstrate that the predictability of TA sentiment indicator in the cross-section are due to investor sentiment rather than microeconomic characteristics captured by technical trading signals. Another potential contribution the future studies could made is to develop a theoretical model to demonstrate the connections between investor sentiment and technical analysis. A certain degree of subjectivity remains in my argument that technical analysis captures investor sentiment. It would be more convincing if in the future a theoretical model demonstrate that investors can make more accurate inference about investor sentiment from both current price and historical prices.

The third essay combines the effect of investor sentiment with the delayed arbitrage theory. Unlike the literature that focuses on the reversal effect of investor sentiment, the third essay argues that the delayed arbitrage makes the mispricing. While most behavioral papers explore the reversal effect of investor sentiment, I find that a trading strategy that ride the sentiment-induced momentum also generates substantial risk-adjusted abnormal returns. My trading strategy is to shift investment allocation between sentiment-prone and sentiment-immune stocks using trading signals based on VIX. To put it in a more straightforward way, the trading strategy is to hold sentiment-prone asset when market is bullish (VIX is low) and to hold sentiment-immune asset when market is bearish (VIX is substantially high). This simple trading strategy that generates substantial abnormal returns after adjusting for Fama-French five factors and Momentum factor. The average annualized risk-adjusted alpha of applying trading strategies on four typical sentiment-based portfolios is higher than 10%. TA sentiment trading strategy outperforms the well-known momentum strategy. I used the break-even transaction costs and the higher than 50 basis points break-even transaction costs indicate that my trading strategy could survive transaction cost adjustments.

The third essay has a strong practical value. The practitioners could apply this trading strategy on any markets with implied volatility index available. To improve the profitability, one can also test this trading strategy with the ETFs, especially switching asset allocation among the small-cap and large-cap ETFs and run more back-testing on the performance of this trading strategy.

In summary, this thesis encompasses the explanation for a few gaps I found in previous literature on investor sentiment. The three essays in this thesis deepen the understanding in the relationship between investor sentiment and stock return in the cross-section. This thesis especially emphasizes the delayed arbitrage theory and explore the momentum effect of investor sentiment on stock return and test the profitability of riding the sentiment-induced momentum in the cross-section.

References

Abreu, D., and M. K. Brunnermeier, 2002, Synchronization risk and delayed arbitrage, *Journal of Financial Economics* 66, 341–360.

Abreu, D., and M. K. Brunnermeier, 2003, Bubbles and crashes, *Econometrica* 71, 173–204.

Albuquerque, R., 2012, Skewness in stock returns: Reconciling the evidence on firm versus aggregate returns, *Review of Financial Studies* 25, 1630–1673.

Allen, H., and M. P. Taylor, 1990, Charts, noise and fundamentals in the london foreign exchange market, *Economic Journal* 100, 49–59.

Amihud, Y., C. M. Hurvich, and Y. Wang, 2009, Multiple-predictor regressions: Hypothesis testing, *Review of Financial Studies* 22, 413–434.

Antoniou, C., J. A. Doukas, and A. Subrahmanyam, 2013, Cognitive dissonance, sentiment, and momentum, *Journal of Financial and Quantitative Analysis* 48, 245–275.

Aruoba, S. B., F. X. Diebold, and C. Scotti, 2009, Real-time measurement of business conditions, *Journal of Business and Economic Statistics* 27, 417–427.

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

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

Baker, M., and J. Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129–151.

Baker, M., J. Wurgler, and Y. Yuan, 2012, Global, local, and contagious investor sentiment, *Journal of Financial Economics* 104, 272–287.

Baker, S., N. Bloom, and S. Davis, 2016, Measuring economic policy uncertainty, *Quarterly Journal of Economics* 131, 1593–1636.

Bakshi, G., and N. Kapadia, 2003, Delta-hedged gains and the negative market volatility risk premium, *Review of Financial Studies* 16, 527–566.

Banerjee, P. S., J. S. Doran, and D. R. Peterson, 2007, Implied volatility and future portfolio returns, *Journal of Banking and Finance* 31, 3183–3199.

Barber, B., T. Odean, and N. Zhu, 2008, Do retail trades move markets?, *Review of Financial Studies* 22, 151–186.

Barber, Brad M, and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *The Review of Financial Studies* 21, 785–818.

Barberis, N., and A. Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

Barberis, N., A. Shleifer, and R. Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Barberis, N., A. Shleifer, and J. Wurgler, 2005, Comovement, *Journal of Financial Economics* 75, 283–317.

Barberis, N., and R. Thaler, 2003, A survey of behavioral finance, *Handbook of the Economics of Finance* 1, 1053–1128.

Bekaert, G., and M. Hoerova, 2014, The vix, the variance premium and stock market volatility, *Journal of Econometrics* 183, 181–192.

Ben-Rephael, A., S. Kandel, and A. Wohl, 2012, Measuring investor sentiment with mutual fund flows, *Journal of Financial Economics* 104, 363–382.

Berger, D., and H. J. Turtle, 2015, Sentiment bubbles, *Journal of Financial Markets* 23, 59–74.

Berger, D., and H.J. Turtle, 2012, Cross-sectional performance and investor sentiment in a multiple risk factor model, *Journal of Banking and Finance* 36, 1107–1121.

Beveridge, S., and C. R. Nelson, 1981, A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the 'business cycle', *Journal of Monetary Economics* 7, 151–174.

Bhojraj, S., R. J. Bloomfield, and W. Tayler, 2009, Margin trading, overpricing, and synchronization risk, *Review of Financial Studies* 22, 2059–2085.

Billingsley, R. S., and D. M. Chance, 1996, Benefits and limitations of diversification among commodity trading advisors - how to diversify a managed, futures program, *Journal of Portfolio Management* 23, 65.

Black, F., 1986, Noise, *Journal of Finance* 41, 528–543.

Blanchard, O., and M. Watson, 1982, Bubbles, rational expectations and financial markets, *National Bureau of Economic Research Working Paper* No. 945.

Blume, L., D. Easley, and M. Ohara, 1994, Market statistics and technical analysis: The role of volume, *Journal of Finance* 49, 153–181.

Brock, W., J. Lakonishok, and B. Lebaron, 1992, Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance* 47, 1731–1764.

Brown, D., and R. H. Jennings, 1989, On technical analysis, *Review of Financial Studies* 2, 527–551.

Brown, G., and M. Cliff, 2004, Investor sentiment and the near-term stock market, *Journal of Empirical Finance* 11, 1–27.

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

Brunnermeier, K., and S. Nagel, 2004, Hedge funds and the technology bubble, *Journal of Finance* 59, 2013–2040.

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

Campbell, J., J. Hilscher, and J. Szilagyi, 2011, Predicting financial distress and the performance of distressed stocks .

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

Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Cespa, G., and X. Vives, 2015, The beauty contest and short-term trading, *Journal of Finance* 70, 2099–2154.

Chan, L., N. Jegadeesh, and J. Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681–1713.

Chau, F., R. Deesomsak, and M. Lau, 2011, Investor sentiment and feedback trading: Evidence from the exchange-traded fund markets, *International Review of Financial Analysis* 20, 292–305.

Chen, J., H. Hong, and J. Stein, 2001, Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices, *Journal of Financial Economics* 61, 345–381.

Chen, N., R. Kan, and M. H. Miller, 1993, Are the discounts on closed-end funds a sentiment index?, *Journal of Finance* 48, 795–800.

Chen, R., N.and Kan, and M. Miller, 1993, A rejoinder, *Journal of Finance* 48, 809–810.

Chopra, N., C. Lee, A. Shleifer, and R. Thaler, 1993a, Summing up, *Journal of Finance* 48, 811–812.

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

Chou, P. H., C. H. Hsieh, and C. H. H. Shen, 2016, What explains the orange juice puzzle: Sentiment, smart money, or fundamentals?, *Journal of Financial Markets* 29, 47–65.

Chung, S., C. Hung, and C. Yeh, 2012, When does investor sentiment predict stock returns?, *Journal of Empirical Finance* 19, 217–240.

Clements, A., and A. Silvennoinen, 2013, Volatility timing: How best to forecast portfolio exposures, *Journal of Empirical Finance* 24, 108–115.

Cochrane, J. H., F. Longstaff, and P. Santa-Clara, 2008, Two trees, *Review of Financial Studies* 21, 347–385.

Cohen, L., and D. Lou, 2012, Complicated firms, *Journal of Financial Economics* 104, 383–400.

Copeland, M., and T. Copeland, 1999, Market timing: Style and size rotation using the vix, *Financial Analysts Journal* 73–81.

Coval, J. D., and T. Shumway, 2001, Expected option returns, *Journal of Finance* 56, 983–1009.

Cowles, A., 1933, Can stock market forecasters forecast?, *Econometrica: Journal of the Econometric Society* 309–324.

Da, Z., J. Engelberg, and P. Gao, 2014, The sum of all fears investor sentiment and asset prices, *Review of Financial Studies* 28, 1–32.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839–1885.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 2001, Overconfidence, arbitrage, and equilibrium asset pricing, *Journal of Finance* 56, 921–965.

Datst, D.M., 2003, The art of asset allocation: Asset allocation principles and investment strateies for any market, *McGraw-Hill Companies, Inc* .

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

De Long, J., A. Shleifer, L. Summers, and R. Waldmann, 1990b, Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379–395.

DeVault, L., R. Sias, and L. Starks, 2014, Who are the sentiment traders? evidence from the cross-section of stock returns and demand .

Ebert, S., and C. Hilpert, 2016, Skewness preference and the popularity of technical analysis, *Working Paper* .

Edmans, A., I. Goldstein, and W. Jiang, 2015, Feedback effects, asymmetric trading, and the limits to arbitrage, *American Economic Review* 105, 3766–97.

Elton, E. J., M. J. Gruber, and J. A. Busse, 1998, Do investors care about sentiment?, *Journal of Business* 71, 477–500.

Engelberg, J., A. Reed, and M. Ringgenberg, 2012, How are shorts informed? short sellers, news, and information processing, *Journal of Financial Economics* 105, 260–278.

Engle, R., and A. Mistry, 2014, Priced risk and asymmetric volatility in the cross section of skewness, *Journal of Econometrics* 182, 135–144.

Fama, E., and M. E Blume, 1966, Filter rules and stock-market trading, *Journal of Business* 39, 226–241.

Fama, E. F., and K. R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Feng, S., N. Wang, and E. Zychowicz, 2016, Sentiment and the performance of technical indicators, *Working Paper* .

Fisher, K., and M. Statman, 2003, Consumer confidence and stock returns, *Journal of Portfolio Management* 30, 115–127.

Fleming, J., C. Kirby, and B. Ostdiek, 2001, The economic value of volatility timing, *Journal of Finance* 56, 329–352.

Fleming, J., C. Kirby, and B. Ostdiek, 2003, The economic value of volatility timing using "realized" volatility, *Journal of Financial Economics* 67, 473–509.

Fleming, Jeff, Barbara Ostdiek, and Robert E Whaley, 1995, Predicting stock market volatility: A new measure, *Journal of Futures Markets* 15, 265–302.

Frazzini, A., R. Israel, and T. Moskowitz, 2012, Trading costs of asset pricing anomalies, *Working Paper* .

Frazzini, A., and O. A. Lamont, 2008, Dumb money: mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* 88, 299–322.

Garcia, D., 2013, Sentiment during recessions, *Journal of Finance* 68, 1267–1300.

Giot, P., 2005, Relationships between implied volatility indexes and stock index returns - are implied volatility indexes leading indicators?, *Journal of Portfolio Management* 31, 92–+.

Glabadanidis, P., 2014, The market timing power of moving averages: evidence from us reits and reit indexes, *International Review of Finance* 14, 161–202.

Goh, J., F. Jiang, J. Tu, and G. Zhou, 2013, Forecasting government bond risk premia using technical indicators .

Greenwood, Robin, and Stefan Nagel, 2009, Inexperienced investors and bubbles, *Journal of Financial Economics* 93, 239–258.

Griffin, J., J. Harris, T. Shu, and S. Topaloglu, 2011, Who drove and burst the tech bubble?, *Journal of Finance* 66, 1251–1290.

Grossman, S., and J. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American economic review* 70, 393–408.

Grundy, B., and M. McNichols, 1989, Trade and the revelation of information through prices and direct disclosure, *Review of Financial Studies* 2, 495–526.

Guo, M., and C. Xia, 2012, Technical trading and strategic liquidity provision, Technical report, Working Paper, Hong Kong University of Science and Technology.

Han, X., and Y. W. Li, 2017, Can investor sentiment be a momentum time-series predictor? evidence from china, *Journal of Empirical Finance* 42, 212–239.

Han, Y., K. Yang, and G. Zhou, 2013, A new anomaly: The cross-sectional profitability of technical analysis, *Journal of Financial and Quantitative Analysis* 48, 1433–1461.

Han, Y., G. Zhou, and Y. Zhu, 2016, A trend factor: Any economic gains from using information over investment horizons?, *Journal of Financial Economics* 122, 352–375.

Harvey, C., and A. Siddique, 2000, Conditional skewness in asset pricing tests, *Journal of Finance* 55, 1263–1295.

Hellwig, M. F., 1982, Rational expectations equilibrium with conditioning on past prices - a mean variance example, *Journal of Economic Theory* 26, 279–312.

Henriksson, R., and R. Merton, 1981, On market timing and investment performance. ii. statistical procedures for evaluating forecasting skills, *Journal of Business* 513–533.

Hirshleifer, D., 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533–1597.

Hoffmann, A., and H. Shefrin, 2014, Technical analysis and individual investors, *Journal of Economic Behavior & Organization* 107, 487–511.

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

Huang, D., F. Jiang, J. Tu, and G. Zhou, 2015, Investor sentiment aligned: A powerful predictor of stock returns, *Review of Financial Studies* 28, 791–837.

Hurst, B., Y. Ooi, and L. Pedersen, 2013, Demystifying managed futures, *Journal of Investment Management* 11, 42–58.

Huynh, T. D., and D. R. Smith, 2017, Stock price reaction to news: The joint effect of tone and attention on momentum, *Journal of Behavioral Finance* 18, 304–328.

Jackwerth, J. C., and M. Rubinstein, 1996, Recovering probability distributions from option prices, *Journal of Finance* 51, 1611–1631.

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

Jensen, M. C., and G. A. Benington, 1970, Random walks and technical theories: Some additional evidence, *Journal of Finance* 25, 469–482.

Jiang, F., J. Lee, X. Martin, and G. Zhou, 2017, Manager sentiment and stock returns, *Working Paper* .

Johannes, M., N. Polson, and J. Stroud, 2002, Sequential optimal portfolio performance: Market and volatility timing, *Working Paper* .

Kaplanski, G., and H. Levy, 2010, Sentiment and stock prices: The case of aviation disasters, *Journal of Financial Economics* 95, 174–201.

Kavajecz, K. A., and E. R. Odders-White, 2004, Technical analysis and liquidity provision, *Review of Financial Studies* 17, 1043–1071.

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

Kurov, A., 2008, Investor sentiment, trading behavior and informational efficiency in index futures markets, *Financial Review* 43, 107–127.

Kurov, A., 2010, Investor sentiment and the stock market's reaction to monetary policy, *Journal of Banking and Finance* 34, 139–149.

LeBaron, B., 1999, Technical trading rule profitability and foreign exchange intervention, *Journal of International Economics* 49, 125–143.

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

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

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

Liao, T., C. Huang, and C. Wu, 2011, Do fund managers herd to counter investor sentiment?, *Journal of Business Research* 64, 207–212.

Ljungqvist, A., and W. Qian, 2016, How constraining are limits to arbitrage?, *Review of Financial Studies* 29, 1975–2028.

Lo, A. W., H. Mamaysky, and J. Wang, 2000, Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation, *Journal of Finance* 55, 1705–1765.

Lo, Andrew W, and Jasmina Hasanhodzic, 2010, The evolution of technical analysis, *Financial Prediction from Babylonian Tablets to Bloomberg Terminals. Hoboken, NI: Wiley* .

Low, Cheekiat, 2004, The fear and exuberance from implied volatility of s&p 100 index options, *Journal of Business* 77, 527–546.

Lucas, R. E., 1978, On the size distribution of business firms, *The Bell Journal of Economics* 508–523.

Lui, Y., and D. Mole, 1998, The use of fundamental and technical analyses by foreign exchange dealers: Hong kong evidence, *Journal of International Money and Finance* 17, 535–545.

Lukac, L., B. Brorsen, and S. Irwin, 1988, A test of futures market disequilibrium using twelve different technical trading systems, *Applied Economics* 20, 623–639.

Lynch, A. W., and P. Balduzzi, 2000, Predictability and transaction costs: The impact on rebalancing rules and behavior, *Journal of Finance* 55, 2285–2309.

Malkiel, Burton Gordon, 1999, *A random walk down Wall Street: Including a life-cycle guide to personal investing* (WW Norton and Company).

McQueen, G., and S. Thorley, 1994, Bubbles, stock returns, and duration dependence, *Journal of Financial and Quantitative Analysis* 29, 379–401.

Menkhoff, L., 1997, Examining the use of technical currency analysis, *International Journal of Finance and Economics* 2, 307–318.

Menkhoff, L., 2010, The use of technical analysis by fund managers: International evidence, *Journal of Banking and Finance* 34, 2573–2586.

Menkhoff, L., and M. Taylor, 2007, The obstinate passion of foreign exchange professionals: technical analysis, *Journal of Economic Literature* 45, 936–972.

Merton, R. C, 1980, On estimating the expected return on the market: An exploratory investigation, *Journal of Financial Economics* 8, 323–361.

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

Nagel, S., 2012, Evaporating liquidity, *Review of Financial Studies* 25, 2005–2039.

Narayan, P., S. Mishra, S. Narayan, and K. Thuraisamy, 2015, Is exchange rate trading profitable?, *Journal of International Financial Markets, Institutions and Money* 38, 217–229.

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

Neely, C., 1997, Technical analysis in the foreign exchange market: a layman's guide, *Federal Reserve Bank of St. Louis Review* 23–38.

Neely, C., and P. Weller, 2001, Technical analysis and central bank intervention, *Journal of International Money and Finance* 20, 949–970.

Neely, C. J., and P. A. Weller, 2003, Intraday technical trading in the foreign exchange market, *Journal of International Money and Finance* 22, 223–237.

Newey, W. K., and K. D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Osler, C. L., 2003, Currency orders and exchange rate dynamics: An explanation for the predictive success of technical analysis, *Journal of Finance* 58, 1791–1819.

Park, C., and S. Irwin, 2007, What do we know about the profitability of technical analysis?, *Journal of Economic Surveys* 21, 786–826.

Pontiff, J., 1996, Costly arbitrage: Evidence from closed-end funds, *Quarterly Journal of Economics* 111, 1135–1151.

Pring, M. J., 1991, *Technical analysis, explained 'the successful investors' guide to spotting investment trends and turning points* (McGraw Hill).

Qi, M., and Y. Wu, 2006, Technical trading-rule profitability, data snooping, and reality check: Evidence from the foreign exchange market, *Journal of Money Credit and Banking* 38, 2135–2158.

Qiu, L., and I. Welch, 2004, Investor sentiment measures, Working paper, National Bureau of Economic Research.

Ritter, Jay R, and Ivo Welch, 2002, A review of ipo activity, pricing, and allocations, *Journal of Finance* 57, 1795–1828.

Schauten, M. B. J., R. Willemstein, and R. C. J. Zwinkels, 2015, A tale of feedback trading by hedge funds, *Journal of Empirical Finance* 34, 239–259.

Scheinkman, Jose A, and Wei Xiong, 2003, Overconfidence and speculative bubbles, *Journal of political Economy* 111, 1183–1220.

Schwager, Jack D, 2012, *Market wizards: Interviews with top traders* (John Wiley and Sons).

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

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

Singer, Eleanor, et al., 2002, The use of incentives to reduce nonresponse in household surveys, *Survey nonresponse* 51, 163–177.

Smith, D. M., N. Wang, Y. Wang, and E. J. Zychowicz, 2016, Sentiment and the effectiveness of technical analysis: Evidence from the hedge fund industry, *Journal of Financial and Quantitative Analysis* 51, 1991–2013.

Solt, M. E., and M. Statman, 1988, How useful is the sentiment index?, *Financial Analysts Journal* 44, 45–55.

Stambaugh, R. F., 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

Stambaugh, R. F., J. Yu, and Y. Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288–302.

Stambaugh, R. F., J. Yu, and Y. Yuan, 2014, The long of it: Odds that investor sentiment spuriously predicts anomaly returns, *Journal of Financial Economics* 114, 613–619.

Stambaugh, R. F., and Y. Yuan, 2017, Mispricing factors, *Review of Financial Studies* 30, 1270–1315.

Sullivan, Ryan, Allan Timmermann, and Halbert White, 1999, Data-snooping, technical trading rule performance, and the bootstrap, *Journal of Finance* 54, 1647–1691.

Sun, L. C., M. Najand, and J. C. Zhen, 2016, Stock return predictability and investor sentiment: A high-frequency perspective, *Journal of Banking and Finance* 73, 147–164.

Taylor, M. P., and H. Allen, 1992, The use of technical analysis in the foreign exchange market, *Journal of International Money and Finance* 11, 304–314.

Taylor, Nick, 2014, The rise and fall of technical trading rule success, *Journal of Banking and Finance* 40, 286–302.

Temin, P., and H. Voth, 2004, Riding the south sea bubble, *American Economic Review* 94, 1654–1668.

Tetlock, P. C., 2007, Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139–1168.

Treynor, J., and K. Mazuy, 1966, Can mutual funds outguess the market, *Harvard business review* 44, 131–136.

Treynor, J. L., and R. Ferguson, 1985, In defense of technical analysis, *Journal of Finance* 40, 757–773.

Tu, A. H., W. L. G. Hsieh, and W. S. Wu, 2016, Market uncertainty, expected volatility and the mispricing of s&p 500 index futures, *Journal of Empirical Finance* 35, 78–98.

Uhl, M. W., 2017, Emotions matter: Sentiment and momentum in foreign exchange, *Journal of Behavioral Finance* 18, 249–257.

Ülkü, N., and E. Prodan, 2013, Drivers of technical trend-following rules' profitability in world stock markets, *International Review of Financial Analysis* 30, 214–229.

Verrecchia, R. E., 2001, Essays on disclosure, *Journal of Accounting and Economics* 32, 97–180.

Whaley, R. E., 2000, The investor fear gauge, *Journal of Portfolio Management* 26, 12–+.

Whaley, R. E., 2009, Understanding the vix, *Journal of Portfolio Management* 35, 98–105.

Xiong, W., and J. Yu, 2011, The chinese warrants bubble, *American Economic Review* 101, 2723–2753.

Yu, J., 2011, Disagreement and return predictability of stock portfolios, *Journal of Financial Economics* 99, 162–183.

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

Zhou, Guofu, 2017, Measuring investor sentiment, *Working Paper* .

Zhu, Y., and G. Zhou, 2009, Technical analysis: An asset allocation perspective on the use of moving averages, *Journal of Financial Economics* 92, 519–544.

Appendix A

List of Abbreviations

- **AAII** American Association of Individual Investor
- **ADS** Aruoba, Diebold, and Scotti's (2009) Daily Macroeconomic Activities Index
- **AMEX** American Stock Exchange
- **ARIMA** Autoregressive Integrated Moving Average
- **Age** Firm Age
- **BE/ME** Book-to-Market ratio
- **BETC** Break-Even Transaction Costs
- **CAPM** Captial Asset Pricing Model
- **CBOE** Chicago Board Options Exchange
- **CCI** Consumer Confidence Index
- **CEFD** Closed-End Fund Discount
- **CMA** Fama-French Conservative Minus Aggressive Factor

- **CRSP** Center for Research in Security Prices Database
- **D/BE** Dividend-to-Book ratio
- **DJIA** Dow Jones Industrial Average Index
- **DP** Dividend Premium
- **DS** Default Spread
- **DSSW** Delong, Shleifer, Summers, Waldmann (1990) noise trader risk model
- **E/BE** Earning-to-Book ratio
- **EF/A** External Finance over Assets
- **EPU** Baker, Bloom, and Davis's (2013) Economic Policy Uncertainty Index
- **ETF** Exchange-Traded Fund
- **FEARS** Financial and Economic Attitudes Revealed by Search
- **GS** Sales Growth ratio
- **H** Top Three Deicles
- **HML** Fama-French High Minus Low Factor
- **I** The Most Sentiment-Immune Stock Decile Portoflio
- **ICS** Michigan Consumer Sentiment Index
- **IRF** Impulse Response Functions
- **L** Bottom Three Deciles
- **M** Middle Four Deciles

- **ME** Market Capitalization
- **NA** Not Available
- **NASDAQ** National Association of Securities Dealers Automated Quotations
- **NBER** National Bureau of Economic Research
- **NIPO** Jay Ritter's Number of the First-Day IPOs
- **NYSE** New York Stock Exchange
- **P** The Most Sentiment-Prone Stock Decile Portoflio
- **PLS** Partial Least Square
- **PPE/A** Property, Plant and Equipment over Assets
- **RD/A** Research and Development over Assets
- **REIT** Real Estate Investment Trust
- **RIPO** Jay Ritter's Return of the First-Day IPOs
- **RMRF** Market Return Premium
- **RMW** Fama-French Robust Minus Weak Factor
- **RTA** Return of the TA Trading Strategy
- **S** Percentage of Equity Shares in Total New Issues
- **SMB** Fama-French Small Minus Big Factor
- **Sigma** Total Risk
- **TA** Technical Analysis

- **TAP** Return Premium of the TA Trading Strategy over Corresponding Benchmark Portfolio
- **TED** Yield Difference of Eurodollar Futures Contract over T-bill
- **TS** Term Spread
- **UMD** Carhart (1997) Winners Minus Losers Momentum Factor
- **VAR** Vector Autoregression
- **VIX** Implied Volatility Index conveyed from S&P index options
- **VOL** Detrended Trading Volume of S&P 500 Index
- **VXD** CBOE DJIA Volatility Index
- **VXN** CBOE Nasdaq Volatility Index
- **VXO** CBOE S&P 100 Volatility Index

Appendix B

Sentiment-Prone Level Measures

Table B.1 gives a detailed description for the variables needed to construct the portfolios. All the three essays in this thesis use the same ten sentiment-prone level measures as below to construct sentiment-based portfolios in the cross-section. I try to follow the framework of Baker and Wurgler (2006) as much as possible. Generally speaking, those sentiment-prone level measures are closely associated with the stocks' information opaqueness, the attractiveness to speculative demands, and the difficulty to arbitrage. The portfolios are all reconstructed every year. The variables used in the Calculation column in Table B.1 are all from WRDS.

Table B.1 Definitions of Sentiment-Prone Level Measures

Var	Name	Description	Calculation
ME	Market equity	Price times shares outstanding in the June prior to t. If there are more than one permanent code for a company, then sum up all the ME for the same company	abs(prc)*shrout
Age	Firm age	The number of months between the firm's first appearance on CRSP and t. The firm age is measured to the nearest month. If the stock is not delisted, I calculate time period between current year t and beginning date, or else the age is ending date minus beginning date.	min(date,enddat)-begdat
σ	Total risk	Annual standard deviation in monthly returns from CRSP for the 12 months ending in the June prior to t, and there should be no less than nine monthly returns available to estimate it.	std(retadj)
E/BE	Earnings-book ratio for profitable firms	Earnings is income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19), if earnings are positive; book equity (BE) is shareholders' equity (Item 60) plus balance sheet deferred taxes (Item 35). The profitability dummy E>0	BE = CEQ + TXDITC; E=IB+TXDI-DVP; E/BE=E/BE if E>0; E/BE=0 if E<0
D/BE	Dividend-book ratio for dividend payers	Dividend is the fiscal year-end dividends per share at the ex-date (Item 26) times Compustat shares outstanding (Item 25) divided by book equity.	D/BE=DVPSX_F*CSHO/BE if D>0; otherwise D/BE=0
PPE/A	Fixed assets ratio	Plant, property, and equipment (Item 7) is scaled by gross total assets (Item 6). I do not replace missing value with zero.	PPE/A=PPEGT/AT;
RD/A	Research and development ratio	Research and development (Item 46) is also scaled by gross total assets (Item 6). The data are extensively available after 1971.	RD/A=XRD/AT;
BE/ME	Book-to-market ratio	This is the log of the ratio of book equity to market equity. I match fiscal year ending calendar year t-1 ME with June t BE	log(1+BE/DEC_ME)
EF/A	External finance over assets	External finance (EF) is equal to the change in assets (Item 6) less the change in retained earnings (Item 36). When Item 36 is not available, I use net income (Item 172) less common dividends (Item 21) instead.	EF1=dif(RE);EF2=dif(NI-DVC);EF/A=(dif(AT)-coalesce(EF1,EF2,0))/AT;
GS	Sales growth	Sales growth is the percentage change in net sales (Item 12). I first calculate the original sales growth ratio and then use its position in the ten-decile to note GS. GS has a range from [1, 10]	GS=dif(SALE)/lag(SALE)

Appendix C

Details of the Wild Bootstrap Procedures

I use the following wild bootstrap procedure to adjust for Stambaugh bias. A similar wild bootstrap procedure has been employed by Huang et al. (2015) and Brown and Cliff (2004). The null of this wild bootstrap p-values is that the independent variable has no predictability. Take the regression in Table 2 as an example. The regression function is

$$R_t = \alpha + \beta_1 \rho_{LR,t} + \beta_2 \Delta\rho_{s,t} + \gamma X + u_t, \tag{C.1}$$

where R_t is the relative returns of more sentiment-prone stocks over less sentiment-prone stocks ($R_t = R_{t,1} - R_{t,2}$). To obtain the simulated data of dependent variable, I first run an OLS regression of the original regression function to get the fitted residuals $\hat{\varepsilon}_t$.

$$\hat{\varepsilon}_t = R_t - (\hat{\alpha} + \hat{\beta}_1 \rho_{LR,t} + \hat{\beta}_2 \Delta\rho_{s,t} + \hat{\gamma} X) \tag{C.2}$$

To obtain the simulated sample of independent variables, I assume the predictors follow an AR(1) process and I run first-order autoregression and get the fitted residuals of the AR(1) regression for each predictor.

$$\hat{\varphi}_{\rho_{LR,t}} = \rho_{LR,t} - (\hat{\vartheta}_{t-1,0} + \hat{\vartheta}_{t-1,1}\rho_{LR,t-1}) \tag{C.3}$$

Then I generate a set of random number, ω_t, from the standard normal distribution. I build up a pseudo sample of observations for relative returns and the variables that have no return predictability under the null hypothesis.

$$\widetilde{R_t} = \bar{R}_t + \hat{\varepsilon}_t \omega_t, \tag{C.4}$$

$$\widetilde{\rho_{LR,t}} = (\hat{\vartheta}_{t-1,0} + \hat{\vartheta}_{t-1,1}\rho_{LR,t-1}) + \hat{\varphi}_{\rho_L R,t}\omega_t, \tag{C.5}$$

where $\bar{R}_t$ is the sample mean of R_t, and ω_t is a drawn from a standard normal distribution.

With the pseudo sample, I estimate the coefficients and the corresponding Newey-West t-statistics for each regressor. I then repeat this process for 500 times and store all the Newey-West robust t-statistics for each regressor. I get a distribution of the bootstrapped t-statistics for each regressor.

Because my model suggests a negative sign of β_1 and a positive sign of β_2, I test null hypotheses H_0: $\beta_1 = 0$ and $\beta_2 = 0$ against alternative hypotheses H_A: $\beta_1 < 0$ and $\beta_2 > 0$. The one-sided tests are more in line with my theory than the two-sided tests, and most of my results remain significant if I consider two-sided tests instead. For a given regressor, the empirical p-value is the proportion of the bootstrapped t-statistics larger (smaller) than the t-statistics when using the original sample.

Appendix D

Description of Technical Trading Rules Employed in Constructing TA Sentiment

This part describes the 2127 technical trading rules that I used in constructing the TA sentiment indicator. In Chapter 3, TA sentiment indicator is built based on Dr Qingwei Wang's PhD thesis on 2008. This thesis uses the same method to construct TA sentiment indicator.

D.1 Filter Rules (FR)

Basic Filter Rules:

When the daily closing price of an asset moves up by over x% from its most recent low, the rule generates a 'buy' forecast. When the daily closing price moves down by at least x% from a recent high, the rule generates a 'sell' forecast. Otherwise, the forecast is 'neutral'.Define the recent high (low) as the highest (lowest) price over the e most recent c is the number of days in a case where a given long or short position is held and during which time all other signals are ignored.

x: increase in the log return required to generate a 'buy' signal

x = 0.0005, 0.001, 0.005, 0.01, 0.05, 0.10 (6 values)

y: decrease in the log return required to generate a 'sell' signal

y = 0.0005, 0.001, 0.005, 0.01, 0.05 (5 values)

e: the number of the most recent days needed to define a low (high) based on which the filters are applied to generate a 'buy' ('sell') signal

e = 1, 2, 5, 10, 20 (5 values)

c: number of days a position is held during which all other signals are ignored

c = 1, 5, 10, 25 (4 values)

Note that y must be less than x, hence there are 15 (x,y) combinations

Number of rules in FR class= x*c+x*e+x*y+((x,y) combinations))= 24+30+15 = 69

D.2 Moving Average Rules (MA)

Basic Moving Average Rule:

First, to calculate the (equally-weighted) moving average of an asset prices for a given day t over the n days. When the short moving average of the index is above the long moving average by an amount larger than the band with b%, it generates a 'buy' forecast; similarly, when the short moving average is below the long moving average by b%, it generates a 'sell' forecast; otherwise, it generates a 'neutral' forecast. In addition to this fixed percentage band filter, d is a time delay filter that requires the long or short signals remain valid for d days before one can any action.

n: number of days in a moving average

n = 2, 5, 10, 15, 20, 25, 50, 100, 150, 200, 250 (11 values)

m: number of fast-slow combinations of n

$m = \sum_{i=1}^{n-1} i = 55$

b: fixed band multiplicative value

b = 0, 0.0005, 0.001, 0.005, 0.01, 0.05 (6 values)

c: number of days a position is held, ignoring all other signals during that time

c = 5, 10, 25 (3 values)

d: number of days for the time delay filter

d = 2, 3, 4, 5 (4 values)

Number of rules in MA class: = b(n+m)+d(n+m)+c(n+m)= 396+264+198 = 858

D.3 Support and Resistance (SR, or Trading Range Break) Rules

Basic Support and Resistance Rule:

Under a trading range break rule, when the price of an asset moves above the maximum price (resistance level) over the previous n days by b%, it generates a 'buy' forecast. When the price falls below the minimum price over the previous n days by b%, it generates a 'sell' forecast. Otherwise, it generates a 'neutral' forecast.

n: number of days in the support and resistance range;

n = 5, 10, 15, 20, 25, 50, 100 (7 values);

e: used for an alternative definition of extreme where a low (high) can be defined as the most recent closing price that is less (greater) than the n previous closing prices;

e = 2, 3, 4, 5, 10, 25, 50 (7 values);

b: fixed band multiplicative value;

b = 0.0005, 0.001, 0.005, 0.01, 0.05 (5 values);

c: number of days a position is held, ignoring all other signals during that time c = 1, 5, 10, 25 (4 values);

d: number of days for the time delay filter;

d = 2, 3, 4, 5 (4 values);

Number of rules in SR class = c*(n+e)+b*(n+e)*c+d*c*(n+e) = 100+800+320 =1220

D.4 Channel Breakout Rules (CBO)

Basic Channel Breakout Rules:

A channel occurs when the high price of an asset over the previous n days is within x% of the low over the previous n days. Under a channel breakout rule, when the closing price of the foreign currency exceeds the channel by b%, it generates a 'Buy' forecast. Likewise, when the closing price of an asset drops below the channel by b%, it generates a 'Sell' forecast. Otherwise, it generates a 'neutral' forecast.

n: number of days for a channel

n = 5, 10, 15, 20, 25, 50, 100, 200 (8 values)

x: difference between the high price and the low price (x times low price) required to form a channel

x = 0.001, 0.005, 0.01, 0.05, 0.10 (5 values)

b: fixed band multiplicative value (b < x)

b = 0.0005, 0.001, 0.005, 0.01, 0.05 (5 values)

c: number of days a position is held, ignoring all other signals during that time

c = 1, 5, 10, 25 (4 values)

Note that b must be less than x. There are 15 (x,b) combinations.

Number of rules in CBO class = n*x*c+n*c*((x,b) combinations)= 160+480 = 640

Therefore, the total number of trading rules = 2127

Appendix E

Some Robustness Tests

This part I present the tables of some robustness tests mention in the three essays of this thesis.

E.1 Robustness Tests for Chapter 3

I test the two hypotheses in Chapter 3 with other sentiment indicators. Table E.1 reports the results when investor sentiment is measured by CCI, ICS, CEFD, and Sent_PLS. I also use the smoothing average of 12-month period and 36-month period to measure the long-run sentiment component.

Table E.2 reports the regression results of the two cases where long-run sentiment component is measured with different horizon choices.

Table E.3 reports the regression results of separated high and low sentiment periods.

Table E.4 takes the effect of investor attention into consideration and find that the results are robust to the effect of investor attention. Panel A of Table E.4 presents the regression results when investor attention $A_{t,1}$ is constructed by abnormal trading volume and Panel

B shows the results when Attention Disparity is constructed by abnormal return. Table E.4 shows that the investor attention disparity does have a pronounced explanatory power on the cross-sectional return premium. After taking the effect of investor attention into account, the effect of decomposed sentiment components on returns remain strong. The results in Panel A and Panel B are almost the same in terms of the sign and significance of the coefficients for long- and short-run sentiment. The long-run sentiment negatively predicts future cross-sectional returns as expected and the short-run sentiment positively contributes to contemporaneous cross-sectional return premium as predicted.

Table E.5 reports the regression results when using value-weighted returns to mitigate the size effect.

Table E.1 Regressions of Monthly Cross-Sectional Returns on Other Decomposed Sentiment Measures

This table reports the regressions of long-short portfolio returns on both the long-run and short-run sentiment.

$$R_{t,1} - R_{t,2} = \alpha + \beta_1 \rho_{LR,t} + \beta_2(\eta_t - \eta_{t-1}) + \gamma X + \varepsilon_t,$$

$R_{t,1} - R_{t,2}$ represents the return disparity of more sentiment-prone portfolio over the less sentiment-prone portfolio. The control variables (X) include the Fama-French Five factors (RMRF, HML, SMB, RMW, CMA), and the momentum factor (UMD). SMB (HML) will not be included in regression when return premium is constructed by ME (BE/ME). The first two columns show how the portfolio is constructed. H, M, L represents the top three, middle four and bottom three decile portfolios respectively. The long-run sentiment component $\rho_{LR,t}$ is the standardised smoothing average of prior $[-25, -2]$ monthly investor sentiment. All coefficients are adjusted for Stambaugh-bias. The p-values reported in parentheses are obtained from wild bootstrap procedures in which all stimulation uses Newey West robust t-statistics. See Appendix B for details of the bootstrap simulation. $***p < 0.01, **p < 0.05, *p < 0.1$.

		Panel A ICS		Panel B CCI		Panel C CEFD		Panel D PLS	
		$\rho_{LR,t}$	$\Delta\eta$	$\rho_{LR,t}$	$\Delta\eta$	$\rho_{LR,t}$	$\Delta\eta$	$\rho_{LR,t}$	$\Delta\eta$
ME	L-H	-0.17***	0.75	-0.16***	0.49	-0.014***	0.309***	0.050	0.410***
		(0.000)	(0.188)	(0.000)	(0.154)	(0.000)	(0.000)	(0.290)	(0.000)
Age	L-H	0.01***	0.31*	0.07***	0.00**	-0.035***	0.111	-0.013***	0.066
		(0.000)	(0.056)	(0.000)	(0.013)	(0.000)	(0.172)	(0.000)	(0.130)
Sigma	H-L	-0.40***	0.18***	-0.04***	-0.05***	-0.075***	0.101**	-0.096***	0.039***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)
E/BE	<0->0	-0.12***	0.32	-0.58	-0.06**	-0.069***	0.290*	-0.078***	0.088***
		(0.000)	(0.254)	(0.309)	(0.030)	(0.000)	(0.072)	(0.000)	(0.000)
D/BE	=0->0	-0.29***	0.30**	-0.29***	-0.07***	-0.072***	0.189*	-0.090***	-0.020***
		(0.000)	(0.046)	(0.000)	(0.000)	(0.000)	(0.078)	(0.000)	(0.000)
PPE/A	L-H	-0.03***	0.17***	-0.02**	-0.04***	-0.049***	0.062***	-0.018***	0.041***
		(0.000)	(0.000)	(0.016)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RD/A	H-L	0.22***	0.00***	0.22***	-0.06***	-0.011***	0.061***	0.012***	0.090***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	H-L	-0.01***	0.15***	-0.11***	0.24***	-0.011***	0.284***	-0.027***	-0.035***
		(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
EF/A	H-L	0.14***	0.00	0.16***	-0.13	-0.005***	0.045***	0.007***	-0.040***
		(0.000)	(0.137)	(0.000)	(0.126)	(0.000)	(0.000)	(0.000)	(0.000)
GS	H-L	0.10***	-0.08	0.22***	-0.22***	-0.003***	-0.074***	0.006***	-0.090***
		(0.000)	(0.295)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	L-M	0.04***	0.03**	0.02***	-0.08	0.002***	-0.145***	0.008**	0.020***
		(0.000)	(0.034)	(0.000)	(0.184)	(0.000)	(0.008)	(0.033)	(0.000)
EF/A	H-M	-0.01***	0.10**	0.02***	-0.05***	-0.017***	0.032	-0.013***	-0.008***
		(0.000)	(0.011)	(0.000)	(0.000)	(0.000)	(0.424)	(0.000)	(0.000)
GS	H-M	0.09***	0.02*	0.18***	-0.07***	-0.024***	0.022	-0.023***	-0.031***
		(0.000)	(0.079)	(0.000)	(0.000)	(0.000)	(0.229)	(0.000)	(0.000)
BE/ME	H-M	0.03**	0.17***	-0.11***	0.15	-0.014	0.139***	-0.017***	-0.012
		(0.014)	(0.001)	(0.000)	(0.216)	(0.332)	(0.000)	(0.000)	(0.176)
EF/A	L-M	-0.13***	0.10	-0.18***	0.08***	-0.014***	-0.013***	-0.013***	0.038***
		(0.000)	(0.241)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
GS	L-M	-0.04***	0.10*	-0.07***	0.15***	-0.023***	0.106***	-0.034***	0.053***
		(0.000)	(0.057)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)

Table E.2 Regression Results when Long-Run Sentiment Measured with Different Horizons

This table reports the regressions of long-short portfolio returns on both the long-run and short-run sentiment.

$$R_{t,1} - R_{t,2} = \alpha + \beta_1 \rho_{LR,t} + \beta_2(\eta_t - \eta_{t-1}) + \gamma X + \varepsilon_t,$$

$R_{t,1} - R_{t,2}$ represents the return disparity of more sentiment-prone portfolio over the less sentiment-prone portfolio. The control variables (X) include the Fama-French Five factors (RMRF, HML, SMB, RMW, CMA), and the momentum factor (UMD). SMB (HML) will not be included in regression when return premium is constructed by ME (BE/ME). The first two columns show how the portfolio is constructed. H, M, L represents the top three, middle four and bottom three decile portfolios respectively. In Panel A (B), the long-run sentiment component $\rho_{LR,t}$ is the standardised smoothing average of prior $[-13,-2]$ ($[-37,-2]$) monthly investor sentiment. All coefficients are adjusted for Stambaugh-bias. The p-values reported in parentheses are obtained from wild bootstrap procedures in which all stimulation uses Newey West robust t-statistics. See Appendix B for details of the bootstrap simulation. $***p < 0.01, **p < 0.05, *p < 0.1$.

		Panel A. Long-Run Component Measured by 12-Month Moving Average		Panel B. Long-Run Component Measured by 36-Month Moving Average	
		$\rho_{LR,t}$	$\eta_t - \eta_{t-1}$	$\rho_{LR,t}$	$\eta_t - \eta_{t-1}$
ME	L-H	-0.202*** (0.000)	0.280*** (0.000)	-0.378*** (0.000)	0.356*** (0.000)
Age	L-H	-0.026* (0.053)	0.194*** (0.000)	-0.029*** (0.000)	0.215*** (0.000)
Sigma	H-L	-0.202*** (0.000)	0.149*** (0.000)	-0.150*** (0.000)	0.176*** (0.000)
E/BE	<0->0	-0.415*** (0.000)	0.205*** (0.000)	-0.230*** (0.000)	0.240*** (0.000)
D/BE	=0->0	-0.335*** (0.000)	0.065*** (0.000)	-0.240*** (0.000)	0.097*** (0.000)
PPE/A	L-H	0.073*** (0.000)	-0.008 (0.311)	-0.048*** (0.000)	0.047*** (0.000)
RD/A	H-L	-0.035*** (0.000)	0.029*** (0.000)	0.044*** (0.000)	-0.001 (0.412)
BE/ME	H-L	-0.071*** (0.000)	0.120*** (0.000)	-0.050*** (0.000)	0.115*** (0.000)
EF/A	H-L	0.007*** (0.000)	-0.001 (0.366)	0.005** (0.011)	-0.005*** (0.000)
GS	H-L	-0.030*** (0.000)	-0.144*** (0.000)	-0.059*** (0.000)	-0.146*** (0.000)
BE/ME	L-M	-0.024*** (0.006)	-0.055*** (0.000)	-0.000 (0.496)	-0.038*** (0.000)
EF/A	H-M	-0.102*** (0.000)	0.005** (0.020)	-0.095*** (0.000)	0.018*** (0.000)
GS	H-M	-0.119*** (0.000)	0.019*** (0.000)	-0.084*** (0.000)	0.024*** (0.000)
BE/ME	H-M	-0.095*** (0.000)	0.065*** (0.000)	-0.051*** (0.000)	0.078*** (0.000)
EF/A	L-M	-0.109*** (0.000)	0.005*** (0.000)	-0.099*** (0.000)	0.022*** (0.000)
GS	L-M	-0.089*** (0.000)	0.163*** (0.000)	-0.025*** (0.000)	0.170*** (0.000)

Table E.3 Regression Results during High/Low Sentiment Periods

This table reports the regressions of long-short portfolio returns on both the long-run and short-run sentiment.

$$R_{t,1} - R_{t,2} = \alpha + \beta_1 \rho_{LR,t} + \beta_2(\eta_t - \eta_{t-1}) + \gamma X + \varepsilon_t,$$

$R_{t,1} - R_{t,2}$ represents the return disparity of more sentiment-prone portfolio over the less sentiment-prone portfolio. The control variables (X) include the Fama-French Five factors (RMRF, HML, SMB, RMW, CMA), and the momentum factor (UMD). SMB (HML) will not be included in regression when return premium is constructed by ME (BE/ME). The first two columns show how the portfolio is constructed. H, M, L represents the top three, middle four and bottom three decile portfolios respectively. The long-run sentiment component $\rho_{LR,t}$ is the standardised smoothing average of prior $[-25,-2]$ monthly investor sentiment. Panel A (B) reports the regression results of a subsample when current sentiment is higher (lower) than long-run sentiment. The coefficients are adjusted for Stambaugh-bias. The p-values reported in parentheses are obtained from wild bootstrap procedures. See Appendix B for details of the bootstrap simulation. $***p < 0.01, **p < 0.05, *p < 0.1$.

		Panel A. High Sentiment Period		Panel B. Low Sentiment Period	
		$\rho_{LR,t}$	$\eta_t - \eta_{t-1}$	$\rho_{LR,t}$	$\eta_t - \eta_{t-1}$
ME	L-H	-0.090***	0.380***	0.429***	0.825***
		(0.000)	(0.000)	(0.000)	(0.000)
Age	L-H	0.133***	0.242***	0.117***	0.511***
		(0.000)	(0.000)	(0.000)	(0.000)
Sigma	H-L	0.120***	0.129***	-0.079***	0.423***
		(0.000)	(0.000)	(0.000)	(0.000)
E/BE	<0->0	-0.110***	0.236***	-0.700***	0.428***
		(0.000)	(0.000)	(0.000)	(0.000)
D/BE	=0->0	-0.248***	-0.028**	-0.347***	0.342***
		(0.000)	(0.019)	(0.000)	(0.000)
PPE/A	L-H	0.063***	0.105***	-0.186***	0.414***
		(0.000)	(0.000)	(0.000)	(0.000)
RD/A	H-L	0.117***	-0.000***	-0.103***	0.051***
		(0.000)	(0.002)	(0.000)	(0.000)
BE/ME	H-L	-0.043***	0.010	0.189***	0.542***
		(0.000)	(0.339)	(0.000)	(0.000)
EF/A	H-L	0.045***	-0.021***	0.004***	0.064***
		(0.000)	(0.000)	(0.003)	(0.000)
GS	H-L	-0.050***	-0.119***	-0.204***	-0.294***
		(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	L-M	0.064***	0.014***	-0.000***	-0.137***
		(0.000)	(0.007)	(0.000)	(0.000)
EF/A	H-M	-0.043***	0.038***	-0.032***	0.112***
		(0.000)	(0.000)	(0.000)	(0.000)
GS	H-M	-0.020*	0.040***	-0.113***	0.062***
		(0.066)	(0.000)	(0.000)	(0.000)
BE/ME	H-M	0.021***	0.025***	0.189***	0.406***
		(0.000)	(0.000)	(0.000)	(0.000)
EF/A	L-M	-0.080***	0.060***	-0.036***	0.048***
		(0.000)	(0.000)	(0.000)	(0.000)
GS	L-M	0.027***	0.159***	0.091***	0.356***
		(0.000)	(0.000)	(0.000)	(0.000)

Table E.4 Effects of Decomposed Investor Sentiment after Controlling for Investor Attention

This table reports the regressions of long-short portfolio returns on both the long-run and short-run sentiment.

$$R_{t,1} - R_{t,2} = \alpha + \beta_1 \rho_{LR,t} + \beta_2(\eta_t - \eta_{t-1}) + \beta_3(A_{t,1} - A_{t,2}) + \gamma X + \varepsilon_t,$$

$R_{t,1}) - R_{t,2}$ $(A_{t,1}) - A_{t,2})$ represents the return (investor attention) disparity of more sentiment-prone portfolio over the less sentiment-prone portfolio. The control variables (X) include the Fama-French Five factors (RMRF, HML, SMB, RMW, CMA), and the momentum factor (UMD). The first two columns show how the portfolio is constructed. H, M, L represents the top three, middle four and bottom three decile portfolios respectively. The long-run sentiment component $\rho_{LR,t)}$ is the standardized smoothing average of prior [-25,-2] monthly investor sentiment.$\eta_t - \eta_{t-1}$ is the standardized incremental change of sentiment deviation from long-run sentiment average. Panel A (B) reports the results when A_t is measured by abnormal trading volume (abnormal return). The p-values reported in parentheses are obtained from wild bootstrap procedures in which all stimulation uses Newey-West robust t-statistics. *** p<0.01, ** p<0.05, * p<0.1.

		Panel A Investor Attention Measured by Abnormal Trading Volume			Panel B Investor Attention Measured by Abnormal Return		
		$\rho_{LR,t}$	$\eta_t - \eta_{t-1}$	$A_{t,1} - At,2$	$\rho_{LR,t}$	$\eta_t - \eta_{t-1}$	$A_{t,1} - At,2$
ME	L-H	-0.124***	0.273***	6.344***	-0.252***	0.332***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	L-H	0.032***	0.163***	3.825***	-0.012**	0.191***	0.003***
		(0.000)	(0.000)	(0.000)	(0.043)	(0.000)	(0.000)
Sigma	H-L	-0.090***	0.125***	5.642***	-0.177***	0.151***	-0.003***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
E/BE	<0->0	-0.283***	0.155***	3.205***	-0.336***	0.176***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D/BE	=0->0	-0.192***	0.060***	6.841***	-0.302***	0.055***	-0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PPE/A	L-H	0.096***	0.008	7.133***	0.077***	0.015***	-0.001***
		(0.000)	(0.381)	(0.000)	(0.000)	(0.000)	(0.000)
RD/A	H-L	0.027***	-0.021***	4.626***	-0.032***	0.010**	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.012)	(0.130)
BE/ME	H-L	-0.024***	0.079***	5.302***	-0.074***	0.115***	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.124)
EF/A	H-L	-0.026***	-0.013***	5.350***	0.003***	-0.002	-0.001***
		(0.000)	(0.000)	(0.000)	(0.001)	(0.128)	(0.000)
GS	H-L	-0.071***	-0.122***	3.502***	-0.048***	-0.130***	-0.003***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	L-M	0.013***	-0.057***	5.769***	-0.003	-0.062***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.385)	(0.000)	(0.000)
EF/A	H-M	-0.095***	0.006**	5.808***	-0.102***	0.007***	-0.001***
		(0.000)	(0.037)	(0.000)	(0.000)	(0.000)	(0.000)
GS	H-M	-0.094***	-0.006***	5.890***	-0.111***	0.019***	-0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	H-M	-0.007	0.019***	5.638***	-0.076***	0.056***	0.001***
		(0.257)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EF/A	L-M	-0.068***	0.019***	5.518***	-0.102***	0.010***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GS	L-M	-0.030***	0.127***	3.655***	-0.061***	0.151***	-0.004***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table E.5 Regressions of Monthly Value-Weighted Returns on Decomposed Sentiment

This table reports the regressions of long-short portfolio returns on both the long-run and short-run sentiment.

$$R_t = \alpha + \beta_1 \rho_{LR,t} + \beta_2 \Delta\rho_{s,t} + \gamma X + \varepsilon_t,$$

R_t represents the value-weighted return disparity of more sentiment-prone portfolio over the less sentiment-prone portfolio. The control variables (X) include the Fama-French Five factors (RMRF, HML, SMB, RMW, CMA), and the momentum factor (UMD). SMB (HML) will not be included in regression when return premium is constructed by ME (BE/ME). The first two columns show how the portfolio is constructed. H, M, L represents the top three, middle four and bottom three decile portfolios respectively. The long-run sentiment component $\rho_{LR,t}$ in Panel A and Panel B is the standardised smoothing average of prior $[-25,-2]$ monthly investor sentiment. Short-run component in Panel A and Panel B are respectively the standardised incremental change of sentiment deviation from long-run sentiment average $\eta_t - \eta_{t-1}$ and the standardised incremental sentiment orthogonalized to long-run sentiment $(\rho_t - \rho_{t-1})^{\perp}$. The long- and short-run sentiment in Panel C are decomposed with Beveridge and Nelson (1981) method and noted as BN_LR and BN_SR respectively. All coefficients are adjusted for Stambaugh-bias. The p-values reported in parentheses are obtained from wild bootstrap procedures in which all stimulation uses Newey West robust t-statistics. See Appendix B for details of the bootstrap simulation. $***p < 0.01, **p < 0.05, *p < 0.1$.

		Panel A		Panel B	
		$\rho_{LR,t}$	$\eta_t - \eta_{t-1}$	$\rho_{LR,t}$	$(\rho_t - \rho_{t-1})^{\perp}$
ME	L-H	-0.235***	0.386***	-0.307***	0.363***
		(0.000)	(0.000)	(0.000)	(0.000)
Age	L-H	-0.099***	-0.045***	-0.091***	-0.042***
		(0.000)	(0.000)	(0.000)	(0.000)
Sigma	H-L	-0.081***	0.077***	-0.096***	0.072***
		(0.000)	(0.000)	(0.000)	(0.000)
E/BE	<0->0	-0.482***	-0.315***	-0.422***	-0.297***
		(0.000)	(0.000)	(0.000)	(0.000)
D/BE	=0->0	-0.237***	-0.247***	-0.191***	-0.233***
		(0.000)	(0.000)	(0.000)	(0.000)
PPE/A	L-H	0.086***	-0.038***	0.093***	-0.036***
		(0.000)	(0.000)	(0.000)	(0.000)
RD/A	H-L	0.353***	-0.325***	0.414***	-0.305***
		(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	H-L	-0.269***	0.225***	-0.312***	0.212***
		(0.000)	(0.000)	(0.000)	(0.000)
EF/A	H-L	0.147***	-0.056***	0.157***	-0.052***
		(0.000)	(0.000)	(0.000)	(0.000)
GS	H-L	0.014***	-0.132***	0.039***	-0.124***
		(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	L-M	0.246***	-0.075***	0.260***	-0.071***
		(0.000)	(0.000)	(0.000)	(0.000)
EF/A	H-M	-0.045***	0.024***	-0.049***	0.023**
		(0.000)	(0.002)	(0.000)	(0.017)
GS	H-M	-0.107***	-0.065***	-0.095***	-0.061***
		(0.000)	(0.000)	(0.000)	(0.000)
BE/ME	H-M	-0.024***	0.150***	-0.052***	0.141***
		(0.000)	(0.000)	(0.000)	(0.000)
EF/A	L-M	-0.191***	0.080***	-0.206***	0.075***
		(0.000)	(0.000)	(0.000)	(0.000)
GS	L-M	-0.121***	0.067***	-0.134***	0.063***
		(0.000)	(0.000)	(0.000)	(0.000)

E.2 Robustness Tests for Chapter 4

E.2.1 Validate TA Sentiment by Predicting Future Crash Risk

To test my hypothesis, I create a 'RANK' variable to measure the extent to which a decile portfolio is prone to investor sentiment.[1] RANK is defined as the following:

$$RANK = \begin{cases} 11 - DR & \text{for portfolios sorted on ME, Age, E/BE, D/BE, PPE/A} \\ DR & \text{for portfolios sorted on Sigma, R/DA} \\ |DR - 5.5| & \text{for portfolios sorted on BE/ME, EF/A, GS} \end{cases} \tag{E.1}$$

where DR is the original decile rank. The high value of a stock's $RANK$ indicates that it is sentiment-prone. Take the size portfolios as an example, the smallest decile portfolio (the most sentiment-prone portfolio with $DR = 1$) has a $RANK$ of 10, while the largest decile portfolio (the least sentiment-prone portfolio with $DR = 10$) has a RANK of 1. For BE/ME sorted portfolios, the two middle deciles (the least sentiment-prone portfolio with DR =5 or 6) have a RANK value of 0.5 while the bottom and top deciles (the most sentiment-prone portfolio with $DR = 1$ or 10) have a RANK value of 4.5. Therefore, $RANK$ is not a simple decile rank, but it rather presents the rank of a decile portfolio's sentiment-prone level among the portfolios sorted by the same characteristics.

Following Chen et al. (2001), I use skewness (denoted as *Skew*) of returns as a proxy for future crash risk. A lower value of *Skew* corresponds to higher crash risk. Unfortunately, theories of synchronisation problem (Abreu and Brunnermeier, 2002; 2003) do not provide clear guidance on when coordinated attacks take place. I calculate *Skew* over a 25-day

[1] I consider the skewness of the decile portfolios instead of the long-short portfolios because the skewness of long-short portfolios depends on both the relative skewness and co-skewness of the long and short portfolios (Albuquerque, 2012). Notwithstanding most of the long-short portfolios have higher future crash risk after an increase in TA sentiment, consistent with my prediction.

rolling window to strike a balance between two considerations: on one hand, the effect of TA sentiment may play itself out over a short horizon; on the other hand, the estimation of *Skew* over very short horizons invites estimation errors (Chen et al., 2001). As an attempt to alleviate the concerns of the estimation errors from computing third moments (*Skew*) with 25 observations, I consider another measure adopted in Chen et al. (2001), the down-to-up volatility (denoted as $DUVOL$), which requires estimation of only the second moments. More specifically, I stratify the returns of the future 25 days into two groups, an 'up' group with returns higher than the period mean and a 'down' group with returns lower than the period mean. I then compute the standard deviation for each group and take the log of the ratio of 'down' group standard deviation to 'up' group standard deviation as the $DUVOL$. Higher $DUVOL$ means higher crash risk. The formula for $DUVOL$ is

$$DUVOL_t = 2log(\frac{SD_{down}}{SD_{up}}). \tag{E.2}$$

I run regressions of the following specification:

$$\begin{aligned} CR_{t+1}^{t+25} =&\alpha + \beta_1 TA_t + \beta_2 RANK + \beta_3 TA_t RANK + \beta_4 CR_{t-24}^{t} + \beta_5 SD_{t-24}^{t} \\ &+ \beta_6 TURN_t + \sum_{i=1}^{5} \gamma_i Ret_{t-i} + \varepsilon_t, \end{aligned} \tag{E.3}$$

where CR_{t+1}^{t+25} is the measure of the crash risk (*Skew* or $DUVOL$) of future decile portfolio returns from day $t+1$ to $t+25$, SD_{t-24}^{t} is the standard deviation of the decile portfolio returns from day $t-24$ to t, $TURN_t$ is the average turnover across stocks within a decile portfolio at time t, detrended by its moving average in the prior one year, and $Ret_{t-1}, \ldots, Ret_{t-5}$ are the daily decile portfolio returns at day t through $t-5$.

The primary variables of interest in the regression above are TA sentiment and its interaction with $RANK$. Note that a low *Skew* or a high $DUVOL$ value indicates high crash risk.

Therefore, I expect the negative (positive) coefficients of TA sentiment, *RANK*, and their interaction term when the dependent variable is measured by *Skew* (*DUVOL*). I include the interaction term of TA sentiment and *RANK* in the regression to capture the cross-sectional predictive power of TA sentiment on future crash risk. Conditional on the increase in TA sentiment, I expect more sentiment-prone stocks to have higher future crash risk. Thus, I predict a negative sign on the interaction term, β_3. Other variables are control variables that have been shown to affect return asymmetry in the prior literature. $TURN_t$ is added in the regressions to control for the effect of the difference in opinion (Chen, Hong and Stein, 2001). SD^t_{t-24} is included to account for the volatility-feedback effect (Campbell and Hentschel, 1992). The lagged returns are included to control for the stochastic bubble explanation by Blanchard and Watson (1982). Although past returns can also partially reflect investor sentiment, adding the past returns into the regression will demonstrate that the incremental predictive power of TA sentiment for crash risk beyond the past returns.

An inspection of Table E.6 reveals that high TA sentiment predicts high future crash risk. Panel A shows that the coefficients of TA sentiment are negative and highly significant in all of the regressions, indicating that portfolio returns become more negatively skewed over the month following a TA sentiment increase.

Table E.6 Forecasting Cross-Sectional Crash Risk

This table reports the results of the following regression:

$$\begin{aligned} CR_{t+1}^{t+25} =& \alpha + \beta_1 TA_t + \beta_2 RANK + \beta_3 TA_t RANK + \beta_4 CR_{t-24}^{t} + \beta_5 SD_{t-24}^{t} \\ & + \beta_6 TURN_t + \sum_{i=1}^{5} \gamma_i Ret_{t-i} + \varepsilon_t, \end{aligned} \tag{E.4}$$

where CR_{t+1}^{t+25} is a measure of crash risk of the decile portfolio returns over the period from $t+1$ to $t+25$, SD_{t-24}^{t} is the standard deviation of the decile portfolio returns over the period from $t-24$ to t, $TURN_t$ is the averaged decile portfolio turnover at time t, detrended by a moving average of portfolio turnover in the prior one year. $Ret_t, Ret_{t-1}, \ldots, Ret_{t-5}$ are the decile portfolio returns for days $t, t-1, \ldots, t-5$, respectively. $RANK$ is a measure of the decile portfolio's exposure to sentiment. Panel A presents regression results with Skewness as the crash risk measure, respectively, while Panel B reports regression results with $DUVOL$ as the crash risk measure. The Newey and West (1987) robust t-statistics are in brackets. The sample period is from 1964/01/01 to 2008/12/31. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

	Panel A Skewness			Panel B DUVOL		
	β_1	β_2	β_3	β_1	β_2	β_3
ME	-0.30***	-0.023***	-0.0084**	0.45***	0.037***	0.012**
	(-13.08)	(-14.24)	(-2.26)	(14.20)	(16.08)	(2.33)
Age	-0.30***	-0.018***	-0.0090**	0.44***	0.028***	0.014***
	(-13.00)	(-10.98)	(-2.39)	(13.63)	(12.29)	(2.58)
Sigma	-0.27***	-0.011***	-0.014***	0.43***	0.019***	0.015***
	(-11.64)	(-6.19)	(-3.55)	(13.09)	(7.67)	(2.74)
E/BE	-0.39***	-0.0034**	0.0029	0.59***	0.0057**	-0.0050
	(-16.44)	(-2.07)	(0.78)	(17.34)	(2.46)	(-0.94)
D/BE	-0.29***	-0.011***	-0.012***	0.44***	0.020***	0.015***
	(-12.08)	(-6.60)	(-3.14)	(13.33)	(8.17)	(2.64)
PPE/A	-0.21***	-0.0065***	-0.023***	0.29***	0.0096***	0.037***
	(-8.74)	(-3.95)	(-6.09)	(8.58)	(4.18)	(7.13)
RD/A	-0.30***	0.00084	-0.0017	0.47***	-0.00025	-0.0012
	(-11.71)	(0.45)	(-0.40)	(13.00)	(-0.10)	(-0.21)
BE/ME	-0.45***	0.0034**	0.019***	0.66***	-0.0069***	-0.026***
	(-18.07)	(1.97)	(4.89)	(18.57)	(-2.88)	(-4.87)
EF/A	-0.36***	-0.013***	0.0012	0.55***	0.023***	-0.0093
	(-16.16)	(-3.87)	(0.15)	(17.61)	(4.91)	(-0.87)
GS	-0.33***	-0.0099***	-0.010	0.48***	0.017***	0.012
	(-14.76)	(-2.93)	(-1.36)	(15.38)	(3.59)	(1.12)

Panel B depicts a similar picture for the role of TA sentiment. The coefficients of TA sentiment are positive and highly significant in all of the regressions, suggesting higher future crash risk following high TA sentiment. The coefficients of the interaction term also reveal a stronger cross-sectional predictive power of TA sentiment on future crash risk for sentiment-prone stocks than for sentiment-immune stocks. For 5 out of 10 regressions, the coefficients of interaction terms are negative in Panel A and positive in Panel B, and are statistically significant at the 1% level, suggesting that conditional on a high level of TA sentiment, the future crash risk is higher for portfolios that are more sentiment-prone.

Several studies show that low BE/ME stocks tend to have more negatively skewed return (e.g., Chen et al., 2001; Engle and Mistry, 2014; Harvey and Siddique, 2000). Therefore, I run another test replacing *RANK* with original decile rank *DR*. When crash risk measured by *Skew*, the regression results (unreported) show significant negative coefficients for the interaction term, and there is no change for the coefficients of TA sentiment regarding their sign and significance. This finding suggests that there is a monotonic instead of a U-shaped pattern in the crash risk of BE/ME decile portfolios in the cross-section following high TA sentiment periods.

Overall, high cross-sectional crash risk following a TA sentiment increase is consistent with my hypothesis. TA indicator performs well in forecasting the future crash risk as a sentiment proxy.

E.2.2 Robustness Tests on Predictive Regression

This section reports the predictive regression table after controlling for more variables. First, I report the results for adding more lagged TA terms into the regression.

Second, I test the fundamental explanation by adding the macroeconomic variables into the predictive regression. Table E.8 report the results of the predictive regression after controlling for the following daily macroeconomic variables: default spread (DS), TED spread, macroeconomic activities index ADS, and economic uncertainty EPU.

Third, I control for the effect of liquidity. I calculate the bid-ask spread premium for each long-short portfolio and use it as an additional control variable in the regression of its corresponding long-short return premium on lagged TA sentiment. For example, in ME(L-H) regression, the BAS control variable is constructed as the average bid-ask spread of bottom three deciles minus that of top three deciles. Table E.9 report the regression results after controlling for liquidity factor, FF five factors and Momentum factor.

Fourth, to see whether TA sentiment indicator performs better or provide additional contribution to the existing daily sentiment indicators, I add lagged VIX terms into the regression. Table E.10 report the regression coefficients of both lagged TA sentiment and lagged VIX sentiment after controlling for FF five factors. I find that VIX also predicts return in a similar way as TA sentiment, but the predictive power of TA sentiment index could not be subsumed by VIX. TA sentiment index provides more information than VIX in predicting the next day return.

Last, in Table E.11, I use the rolling estimates of residuals of TA_{t-2} regressed on TA_{t-1} to replace TA_{t-2} to mitigate the multicollinearity issue. I use the rolling estimates is to overcome the look-ahead bias. I find the results strongly consistent with our previous results with positive and significant coefficients for TA_{t-1} and significantly negative coefficients for orthogonalized TA_{t-2}. The intuition here is that orthogonalized TA_{t-2} could be seen as the negative value of sentiment changes from TA_{t-2} to TA_{t-1} . The negative coefficients means that incremental sentiment increase will positively contribute to the return premiums, even conditional on the high TA_{t-1} .

Table E.7 Predictive Regressions of Portfolio Returns on More TA lags

This table reports the coefficients for lagged TA terms in the two regressions below.

$$R_t = \alpha + \sum_{i=1}^{3} \beta_i TA_{t-i} + \gamma CV_t + \varepsilon_t.$$

$$R_t = \alpha + \beta_1 TA_{t-1} + \beta_2 SMTA_{t-26}^{t-2} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the long-short portfolios constructed from the sentiment-prone variables. H, M, and L are respectively the top three, middle four, and bottom three deciles.$SMTA_{t-26}^{t-2}$ is the smoothing average of lagged TA terms from $t-2$ to $t-26$. CV_t is a vector of control variables, which includes the Fama and French five factors and the momentum factor (UMD). A factor is excluded from the list of control variables when it is the dependent variable in the regressions. The Newey and West (1987) robust t-statistics are in brackets. The sample period is from 1964/01/01 to 2008/12/31. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		Panel A Regress on three lagged terms			Panel B Regress on TA and Smoothing Average	
		β_1	β_2	β_3	β_1	β_2
ME	L-H	2.36***	-1.45***	-0.78***	0.44***	-0.36***
		(11.79)	(-4.27)	(-3.90)	(13.51)	(-10.29)
Age	L-H	0.74***	-0.49**	-0.18*	0.16***	-0.10***
		(5.89)	(-2.46)	(-1.66)	(9.05)	(-5.54)
Sigma	H-L	0.47***	-0.37	-0.062	0.091***	-0.066***
		(3.16)	(-1.64)	(-0.53)	(4.46)	(-3.11)
E/BE	<0->0	0.29	0.13	-0.32**	0.17***	-0.075**
		(1.45)	(0.45)	(-2.10)	(5.86)	(-2.43)
D/BE	=0->0	0.39**	-0.13	-0.18	0.13***	-0.066***
		(2.24)	(-0.53)	(-1.54)	(5.79)	(-2.74)
PPE/A	L-H	0.62***	-0.66***	0.048	0.071***	-0.074***
		(4.94)	(-3.30)	(0.43)	(3.55)	(-3.67)
RD/A	H-L	0.19*	-0.18	-0.011	0.013	-0.020
		(1.84)	(-1.07)	(-0.12)	(0.89)	(-1.28)
BE/ME	H-L	0.35***	-0.19	-0.11	0.10***	-0.061***
		(2.94)	(-0.95)	(-1.00)	(5.82)	(-3.15)
EF/A	H-L	0.073	-0.14	0.047	-0.026***	0.0091
		(0.92)	(-1.01)	(0.65)	(-2.66)	(0.85)
GS	H-L	0.16**	-0.37***	0.18**	-0.032***	0.00091
		(2.09)	(-2.80)	(2.47)	(-2.96)	(0.08)
BE/ME	L-M	0.19*	-0.29*	0.087	0.00017	-0.0074
		(1.90)	(-1.73)	(0.99)	(0.01)	(-0.50)
EF/A	H-M	0.23***	-0.11	-0.097	0.047***	-0.033***
		(2.79)	(-0.81)	(-1.34)	(5.08)	(-3.19)
GS	H-M	0.17*	-0.19	0.032	0.021**	-0.011
		(1.90)	(-1.26)	(0.41)	(2.13)	(-1.04)
BE/ME	H-M	0.55***	-0.48***	-0.026	0.10***	-0.068***
		(5.90)	(-3.02)	(-0.30)	(7.67)	(-4.84)
EF/A	L-M	0.15**	0.028	-0.14**	0.074***	-0.042***
		(2.09)	(0.21)	(-2.01)	(7.56)	(-4.01)
GS	L-M	0.0077	0.18	-0.14*	0.053***	-0.012
		(0.09)	(1.29)	(-1.90)	(4.66)	(-1.01)

Table E.8 Predictive Regressions of Portfolio Returns on TA Sentiment Controlled for Macroeconomic Variables

This table reports the coefficients for lagged TA sentiment after controlling for macroeconomic effect.

$$R_t = \alpha + \sum \beta_i TA_{t-i} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the long-short portfolios constructed from the sentiment-prone variables. H, M, and L are respectively the top three, middle four, and bottom three deciles. CV_t is a vector of control variables, which includes the Fama and French five factors, the momentum factor (UMD) and macroeconomic variables including default spread (DS), TED spread, macroeconomics activities (ADS), and economic policy uncertainty (EPU). A control factor will be excluded from the list of control variables when it is the dependent variable in the regressions. This table reports the results of the regressions with the two lagged TA terms, FF five factors, Momentum factor, and four macroeconomics factors. The number of observations is 5,769. The Newey and West (1987) robust t-statistics are in brackets. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		β_1	β_2	γ_{ds}	γ_{ted}	γ_{ads}	γ_{epu}
ME	L-H	2.18***	-2.06***	0.044	-0.11***	-0.043**	0.000062
		(8.41)	(-7.89)	(1.08)	(-2.84)	(-2.30)	(0.43)
Age	L-H	1.12***	-1.05***	-0.038	-0.039**	-0.011	0.00028***
		(7.43)	(-6.82)	(-1.58)	(-2.53)	(-1.04)	(3.51)
Sigma	H-L	1.54***	-1.47***	-0.0084	-0.018	-0.011	0.00016**
		(9.10)	(-8.73)	(-0.29)	(-1.02)	(-0.96)	(2.05)
E/BE	<0->0	1.68***	-1.55***	-0.014	-0.033	0.0089	0.00032***
		(7.00)	(-6.43)	(-0.34)	(-1.37)	(0.55)	(3.00)
D/BE	=0->0	1.63***	-1.51***	-0.014	-0.043**	-0.00100	0.00021**
		(7.64)	(-7.06)	(-0.41)	(-2.08)	(-0.07)	(2.25)
PPE/A	L-H	0.44***	-0.44***	-0.052**	0.019	-0.036***	0.00022**
		(3.32)	(-3.34)	(-2.10)	(0.67)	(-2.81)	(2.49)
RD/A	H-L	0.47***	-0.47***	-0.0061	0.0014	-0.0023	-0.000050
		(4.54)	(-4.57)	(-0.36)	(0.11)	(-0.30)	(-0.84)
BE/ME	H-L	0.37***	-0.32**	0.0020	-0.047***	-0.0058	-0.000029
		(2.71)	(-2.34)	(0.07)	(-2.83)	(-0.54)	(-0.33)
EF/A	H-L	0.32***	-0.32***	-0.0095	0.020**	-0.0081	0.000029
		(3.64)	(-3.77)	(-0.79)	(2.33)	(-1.57)	(0.64)
GS	H-L	0.16*	-0.18**	-0.026*	0.029***	-0.0067	0.000019
		(1.79)	(-2.05)	(-1.88)	(3.03)	(-1.25)	(0.37)
BE/ME	L-M	0.46***	-0.46***	-0.0028	0.0035	-0.0033	0.00012*
		(4.12)	(-4.13)	(-0.14)	(0.32)	(-0.43)	(1.96)
EF/A	H-M	0.67***	-0.63***	-0.0095	-0.015**	-0.0066	0.00013***
		(7.28)	(-6.88)	(-0.73)	(-1.98)	(-1.18)	(3.03)
GS	H-M	0.57***	-0.54***	-0.014	-0.0046	-0.0062	0.000095**
		(6.33)	(-5.96)	(-1.05)	(-0.59)	(-0.98)	(2.10)
BE/ME	H-M	0.83***	-0.78***	-0.00082	-0.044***	-0.0090	0.000088
		(8.53)	(-8.04)	(-0.05)	(-4.15)	(-1.26)	(1.38)
EF/A	L-M	0.35***	-0.31***	0.000034	-0.034***	0.0016	0.000098**
		(4.18)	(-3.68)	(0.00)	(-4.30)	(0.30)	(2.15)
GS	L-M	0.41***	-0.36***	0.013	-0.034***	0.00056	0.000076
		(4.08)	(-3.52)	(0.74)	(-2.98)	(0.08)	(1.53)

Table E.9 Predictive Regressions of Portfolio Returns Controlled for Liquidity

This table reports the coefficients for lagged TA sentiment after controlling for the liquidity factor.

$$R_t = \alpha + \sum \beta_i TA_{t-i} + \gamma CV_t + \lambda BAS + \varepsilon_t.$$

R_t is the daily return of the long-short portfolios constructed from the sentiment-prone variables. H, M, and L are respectively the top three, middle four, and bottom three deciles. CV_t is a vector of control variables, which includes the Fama and French five factors, the momentum factor (UMD) and BAS. A factor is excluded from the list of control variables when it is the dependent variable in the regressions. Panel A reports the results of the regressions with the previous period TA as the only independent variables, i.e., $i = 1$. Panel B reports results of regressions with two TA lags as the independent variables, i.e., $i = 2$. The Newey and West (1987) robust t-statistics are in brackets. The sample period is from 1964/01/01 to 2008/12/31. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		Panel A		Panel B			
		No CV	With CV	No CV		With CV	
		β_1	β_1	β_1	β_2	β_1	β_2
ME	L-H	0.14***	0.11***	2.51***	-2.38***	2.36***	-2.25***
		(5.37)	(4.28)	(10.13)	(-9.54)	(9.90)	(-9.51)
Age	L-H	0.13***	0.070***	2.72***	-2.60***	1.08***	-1.01***
		(4.50)	(4.04)	(10.75)	(-10.15)	(7.28)	(-6.71)
Sigma	H-L	0.12***	0.051***	3.15***	-3.05***	1.32***	-1.27***
		(3.23)	(2.94)	(12.05)	(-11.55)	(8.42)	(-8.11)
E/BE	<0->0	0.16***	0.14***	2.11***	-1.97***	1.33***	-1.19***
		(5.19)	(5.12)	(8.61)	(-7.86)	(5.88)	(-5.27)
D/BE	=0->0	0.14***	0.11***	2.51***	-2.39***	1.32***	-1.21***
		(4.64)	(5.17)	(10.60)	(-9.90)	(6.73)	(-6.13)
PPE/A	L-H	0.0084	-0.0090	1.14***	-1.14***	0.45***	-0.46***
		(0.40)	(-0.55)	(7.11)	(-7.05)	(3.61)	(-3.74)
RD/A	H-L	0.014	0.00053	1.06***	-1.05***	0.46***	-0.46***
		(0.76)	(0.05)	(6.76)	(-6.66)	(4.71)	(-4.77)
BE/ME	H-L	0.038	0.059***	-0.67***	0.71***	0.26**	-0.20
		(1.50)	(3.65)	(-3.45)	(3.62)	(1.99)	(-1.57)
EF/A	H-L	-0.0098	-0.017**	0.76***	-0.78***	0.26***	-0.28***
		(-0.74)	(-2.34)	(6.77)	(-6.81)	(3.25)	(-3.48)
GS	H-L	-0.032**	-0.031***	0.55***	-0.59***	0.11	-0.14*
		(-2.49)	(-3.69)	(4.57)	(-4.81)	(1.39)	(-1.79)
BE/ME	L-M	0.012	-0.0086	1.06***	-1.06***	0.43***	-0.44***
		(0.58)	(-0.70)	(7.38)	(-7.23)	(4.13)	(-4.27)
EF/A	H-M	0.044***	0.027***	1.18***	-1.14***	0.58***	-0.56***
		(3.08)	(3.42)	(10.37)	(-9.83)	(6.97)	(-6.61)
GS	H-M	0.043**	0.022**	1.25***	-1.21***	0.47***	-0.45***
		(2.53)	(2.56)	(9.64)	(-9.18)	(5.66)	(-5.38)
BE/ME	H-M	0.052***	0.054***	0.39***	-0.34***	0.69***	-0.64***
		(4.73)	(5.25)	(3.30)	(-2.88)	(7.44)	(-6.97)
EF/A	L-M	0.052***	0.042***	0.41***	-0.36***	0.32***	-0.28***
		(6.97)	(5.88)	(4.98)	(-4.31)	(4.13)	(-3.58)
GS	L-M	0.076***	0.053***	0.70***	-0.62***	0.35***	-0.30***
		(6.26)	(5.36)	(6.32)	(-5.57)	(3.89)	(-3.29)

Table E.10 Predictive Regressions of Portfolio Returns Controlled for VIX

This table reports the coefficients for lagged TA sentiment and lagged VIX terms in the regressions.

$$R_t = \alpha + \sum \beta_i TA_{t-i} + \sum \beta_i VIX_{t-i} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the long-short portfolios constructed from the sentiment-prone variables. H, M, and L are respectively the top three, middle four, and bottom three deciles. CV_t is a vector of control variables, which includes the Fama and French five factors and the momentum factor (UMD). A factor is excluded from the list of control variables when it is the dependent variable in the regressions. $i = 2$. The Newey and West (1987) robust t-statistics are in brackets. The sample period is from 1964/01/01 to 2008/12/31. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		TA_1	TA_2	VIX_1	VIX_2
ME	L-H	2.18***	-2.10***	0.83	-0.95
		(6.99)	(-6.72)	(0.74)	(-0.84)
Age	L-H	1.29***	-1.19***	-0.67	0.82
		(7.36)	(-6.73)	(-1.15)	(1.45)
Sigma	H-L	1.75***	-1.64***	-1.68***	1.94***
		(9.32)	(-8.78)	(-3.51)	(4.18)
E/BE	<0->0	1.88***	-1.68***	-2.97***	3.25***
		(6.95)	(-6.25)	(-3.32)	(3.86)
D/BE	=0->0	1.78***	-1.62***	-2.83***	2.95***
		(7.75)	(-7.04)	(-3.68)	(3.87)
PPE/A	L-H	0.34*	-0.36*	-0.26	0.32
		(1.74)	(-1.84)	(-0.33)	(0.39)
RD/A	H-L	0.49***	-0.48***	-0.52	0.57
		(4.09)	(-3.99)	(-1.37)	(1.50)
BE/ME	H-L	-0.11	0.14	-2.31***	2.01**
		(-0.54)	(0.74)	(-2.74)	(2.55)
EF/A	H-L	0.32***	-0.32***	-0.18	0.32
		(3.26)	(-3.32)	(-0.60)	(1.00)
GS	H-L	0.16	-0.18	0.40	-0.37
		(1.37)	(-1.60)	(0.98)	(-0.86)
BE/ME	L-M	0.69***	-0.68***	0.48	-0.27
		(4.87)	(-4.82)	(0.89)	(-0.52)
EF/A	H-M	0.75***	-0.71***	-0.42	0.51*
		(7.34)	(-6.96)	(-1.52)	(1.91)
GS	H-M	0.64***	-0.60***	-0.55**	0.65**
		(6.09)	(-5.70)	(-2.03)	(2.37)
BE/ME	H-M	0.59***	-0.54***	-1.83***	1.74***
		(4.58)	(-4.32)	(-4.03)	(4.10)
EF/A	L-M	0.43***	-0.39***	-0.24	0.19
		(4.29)	(-3.86)	(-0.86)	(0.63)
GS	L-M	0.49***	-0.42***	-0.95**	1.02***
		(4.11)	(-3.53)	(-2.52)	(2.66)

Table E.11 Predictive Regressions of Portfolio Returns on Orthogonalized TA lagged Terms

This table reports the coefficients for orthogonalized lagged TA sentiment terms in the regressions.

$$R_t = \alpha + \beta_1 TA_{t-1} + \beta_2 TA^{\perp}_{t-2} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the long-short portfolios constructed from the sentiment-prone variables. H, M, and L are respectively the top three, middle four, and bottom three deciles. CV_t is a vector of control variables, which includes the Fama and French five factors and the momentum factor (UMD). A factor is excluded from the list of control variables when it is the dependent variable in the regressions. $TA^{\perp}_{t-2}$ is orthogonalized to TA_{t-1}. Panel A (B) report the results without (with) control variables. The Newey and West (1987) robust t-statistics are in brackets. The sample period is from 1964/01/01 to 2008/12/31. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		Panel A No CV		Panel B With CV	
		TA_1	$TA^{\perp}_{t-2}$	TA_1	$TA^{\perp}_{t-2}$
ME	L-H	0.16***	-2.34***	0.15***	-2.69***
		(8.79)	(-12.95)	(8.64)	(-14.82)
Age	L-H	0.14***	-2.30***	0.078***	-0.78***
		(8.55)	(-14.15)	(7.17)	(-7.15)
Sigma	H-L	0.12***	-2.91***	0.039***	-0.48***
		(5.35)	(-15.01)	(3.30)	(-3.76)
E/BE	<0->0	0.15***	-1.36***	0.11***	-0.38**
		(7.82)	(-7.50)	(6.26)	(-2.17)
D/BE	=0->0	0.13***	-1.87***	0.082***	-0.43***
		(7.16)	(-11.17)	(5.80)	(-2.81)
PPE/A	L-H	0.040***	-1.45***	0.012	-0.58***
		(2.86)	(-11.76)	(1.03)	(-5.09)
RD/A	H-L	0.0094	-0.84***	-0.0025	-0.20**
		(0.76)	(-7.03)	(-0.29)	(-2.38)
BE/ME	H-L	0.032**	0.68***	0.055***	-0.37***
		(1.97)	(4.70)	(4.88)	(-3.45)
EF/A	H-L	-0.0065	-0.62***	-0.019***	-0.064
		(-0.77)	(-7.68)	(-3.81)	(-1.04)
GS	H-L	-0.022**	-0.62***	-0.031***	-0.082
		(-2.54)	(-7.13)	(-5.41)	(-1.33)
BE/ME	L-M	0.012	-0.84***	-0.0054	-0.15*
		(0.98)	(-8.05)	(-0.65)	(-1.74)
EF/A	H-M	0.043***	-0.96***	0.022***	-0.27***
		(4.78)	(-11.81)	(4.01)	(-4.11)
GS	H-M	0.039***	-1.03***	0.013**	-0.14**
		(3.79)	(-11.30)	(2.20)	(-2.05)
BE/ME	H-M	0.043***	-0.16*	0.050***	-0.51***
		(5.66)	(-1.91)	(6.99)	(-6.67)
EF/A	L-M	0.049***	-0.34***	0.040***	-0.20***
		(9.17)	(-5.49)	(8.06)	(-3.49)
GS	L-M	0.061***	-0.41***	0.044***	-0.056
		(7.98)	(-5.25)	(6.78)	(-0.83)

E.2.3 Construct TA Sentiment (Returns) with Different Methods

TA sentiment index is constructed with the forecasts of technical trading rules applied on the overall market index. I replicate the two key tables in Chapter 4 to demonstrate that TA sentiment still has strong predictability and profitability when TA sentiment is based on DJIA. Table E.12 report the predictive regression results when using the TA sentiment index constructed from DJIA index instead of S&P 500 index. Table E.13 reports the profitability of TADJ (DJIA-Based TA Sentiment Index).

I also use the performance-weighted average of the technical trading rule forecasts to measure TA sentiment. The test results on predictability and profitability are reported in Table E.14 and Table E.15 separately.

To mitigate the size effect, I also construct the long-short portfolio returns using value-weighted average return. Table E.16 and Table E.17 respectively reports the predictability and profitability of TA sentiment on the value-weighted cross-sectional return.

Table E.12 Predictive Regressions of Portfolio Returns on DJIA-Based TA Sentiment

This table reports the coefficients for lagged DJIA-Based TA sentiment of regressions of long-short portfolio returns on lagged DJIA-Based TA sentiment and a set of control variables.

$$R_t = \alpha + \sum \beta_i TADJ_{t-i} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the long-short portfolios constructed from the sentiment-prone variables. H, M, and L are respectively the top three, middle four, and bottom three deciles. CV_t is a vector of control variables, which includes the Fama and French five factors and the momentum factor (UMD). A factor is excluded from the list of control variables when it is the dependent variable in the regressions. TADJ is the DJIA-Based TA sentiment. Panel A reports the results of the regressions with the previous period TADJ as the only independent variables, i.e., $i = 1$. Panel B reports results of regressions with two TA lags as the independent variables, i.e., $i = 2$. The Newey and West (1987) robust t-statistics are in brackets. The sample period is from 1964/01/01 to 2008/12/31. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		Panel A		Panel B			
		No Control Variables	With Control Variables	No Control Variables		With Control Variables	
		β_1	β_1	β_1	β_2	β_1	β_2
ME	L-H	0.13*** (8.99)	0.12*** (8.25)	2.07*** (12.75)	-1.95*** (-12.00)	2.32*** (13.71)	-2.20*** (-13.13)
Age	L-H	0.11*** (8.31)	0.062*** (7.69)	1.84*** (12.89)	-1.74*** (-12.25)	0.57*** (5.94)	-0.51*** (-5.33)
Sigma	H-L	0.079*** (4.25)	0.028*** (3.07)	2.26*** (12.92)	-2.19*** (-12.60)	0.30*** (2.76)	-0.27** (-2.53)
E/BE	<0->0	0.11*** (8.06)	0.085*** (6.73)	1.10*** (6.90)	-0.99*** (-6.21)	0.26 (1.60)	-0.17 (-1.09)
D/BE	=0->0	0.093*** (6.54)	0.062*** (5.86)	1.40*** (9.70)	-1.32*** (-9.12)	0.25* (1.83)	-0.19 (-1.40)
PPE/A	L-H	0.024** (2.08)	0.0060 (0.64)	1.16*** (10.43)	-1.14*** (-10.28)	0.49*** (4.78)	-0.48*** (-4.76)
RD/A	H-L	0.0031 (0.30)	0.00035 (0.05)	0.65*** (6.10)	-0.65*** (-6.12)	0.19** (2.52)	-0.19** (-2.55)
BE/ME	H-L	0.043*** (3.54)	0.050*** (5.62)	-0.40*** (-3.20)	0.45*** (3.53)	0.36*** (3.97)	-0.31*** (-3.44)
EF/A	H-L	-0.013* (-1.92)	-0.016*** (-3.98)	0.39*** (5.31)	-0.40*** (-5.47)	-0.0047 (-0.09)	-0.012 (-0.23)
GS	H-L	-0.028*** (-3.89)	-0.029*** (-6.11)	0.43*** (5.59)	-0.46*** (-5.95)	0.058 (1.11)	-0.088* (-1.68)
BE/ME	L-M	-0.0035 (-0.40)	-0.0095 (-1.53)	0.55*** (6.09)	-0.56*** (-6.13)	0.054 (0.73)	-0.063 (-0.86)
EF/A	H-M	0.028*** (3.99)	0.017*** (3.87)	0.72*** (9.88)	-0.70*** (-9.49)	0.19*** (3.38)	-0.17*** (-3.11)
GS	H-M	0.021** (2.54)	0.0063 (1.41)	0.80*** (9.63)	-0.78*** (-9.44)	0.11* (1.92)	-0.10* (-1.83)
BE/ME	H-M	0.039*** (6.21)	0.041*** (6.79)	0.15** (2.00)	-0.11 (-1.48)	0.41*** (6.17)	-0.37*** (-5.63)
EF/A	L-M	0.041*** (9.09)	0.033*** (7.85)	0.33*** (6.38)	-0.29*** (-5.59)	0.19*** (3.93)	-0.16*** (-3.28)
GS	L-M	0.049*** (7.79)	0.036*** (6.80)	0.37*** (5.64)	-0.32*** (-4.93)	0.051 (0.89)	-0.016 (-0.28)

Table E.13 Profitability of DJIA-Based TA Trading Strategies

This table reports the summary statistics of the original long-short portfolio returns, the DJIA-Based TA timing returns, and the *TAP* returns. The original portfolios are constructed by longing the most sentiment-prone deciles and shorting the least sentiment-prone deciles. TA timing rule represents holding the original portfolio when current TA sentiment is no less than the average TA sentiment over prior five trading days and shorting the original portfolio otherwise. *TAP* is the abnormal returns on the sentiment timing strategy over original portfolio returns. *AvgRet* is the average return. *SRatio* is the Sharpe ratio. *SD* is the standard deviation. *Skew* is the return skewness. *Success* in Panel C is the percentage of non-negative *TAP* returns. All the returns are annualised and in percentages. The sample period is between 01/1964 and 12/2008. The asterisks $***$, $**$ and $*$ indicates the t-test significance at 1%, 5% and 10% level, respectively.

		Panel A Original Portfolio				Panel B TA Timing Strategy				Panel C TAP			
		Avg Ret	SD	Skew	SRatio	Avg Ret	SD	Skew	SRatio	Avg Ret	SD	Skew	Success
ME	1-10	18.73***	13.34	-0.85	1.4	35.31***	13.2	0.91	2.67	16.58***	19.53	2.34	0.77
Age	1-10	7.21***	9.9	-0.26	0.73	22.47***	9.81	0.48	2.29	15.25***	14.48	1.09	0.78
Sigma	10-1	12.80***	13.17	-0.19	0.97	24.85***	13.1	0.17	1.9	12.05***	20.09	0.48	0.76
E/BE	1-10	9.71***	7.06	-0.04	1.37	10.14***	7.06	0.37	1.44	0.43	10.02	0.57	0.76
D/BE	1-10	9.05***	8.4	-0.26	1.08	17.29***	8.35	0.21	2.07	8.23***	12.31	0.7	0.77
PPE/A	1-10	-2.39**	8.13	0.03	-0.29	7.11***	8.12	0.23	0.88	9.51***	11.52	0.44	0.78
RD/A	10-1	5.34***	11.01	0.03	0.49	5.97***	11	-0.21	0.54	0.62	16.17	-0.29	0.8
BE/ME	10-1	17.13***	10.15	-0.33	1.69	4.65***	10.21	0.25	0.46	-12.48***	15.05	0.59	0.75
EF/A	10-1	-12.66***	7.36	0.17	-1.72	1.8	7.4	0.09	0.24	14.46***	10.76	0.13	0.79
GS	10-1	-10.90***	6.87	0.17	-1.59	-2.21**	6.9	0.01	-0.32	8.69***	9.98	-0.06	0.78
BE/ME	1-5	-2.41**	7.83	0.35	-0.31	2.17*	7.83	-0.18	0.28	4.58***	11.63	-0.59	0.77
EF/A	10-5	-4.34***	7.34	0.12	-0.59	10.56***	7.31	0.13	1.44	14.90***	10.89	0.21	0.78
GS	10-5	-3.81***	7.76	0.07	-0.49	7.73***	7.75	0.12	1	11.54***	11.62	0.21	0.77
BE/ME	10-5	14.72***	6.48	0.15	2.27	6.82***	6.53	0.34	1.04	-7.91***	8.99	0.11	0.74
EF/A	1-5	8.32***	5.32	0.09	1.56	8.76***	5.32	0.14	1.65	0.44	7.47	0.09	0.76
GS	1-5	7.09***	6.53	0.09	1.08	9.94***	6.52	0.16	1.52	2.85**	9.28	0.16	0.77

Table E.14 Predictive Regressions of Portfolio Returns on Performance-Weighted TA Sentiment

This table reports the coefficients for lagged Performance-Weighted TA sentiment of regressions of long-short portfolio returns on lagged Performance-Weighted TA sentiment and a set of control variables.

$$R_{t,1} - R_{t,2} = \alpha + \sum \beta_i TAPW_{t-i} + \gamma CV_t + \varepsilon_t.$$

R_t is the daily return of the long-short portfolios constructed from the sentiment-prone variables. H, M, and L are respectively the top three, middle four, and bottom three deciles. CV_t is a vector of control variables, which includes the Fama and French five factors and the momentum factor (UMD). A factor is excluded from the list of control variables when it is the dependent variable in the regressions. TAPW is the Performance-Weighted TA sentiment. Panel A (B) reports the results of the regressions with one (two) lagged TA terms, i.e. $i = 1$ ($i = 2$). The Newey and West (1987) robust t-statistics are in brackets. The sample period is from 1964/01/01 to 2008/12/31. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		Panel A		Panel B			
		No CV	With CV	No CV		With CV	
		β_1	β_1	β_1	β_2	β_1	β_2
ME	L-H	0.062*** (6.65)	0.067*** (7.17)	0.12*** (3.92)	-0.065** (-2.19)	0.19*** (6.23)	-0.13*** (-4.46)
Age	L-H	0.061*** (7.02)	0.030*** (5.49)	0.17*** (6.72)	-0.11*** (-4.48)	0.046*** (3.52)	-0.017 (-1.32)
Sigma	H-L	0.060*** (5.49)	0.0092* (1.66)	0.26*** (8.78)	-0.21*** (-7.10)	0.0055 (0.36)	0.0039 (0.27)
E/BE	<0->0	0.046*** (4.88)	0.026*** (3.02)	0.069*** (3.05)	-0.024 (-1.02)	-0.016 (-0.84)	0.044** (2.33)
D/BE	=0->0	0.051*** (5.57)	0.023*** (3.24)	0.14*** (6.05)	-0.092*** (-3.92)	-0.0030 (-0.19)	0.027* (1.78)
PPE/A	L-H	0.021*** (3.26)	0.0043 (0.86)	0.14*** (7.49)	-0.12*** (-6.44)	0.050*** (3.92)	-0.048*** (-3.76)
RD/A	H-L	0.0062 (1.08)	-0.0052 (-1.41)	0.084*** (5.12)	-0.082*** (-4.86)	0.0054 (0.53)	-0.011 (-1.15)
BE/ME	H-L	-0.0052 (-0.70)	0.015*** (3.02)	-0.12*** (-6.03)	0.12*** (5.81)	0.016 (1.47)	-0.0013 (-0.12)
EF/A	H-L	0.0028 (0.73)	-0.0073*** (-3.20)	0.069*** (5.65)	-0.070*** (-5.45)	-0.0032 (-0.40)	-0.0043 (-0.55)
GS	H-L	0.0036 (0.91)	-0.0058** (-2.23)	0.095*** (8.32)	-0.096*** (-8.20)	0.022*** (2.91)	-0.029*** (-3.88)
BE/ME	L-M	0.014** (2.42)	0.00073 (0.19)	0.10*** (6.63)	-0.094*** (-5.59)	0.013 (1.26)	-0.012 (-1.22)
EF/A	H-M	0.020*** (4.71)	0.0069*** (2.74)	0.083*** (6.90)	-0.066*** (-5.28)	0.0080 (0.99)	-0.0011 (-0.14)
GS	H-M	0.022*** (4.43)	0.0044 (1.64)	0.12*** (8.38)	-0.099*** (-6.99)	0.018* (1.88)	-0.014 (-1.53)
BE/ME	H-M	0.0090*** (2.70)	0.015*** (4.84)	-0.019* (-1.73)	0.029*** (2.69)	0.029*** (3.25)	-0.014 (-1.58)
EF/A	L-M	0.017*** (6.25)	0.014*** (5.62)	0.014* (1.75)	0.0034 (0.43)	0.011 (1.50)	0.0031 (0.43)
GS	L-M	0.018*** (4.92)	0.010*** (3.35)	0.021** (2.00)	-0.0031 (-0.29)	-0.0047 (-0.55)	0.016* (1.87)

Table E.15 Profitability of Performance-Weighted TA Trading Strategies

This table reports the summary statistics of the original long-short portfolio returns, the Performance-Weighted TA timing returns, and the *TAP* returns. The original portfolios are constructed by longing the most sentiment-prone deciles and shorting the least sentiment-prone deciles. TA timing rule represents holding the original portfolio when current Performance-Weighted TA sentiment is no less than the average TA sentiment over prior five trading days and shorting the original portfolio otherwise. *TAP* is the abnormal returns on the sentiment timing strategy over original portfolio returns. *AvgRet* is the average return. *SRatio* is the Sharpe ratio. *SD* is the standard deviation. *Skew* is the return skewness. *Success* in Panel C is the percentage of non-negative *TAP* returns. All the returns are annualised and in percentages. The sample period is between 01/1964 and 12/2008. The asterisks $***$, $**$ and $*$ indicates the t-test significance at 1%, 5% and 10% level, respectively.

		Panel A Original Portfolio				Panel B TA Timing Strategy				Panel C TAP			
		Avg Ret	SD	Skew	SRatio	Avg Ret	SD	Skew	SRatio	Avg Ret	SD	Skew	Success
ME	1-10	18.54***	13.58	-0.83	1.36	19.26***	13.58	0.2	1.42	0.73	18.91	1.54	0.75
Age	1-10	7.15***	10.06	-0.25	0.71	16.41***	10.02	0.3	1.64	9.26***	14.08	0.93	0.77
Sigma	10-1	12.36***	13.36	-0.19	0.93	23.96***	13.3	0.45	1.8	11.60***	19	0.98	0.75
E/BE	1-10	9.95***	7.13	-0.03	1.4	1.24	7.16	0.32	0.17	-8.71***	9.8	0.36	0.74
D/BE	1-10	9.00***	8.53	-0.26	1.06	14.73***	8.49	0.57	1.73	5.73***	12.08	1.25	0.76
PPE/A	1-10	-2.80**	8.22	0.03	-0.34	8.93***	8.2	0.06	1.09	11.73***	11.26	0.27	0.78
RD/A	10-1	5.35***	11.01	0.03	0.49	10.76***	10.99	0.52	0.98	5.40**	15.62	0.76	0.79
BE/ME	10-1	17.62***	10.3	-0.34	1.71	-5.39***	10.35	-0.25	-0.52	-23.02***	14.49	-0.19	0.73
EF/A	10-1	-12.77***	7.42	0.18	-1.72	6.72***	7.45	0.38	0.9	19.50***	10.36	0.69	0.79
GS	10-1	-11.00***	6.89	0.18	-1.6	4.78***	6.92	0.2	0.69	15.77***	9.6	0.37	0.79
BE/ME	1-5	-2.87**	7.96	0.36	-0.36	6.23***	7.95	0.32	0.78	9.10***	11.13	0.11	0.77
EF/A	10-5	-4.53***	7.43	0.13	-0.61	9.97***	7.41	0.5	1.34	14.50***	10.36	0.82	0.78
GS	10-5	-4.07***	7.85	0.07	-0.52	9.36***	7.84	0.44	1.19	13.43***	11	0.77	0.78
BE/ME	10-5	14.76***	6.48	0.16	2.28	0.84	6.55	0.03	0.13	-13.92***	8.8	-0.55	0.72
EF/A	1-5	8.24***	5.32	0.07	1.55	3.25***	5.34	0.25	0.61	-5.00***	7.32	0.14	0.74
GS	1-5	6.93***	6.58	0.07	1.05	4.58***	6.59	0.51	0.7	-2.35*	8.9	0.65	0.75

Table E.16 Predictive Regressions of Value-Weighted Returns on TA Sentiment

This table reports the coefficients for lagged Performance-Weighted TA sentiment of regressions of long-short portfolio returns on lagged Performance-Weighted TA sentiment and a set of control variables.

$$Rv_{t,1} - Rv_{t,2} = \alpha + \sum \beta_i TA_{t-i} + \gamma CV_t + \varepsilon_t.$$

$Rv_{t,1} - Rv_{t,2}$ is the daily value-weighted return of the long-short portfolios constructed from the sentiment-prone variables. H, M, and L are respectively the top three, middle four, and bottom three deciles. CV_t is a vector of control variables, which includes the Fama and French five factors and the momentum factor (UMD). A factor is excluded from the list of control variables when it is the dependent variable in the regressions. Panel A (B) reports the results of the regressions with one (two) lagged TA terms, i.e. $i = 1$ ($i = 2$). The Newey and West (1987) robust t-statistics are in brackets. The sample period is from 1964/01/01 to 2008/12/31. The asterisks $***$, $**$ and $*$ indicates the statistical significance at 1%, 5% and 10% level, respectively.

		Panel A		Panel B			
		No CV	With CV	No CV		With CV	
		β_1	β_1	β_1	β_2	β_1	β_2
ME	L-H	0.14*** (8.08)	0.13*** (7.26)	2.68*** (14.65)	-2.55*** (-13.87)	2.87*** (15.30)	-2.75*** (-14.68)
Age	L-H	0.095*** (4.28)	0.0076 (0.67)	2.88*** (15.62)	-2.80*** (-14.84)	0.53*** (4.28)	-0.52*** (-4.19)
Sigma	H-L	0.062** (2.05)	-0.041** (-2.52)	2.70*** (10.33)	-2.65*** (-10.06)	-0.65*** (-3.90)	0.61*** (3.67)
E/BE	<0->0	0.098*** (3.59)	0.013 (0.60)	1.91*** (8.34)	-1.82*** (-7.86)	-0.57*** (-2.70)	0.59*** (2.77)
D/BE	=0->0	0.063*** (2.69)	-0.0043 (-0.29)	1.79*** (8.28)	-1.73*** (-7.93)	-0.65*** (-3.90)	0.65*** (3.89)
PPE/A	L-H	0.020 (0.96)	-0.016 (-0.98)	1.50*** (8.17)	-1.49*** (-8.06)	0.20 (1.23)	-0.21 (-1.36)
RD/A	H-L	-0.030 (-1.30)	-0.031* (-1.73)	-0.046 (-0.20)	0.016 (0.07)	-0.61*** (-3.22)	0.58*** (3.08)
BE/ME	H-L	0.032* (1.71)	-0.0057 (-0.37)	0.39** (2.26)	-0.36** (-2.08)	-0.13 (-0.76)	0.13 (0.75)
EF/A	H-L	0.00027 (0.02)	-0.021*** (-2.59)	0.26* (1.84)	-0.26* (-1.83)	-0.65*** (-6.64)	0.63*** (6.50)
GS	H-L	-0.023 (-1.33)	-0.023** (-2.08)	0.048 (0.29)	-0.072 (-0.43)	-0.54*** (-4.73)	0.52*** (4.59)
BE/ME	L-M	-0.018 (-1.32)	-0.0032 (-0.28)	-0.18 (-1.44)	0.16 (1.29)	-0.11 (-1.02)	0.11 (1.00)
EF/A	H-M	0.024 (1.61)	-0.012 (-1.46)	1.13*** (8.36)	-1.11*** (-8.10)	-0.083 (-0.80)	0.070 (0.68)
GS	H-M	0.027* (1.76)	-0.0042 (-0.45)	0.73*** (5.08)	-0.71*** (-4.88)	-0.48*** (-4.50)	0.47*** (4.48)
BE/ME	H-M	0.014 (1.12)	-0.0089 (-0.72)	0.21* (1.71)	-0.20 (-1.62)	-0.25* (-1.80)	0.24* (1.77)
EF/A	L-M	0.024*** (2.69)	0.0091 (1.14)	0.87*** (9.71)	-0.85*** (-9.50)	0.57*** (6.39)	-0.56*** (-6.33)
GS	L-M	0.050*** (4.41)	0.019** (2.02)	0.68*** (6.28)	-0.64*** (-5.80)	0.065 (0.69)	-0.046 (-0.49)

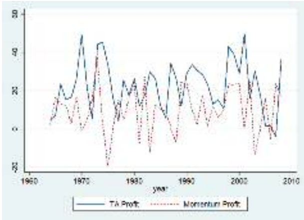
Table E.17 Profitability of TA Trading Strategies on Value-Weighted Portfolio

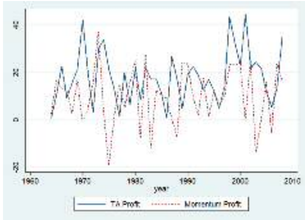
This table reports the summary statistics of the original value-weighted long-short portfolio returns, the TA timing returns, and the *TAP* returns. The original portfolios are constructed by longing the most sentiment-prone deciles and shorting the least sentiment-prone deciles. TA timing rule represents holding the original portfolio when current TA sentiment is no less than the average TA sentiment over prior five trading days and shorting the original portfolio otherwise. *TAP* is the abnormal returns on the sentiment timing strategy over original portfolio returns. *AvgRet* is the average return. *SRatio* is the Sharpe ratio. *SD* is the standard deviation. *Skew* is the return skewness. *Success* in Panel C is the percentage of non-negative *TAP* returns. All the returns are annualised and in percentages. The sample period is between 01/1964 and 12/2008. The asterisks $***$, $**$ and $*$ indicates the t-test significance at 1%, 5% and 10% level, respectively.

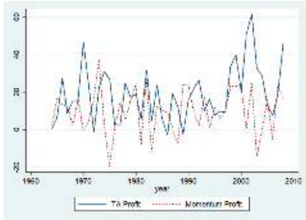
		Panel A Original Portfolio				Panel B TA Timing Strategy				Panel C TAP			
		Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	Success
ME	1-10	12.02***	12.94	-1.2	0.93	36.86***	12.75	1.2	2.89	24.83***	19.04	3.14	0.78
Age	1-10	-0.22	12.22	0.08	-0.02	25.08***	12.11	0.75	2.07	25.30***	17.7	1.1	0.79
Sigma	10-1	1.82	20.46	0.25	0.09	22.09***	20.41	0.27	1.08	20.27***	30.19	0.13	0.77
E/BE	1-10	1.5	10.88	0.33	0.14	11.62***	10.86	0.01	1.07	10.13***	15.63	-0.32	0.78
D/BE	1-10	1.03	13.65	0.61	0.08	13.55***	13.62	0.48	0.99	12.51***	19.84	-0.07	0.77
PPE/A	1-10	-1.84	14.21	0.89	-0.13	5.32**	14.2	-0.52	0.37	7.15**	20.86	-1.73	0.78
RD/A	10-1	0.98	14.16	0.04	0.07	-7.31***	14.15	-0.07	-0.52	-8.29**	20.5	-0.21	0.8
BE/ME	10-1	8.13***	12.62	0.01	0.64	12.60***	12.61	0.09	1	4.47	18.35	0.15	0.77
EF/A	10-1	-6.43***	11.38	0.64	-0.57	-1.37	11.38	0.3	-0.12	5.06**	16.53	-0.39	0.77
GS	10-1	-1.8	11.3	0.24	-0.16	-3.01*	11.3	0.05	-0.27	-1.21	16.09	-0.28	0.76
BE/ME	1-5	-2.23	10.06	0.25	-0.22	-5.49***	10.05	0.04	-0.55	-3.26	14.5	-0.32	0.76
EF/A	10-5	-3.86**	10.72	0.28	-0.36	10.13***	10.71	0.21	0.95	13.99***	15.94	0.05	0.78
GS	10-5	-1.83	11.05	-0.05	-0.17	6.62***	11.05	0.11	0.6	8.45***	16.25	0.29	0.78
BE/ME	10-5	5.90***	9.64	0.21	0.61	7.11***	9.64	0.2	0.74	1.21	13.39	0.01	0.77
EF/A	1-5	2.57**	7.7	-0.16	0.33	11.50***	7.66	0.14	1.5	8.93***	10.9	0.57	0.78
GS	1-5	-0.03	9.43	-0.1	0	9.63***	9.41	0.11	1.02	9.66***	13.06	0.46	0.78

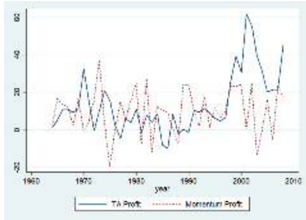
E.2.4 Robustness Tests on Profitability of TA Sentiment

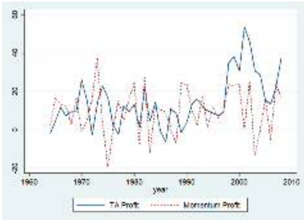
This section reports the robustness tests on the TA Sentiment trading strategy profit. I first compare the TA Trading Strategy returns with Momentum Trading Strategy. I calculate the annual average of the TA Trading Strategy profit for each long-short portfolio and the annual average of the Momentum Trading Strategy return. In Figure E.1, each graph reports the annual return of TA Trading Strategy with solid line and reports the Momentum Trading Strategy return as a benchmark with a dashed line. Figure E.2 also shows the persistency of my trading strategy. In those graphs, I set the benchmark return as the S&P 500 index annual returns. Both Figure E.1 and Figure E.2 show that the TA trading strategy consistently outperforms the momentum trading strategy or the overall market for the first six long-short portfolios.

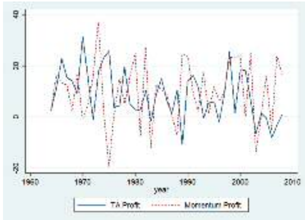

(a) ME(L-H)

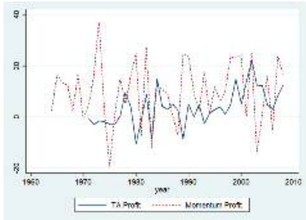

(b) Age(L-H)

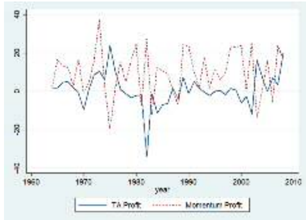

(c) Sigma(H-L)

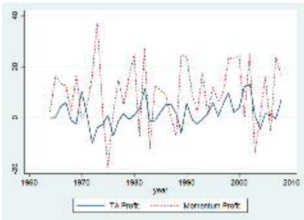

(d) E/BE(L-H)

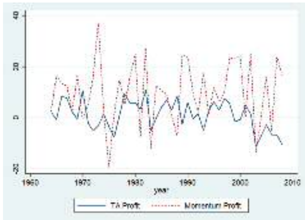

(e) D/BE(L-H)

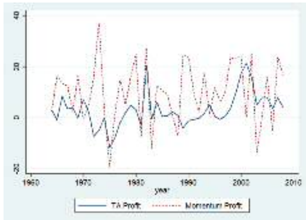

(f) PPE/A(L-H)

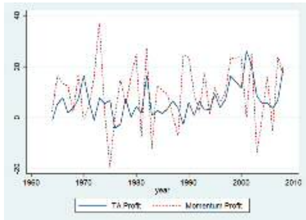

(g) RD/A(H-L)

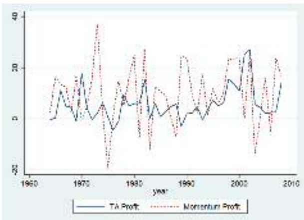

(h) BE/ME(H-L)

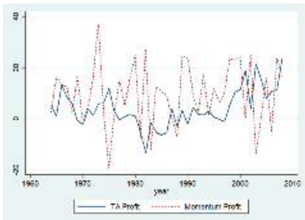

(i) EF/A(H-L)

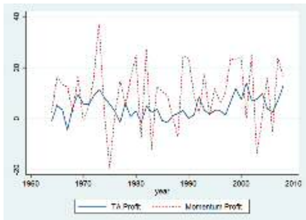

(j) GS(H-L)

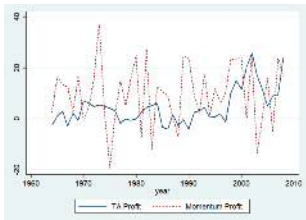

(k) BE/ME(L-M)


(l) EF/A(H-M)


(m) GS(H-M)

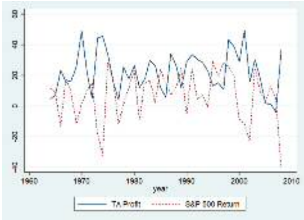

(n) BE/ME(H-M)


(o) EF/A(L-M)

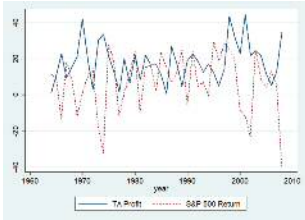

(p) GS(L-M)

Annual Profits of TA Trading Strategy and Momentum Trading Strategy The solid line is the annual returns of TA trading signal. The dashed line is the annual Momentum Trading Strategy returns. The sample period is from 1964 to 2008.

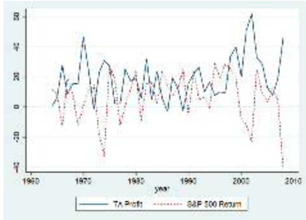
Fig. E.1 TA Trading Strategy Profit Compared with Momentum Returns



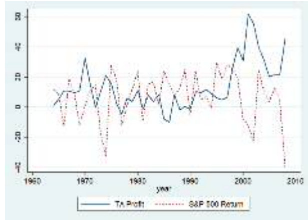
(a) ME(L-H)



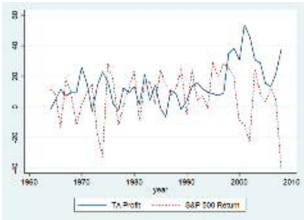
(b) Age(L-H)



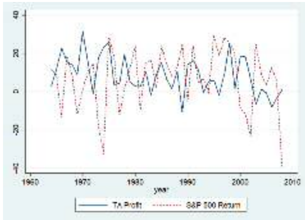
(c) Sigma(H-L)



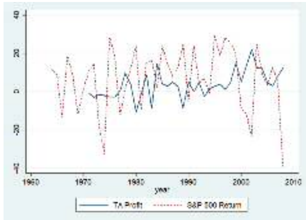
(d) E/BE(L-H)



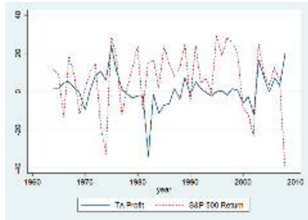
(e) D/BE(L-H)



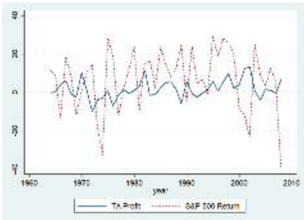
(f) PPE/A(L-H)



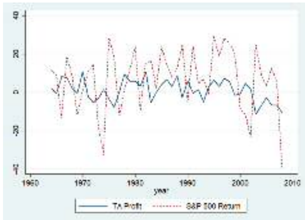
(g) RD/A(H-L)



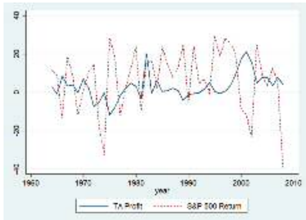
(h) BE/ME(H-L)



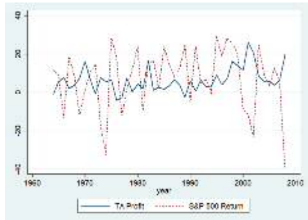
(i) EF/A(H-L)



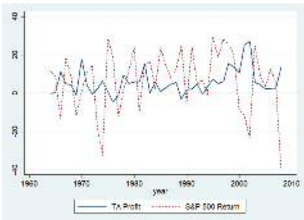
(j) GS(H-L)



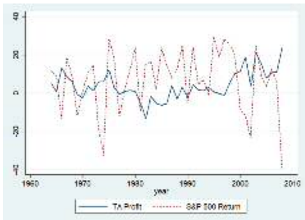
(k) BE/ME(L-M)



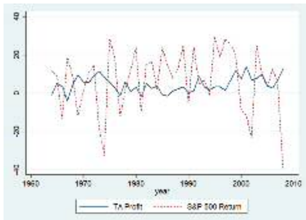
(l) EF/A(H-M)



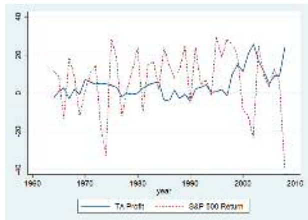
(m) GS(H-M)



(n) BE/ME(H-M)



(o) EF/A(L-M)



(p) GS(L-M)

Annual Profits of TA Trading Strategy and S&P 500 Returns The solid line is the annual returns of TA trading signal. The dashed line is the annual S&P 500 returns. The sample period is from 1964 to 2008.

Fig. E.2 TA Trading Strategy Profit Compared with S&P 500 Index Returns

E.3 Robustness Tests for Chapter 5

This section contains some key robustness tests on the predictability and profitability of VIX as a sentiment indicator.

Table E.18 reports the predictive power of VIX after controlling for macroeconomic variables (Default Spread and TED Spread) in addition to the FF five factors and momentum factor in Panel A. Panel B of Table E.18 reports the abnormal alphas of the excess return of VIX Trading Strategy over the benchmark portfolio adjusted for macroeconomic variables. The predictive power of VIX remains strong after taking macroeconomic conditions into consideration. Interestingly, the Default Spread performs well in explaining the excess returns of VIX trading strategy. Yet, the macroeconomic variables could not fully explain the abnormal returns of VIX trading strategy for all the sixteen cases.

Table E.19 has a similar structure as Table E.18. In Table E.19, Panel A documents the predictive power of VIX controlled for the cross-sectional liquidity disparity, and Panel B tests whether the cross-sectional liquidity disparity is the explanation for the strong profitability of VIX in the cross-section. *BAS* is the bid-ask spread difference of a sentiment-prone decile over a sentiment-immune decile. For each regression, *BAS* is calculated separately, corresponding to the construction of sentiment-prone and sentiment-immune decile portfolio. For example, in the regression of RVIX (ME 1-10), the BAS is the bid-ask spread of the small stock decile minus the bid-ask spread of the large stock decile. The predictive regression results in Panel A show that bid-ask spread difference in the cross-section significantly correlates with the cross-sectional return premium. However, Panel B shows that the profitability of my VIX trading strategy is not a result of the asymmetric liquidity in the cross-section.

Table E.20 to Table E.22 test the profitability of designing the trading strategy with the same trading philosophy and different implied volatility index, namely VXO, VXN, and VXD. VXO is available from 1986, VXN starts from 2001/02/01, and VXD is available from

1997/10/07. The results provide strong evidence that the trading philosophy works well with other implied volatility index.

Table E.23 use value-weighted portfolio returns to mitigate the size effect. VIX still shows demonstrated profitability when used in timing the value-weighted portfolios in the cross-section.

I conduct the sensitivity analysis on the threshold choices for the definition of substantially high VIX. Table E.24 report the performance of VIX trading strategy and the BETCs when using 0%, 5%, 15% and 20% as alternative thresholds.

Table E.25 reports the profitability of VIX on the long-short portfolios. Table E.26 shows that applies the VIX timing signal on the decile portfolios. These two tables show that VIX is more profitable when I use the signal to shift asset allocation in the cross-section.

Figure E.3 compares the annual performance of my VIX trading strategy with the S&P 500 index returns from 1990 to 2016. My VIX trading strategy persistently outperforms the market index.

Table E.18 Regressions of Portfolio Returns Controlled for Controlled for Macroeconomic Variables

Panel A reports the predictive power of VIX on long-short portfolio returns after controlling for default spread and TED spread.

$$R_{P-I,t} = \alpha + \beta_1 VIX_{t-1} + \gamma CV_t + \lambda_1 DS_t + \lambda_2 TED_t + \varepsilon_t.$$

Panel B reports the profitability of RVIX adjusted for DS and TED.

$$RVIX_t = \alpha + \lambda_1 DS_t + \lambda_2 TED_t + \varepsilon_t.$$

The first two columns indicate the decile rank of sentiment-prone and sentiment-immune portfolios. CV_t is a vector of control variables, which includes the Fama and French five factors, the momentum factor (UMD) and acroeconomic variables, default spread (DS) and TED spread. A factor is excluded from the list of control variables when it is the dependent variable in the regressions. The Newey and West (1987) robust t-statistics are in brackets. ***, ** and * indicates the statistical significance at 1%, 5% and 10% level, respectively. The sample period is from 1990/01/01 to 2008/12/31.

		Panel A			Panel B		
		VIX_{t-1}	DS_t	TED_t	α	DS_t	TED_t
ME	1-10	-0.077***	0.167**	-0.148***	22.283	0.026	-0.096
		(-3.349)	(2.438)	(-3.487)	(0.860)	(0.251)	(-0.520)
Age	1-10	-0.015	-0.004	-0.049*	19.380	0.090	-0.194
		(-0.920)	(-0.100)	(-1.797)	(0.980)	(1.092)	(-1.292)
Sigma	10-1	-0.036**	0.066	-0.030	17.938**	0.042	-0.073**
		(-2.095)	(1.291)	(-0.790)	(2.370)	(1.073)	(-1.977)
E/BE	1-10	-0.021	-0.016	-0.022	26.011	0.072	-0.196
		(-1.436)	(-0.389)	(-0.722)	(1.170)	(0.771)	(-1.319)
D/BE	1-10	-0.030**	0.024	-0.019	30.543	0.039	-0.182
		(-2.071)	(0.558)	(-0.616)	(1.470)	(0.460)	(-1.492)
PPE/A	1-10	-0.006	0.009	0.102	65.258**	0.016	-0.346*
		(-0.360)	(0.187)	(1.482)	(2.460)	(0.153)	(-1.781)
RD/A	10-1	0.015	-0.005	0.015	30.606	0.083	-0.221**
		(1.085)	(-0.130)	(0.511)	(1.620)	(1.058)	(-2.028)
BE/ME	10-1	-0.033***	0.017	-0.069**	35.316	0.038	-0.198
		(-2.712)	(0.491)	(-2.153)	(1.410)	(0.336)	(-1.318)
EF/A	10-1	0.003	-0.033	-0.039**	40.154	0.015	-0.223
		(0.438)	(-1.114)	(-2.457)	(1.440)	(0.121)	(-1.547)
GS	10-1	-0.001	-0.006	-0.035**	37.136	0.037	-0.217
		(-0.190)	(-0.243)	(-2.023)	(1.420)	(0.322)	(-1.449)
BE/ME	1-5	0.006	0.025	-0.030*	32.968*	0.050	-0.183*
		(0.550)	(0.897)	(-1.652)	(1.730)	(0.578)	(-1.756)
EF/A	10-5	-0.016	0.029	-0.025	31.042*	0.066	-0.164*
		(-1.513)	(0.856)	(-1.190)	(1.810)	(0.889)	(-1.709)
GS	10-5	-0.014	0.020	-0.012	32.433**	0.067	-0.184**
		(-1.463)	(0.662)	(-0.546)	(2.010)	(0.967)	(-2.093)
BE/ME	10-5	-0.027***	0.042	-0.099***	2.864	0.059	-0.112
		(-2.823)	(1.487)	(-3.940)	(0.130)	(0.552)	(-0.917)
EF/A	1-5	-0.013*	-0.004	-0.064***	34.508*	0.039	-0.163
		(-1.701)	(-0.171)	(-3.929)	(1.830)	(0.479)	(-1.545)
GS	1-5	-0.016	0.015	-0.046*	37.820**	0.033	-0.184*
		(-1.334)	(0.411)	(-1.753)	(2.130)	(0.462)	(-1.817)

Table E.19 Regressions of Portfolio Returns Controlled for Liquidity

Panel A reports the predictive power of VIX on long-short portfolio returns after controlling for bid-ask spread.

$$R_{P-I,t} = \alpha + \beta_1 VIX_{t-1} + \gamma CV_t + \lambda BAS + \varepsilon_t.$$

Panel B reports the profitability of RVIX adjusted for liquidity.

$$RVIX_t = \alpha + \lambda BAS + \varepsilon_t.$$

The first two columns indicate the decile rank of sentiment-prone and sentiment-immune portfolios. CV_t is a vector of control variables, which includes the Fama and French five factors, the momentum factor (UMD) and BAS. A factor is excluded from the list of control variables when it is the dependent variable in the regressions. The Newey and West (1987) robust t-statistics are in brackets. ***, ** and * indicates the statistical significance at 1%, 5% and 10% level, respectively. The sample period is from 1990/01/01 to 2008/12/31.

		Panel A		Panel B	
		VIX_{t-1}	BAS_t	α	BAS_t
ME	1-10	-0.069***	0.024***	21.323***	-0.006
		(-3.813)	(3.280)	(2.980)	(-0.640)
Age	1-10	-0.024**	0.003	17.309***	-0.003
		(-2.152)	(0.937)	(4.230)	(-0.580)
Sigma	10-1	-0.024*	0.035***	20.619***	-0.006
		(-1.767)	(4.100)	(5.300)	(-0.705)
E/BE	1-10	-0.030***	0.017***	18.104**	0.001
		(-3.451)	(3.473)	(2.470)	(0.099)
D/BE	1-10	-0.031***	0.018***	13.628**	0.008
		(-3.107)	(3.309)	(2.560)	(0.973)
PPE/A	1-10	0.013	0.019	25.703***	-0.089**
		(0.958)	(1.282)	(5.580)	(-2.228)
RD/A	10-1	0.018*	-0.039*	17.865***	-0.040
		(1.878)	(-1.666)	(3.070)	(-0.915)
BE/ME	10-1	-0.048***	0.011	10.791	0.021
		(-3.645)	(1.332)	(1.180)	(0.915)
EF/A	10-1	-0.015*	-0.014***	2.110	-0.063***
		(-1.923)	(-2.731)	(0.240)	(-2.907)
GS	10-1	-0.014**	-0.012**	8.584	-0.032
		(-2.388)	(-2.380)	(0.960)	(-1.538)
BE/ME	1-5	0.005	-0.005	21.705***	-0.007
		(0.632)	(-0.282)	(5.940)	(-0.247)
EF/A	10-5	-0.012	-0.003	28.821***	-0.049
		(-1.407)	(-0.165)	(7.200)	(-1.624)
GS	10-5	-0.011	-0.003	25.211***	-0.019
		(-1.614)	(-0.300)	(7.680)	(-0.752)
BE/ME	10-5	-0.045***	0.034***	6.626	-0.009
		(-5.141)	(4.316)	(0.750)	(-0.448)
EF/A	1-5	-0.024***	0.029***	17.873***	0.020
		(-4.061)	(5.332)	(3.060)	(1.367)
GS	1-5	-0.023***	0.024***	18.426***	0.014
		(-2.948)	(2.999)	(3.050)	(0.927)

Table E.20 Profitability of VXO Trading Strategies

This table reports average returns (Avg Ret), the standard deviation (Std Dev), skewness (Skew) and the Sharpe ratio (SRatio) for benchmark portfolios, VXO timing strategy, and the RVXO returns. RVXO is the excess returns of VXO strategy return over the benchmark long-short portfolio return. The benchmark portfolio is to long the sentiment-prone decile (P) and short the sentiment-immune decile (I), and that the timing strategy is to hold the sentiment-prone decile after low VXO and hold the sentiment-immune decile after high VXO. VIX-based trading strategy is to buy and hold the sentiment-immune decile following a high VXO trading day and to buy and hold the sentiment-prone decile otherwise. A high VXO trading day is defined as current VIX is at least 10% higher than its prior 25-day average. Last column, the success ratio (Success), is the percentage of non-negative RVXO return. All the average returns are annualised and are in percentages. ***and ** indicates the t-test significance at 1% and 5% level, respectively. The sample period is from 1986/01/01 to 2016/04/30.

		Panel A Original Long-Short Portfolio				Panel B VIX Strategy Return				Panel C RVIX			
		Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	Success
ME	1-10	19.73***	14.39	-0.84	1.37	42.22***	15.79	-0.74	2.67	22.54***	24.41	0.26	0.55
Age	1-10	8.47***	11.33	-0.24	0.75	28.18***	16.76	-0.91	1.68	19.75***	18.6	-1.21	0.56
Sigma	10-1	16.21***	14.9	-0.23	1.09	36.49***	17.24	-0.33	2.12	20.32***	10.03	-0.17	0.6
E/BE	1-10	12.25***	7.71	-0.02	1.59	31.89***	17.56	-0.6	1.82	19.65***	18.71	-0.48	0.57
D/BE	1-10	9.96***	8.66	-0.45	1.15	30.02***	16.47	-0.5	1.82	20.11***	16.16	-0.24	0.57
PPE/A	1-10	-5.02***	9.75	-0.15	-0.51	21.34***	15.49	-0.38	1.38	26.35***	19.1	-0.12	0.58
RD/A	10-1	7.61***	12.01	-0.05	0.63	29.60***	19.62	-0.4	1.51	22.00***	15.08	-0.36	0.6
BE/ME	10-1	17.62***	11.46	-0.24	1.54	39.08***	17.19	-0.37	2.27	21.48***	23.33	0.05	0.58
EF/A	10-1	11.87***	8.32	-0.19	1.43	27.99***	17.41	-0.65	1.61	16.13***	22.12	-0.38	0.58
GS	10-1	11.65***	7.38	-0.13	1.58	30.16***	17.94	-0.6	1.68	18.51***	21.74	-0.36	0.58
BE/ME	1-5	9.03***	12.84	-0.09	0.7	20.62***	18.83	-0.47	1.1	11.61***	8.83	-0.47	0.58
EF/A	10-5	6.97***	13.17	-0.35	0.53	21.99***	18.25	-0.5	1.21	15.04***	7.99	-0.15	0.59
GS	10-5	7.22***	13.45	-0.35	0.54	21.29***	18.14	-0.44	1.17	14.09***	7.65	-0.21	0.6
BE/ME	10-5	26.64***	8.9	0.15	2.99	40.09***	15.83	-0.5	2.53	13.47***	10.54	-0.19	0.58
EF/A	1-5	18.84***	8.88	-0.57	2.12	31.87***	15.61	-0.62	2.04	13.05***	8.49	-0.35	0.58
GS	1-5	18.88***	10.37	-0.49	1.82	33.16***	16.04	-0.52	2.07	14.31***	8.28	-0.06	0.59

Table E.21 Profitability of VXN Trading Strategies

This table reports average returns (Avg Ret), the standard deviation (Std Dev), skewness (Skew) and the Sharpe ratio (SRatio) for benchmark portfolios, VXN timing strategy, and the RVXN returns. RVXN is the excess returns of VXN strategy return over the benchmark long-short portfolio return. The benchmark portfolio is to long the sentiment-prone decile (P) and short the sentiment-immune decile (I), and that the timing strategy is to hold the sentiment-prone decile after low VXN and hold the sentiment-immune decile after high VXN. VIX-based trading strategy is to buy and hold the sentiment-immune decile following a high VXN trading day and to buy and hold the sentiment-prone decile otherwise. A high VXN trading day is defined as current VIX is at least 10% higher than its prior 25-day average. Last column, the success ratio (Success), is the percentage of non-negative RVXN return. All the average returns are annualised and are in percentages. ***and ** indicates the t-test significance at 1% and 5% level, respectively. The sample period is from 2001/02/01 to 2016/04/30.

		Panel A Original Long-Short Portfolio				Panel B VIX Strategy Return				Panel C RVIX			
		Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	Success
ME	1-10	15.09***	13.68	-0.7	1.1	30.53***	17.35	0.12	1.76	15.60**	25.39	0.74	0.54
Age	1-10	1.57	10.4	-0.31	0.15	19.39***	19.75	-0.13	0.98	17.78***	20.21	0.31	0.55
Sigma	10-1	4.78	16.28	-0.04	0.29	26.05***	21.15	-0.13	1.23	21.14***	11.36	0.09	0.57
E/BE	1-10	5.78***	7.61	0.07	0.76	23.24***	20.67	-0.23	1.12	17.44***	21.49	-0.12	0.55
D/BE	1-10	4.42**	7.76	-0.17	0.57	22.04***	19.97	-0.18	1.1	17.57***	19.23	-0.05	0.55
PPE/A	1-10	-3.94	11.16	-0.05	-0.35	12.79***	19.23	-0.08	0.66	16.64***	24.28	-0.07	0.55
RD/A	10-1	3.19	11.29	-0.06	0.28	21.73***	22.21	-0.18	0.98	18.38***	19.23	-0.26	0.56
BE/ME	10-1	14.63***	12.09	-0.03	1.21	31.07***	19.68	-0.13	1.58	16.66**	25.23	-0.08	0.55
EF/A	10-1	9.36***	8.54	-0.36	1.1	20.09***	20.35	-0.29	0.99	10.86*	24.4	-0.05	0.55
GS	10-1	8.79***	7.63	-0.27	1.15	21.93***	20.82	-0.23	1.05	13.23**	24.65	0	0.55
BE/ME	1-5	4.97	13.77	-0.02	0.36	15.76***	22.47	-0.14	0.7	10.63***	10.57	-0.03	0.55
EF/A	10-5	2.93	14.63	-0.13	0.2	16.59***	21.78	-0.16	0.76	13.53***	9.44	-0.11	0.56
GS	10-5	2.37	15.11	-0.1	0.16	15.47***	21.88	-0.18	0.71	12.95***	9.22	-0.08	0.57
BE/ME	10-5	19.60***	10.43	0.3	1.88	33.86***	19.05	-0.1	1.78	14.32***	12.29	0.23	0.55
EF/A	1-5	12.29***	10.62	-0.4	1.16	24.42***	19.06	-0.26	1.28	12.12***	9.63	0.02	0.55
GS	1-5	11.17***	11.72	-0.31	0.95	25.53***	19.4	-0.27	1.32	14.32***	9.72	0.05	0.57

Table E.22 Profitability of VXD Trading Strategies

This table reports average returns (Avg Ret), the standard deviation (Std Dev), skewness (Skew) and the Sharpe ratio (SRatio) for benchmark portfolios, VXD timing strategy, and the RVXD returns. RVXD is the excess returns of VXD strategy return over the benchmark long-short portfolio return. The benchmark portfolio is to long the sentiment-prone decile (P) and short the sentiment-immune decile (I), and that the timing strategy is to hold the sentiment-prone decile after low VXD and hold the sentiment-immune decile after high VXD. VIX-based trading strategy is to buy and hold the sentiment-immune decile following a high VXD trading day and to buy and hold the sentiment-prone decile otherwise. A high VXD trading day is defined as current VIX is at least 10% higher than its prior 25-day average. Last column, the success ratio (Success), is the percentage of non-negative RVXD return. All the average returns are annualised and are in percentages. ***and ** indicates the t-test significance at 1% and 5% level, respectively. The sample period is from 1997/10/07 to 2016/04/30.

		Panel A Original Long-Short Portfolio				Panel B VIX Strategy Return				Panel C RVIX			
		Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	Success
ME	1-10	16.17***	15.02	-0.54	1.08	36.23***	17.7	0.08	2.05	20.05***	26.38	0.86	0.54
Age	1-10	4.55	12.21	-0.16	0.37	22.84***	19.49	-0.18	1.17	18.30***	19.85	0.39	0.55
Sigma	10-1	9.47**	17.42	-0.09	0.54	30.09***	20.94	-0.25	1.44	20.63***	11.43	-0.16	0.57
E/BE	1-10	8.40***	8.36	0	1	27.06***	20.45	-0.3	1.32	18.65***	20.78	-0.12	0.55
D/BE	1-10	6.56***	9.54	-0.24	0.69	25.70***	19.49	-0.23	1.32	19.14***	18.54	0.06	0.55
PPE/A	1-10	-4.15	11.03	-0.1	-0.38	14.74***	18.38	-0.1	0.8	18.90***	22.95	-0.06	0.55
RD/A	10-1	9.03***	13.62	0.01	0.66	27.16***	22.92	-0.3	1.18	18.12***	18.14	-0.3	0.57
BE/ME	10-1	14.50***	13.42	-0.24	1.08	33.98***	19.65	-0.1	1.73	19.48***	27	0.15	0.56
EF/A	10-1	10.24***	9.19	-0.31	1.11	22.66***	20.07	-0.31	1.13	12.41**	25.09	-0.06	0.55
GS	10-1	11.11***	7.86	-0.3	1.41	24.95***	20.79	-0.31	1.2	13.82**	24.7	-0.06	0.55
BE/ME	1-5	7.11**	15.16	0.07	0.47	17.89***	22.51	-0.19	0.79	10.80***	10.31	-0.19	0.55
EF/A	10-5	4.33	15.24	-0.13	0.28	18.88***	21.49	-0.22	0.88	14.56***	9.15	-0.16	0.56
GS	10-5	3.63	15.51	-0.11	0.23	17.75***	21.41	-0.21	0.83	14.15***	8.89	-0.11	0.58
BE/ME	10-5	21.61***	10.08	0.25	2.14	36.29***	18.31	-0.19	1.98	14.70***	12.07	0.15	0.55
EF/A	1-5	14.57***	10.4	-0.44	1.4	27.35***	18.33	-0.33	1.49	12.78***	9.38	0.02	0.56
GS	1-5	14.74***	12.19	-0.33	1.21	29.37***	18.98	-0.36	1.55	14.65***	9.33	0.05	0.57

Table E.23 Profitability of VIX Trading Strategy on Value-Weighted Portfolios

This table reports average value-weighted returns (Avg Ret), the standard deviation (Std Dev), skewness (Skew) and the Sharpe ratio (SRatio) for benchmark portfolios, VIX timing strategy, and the RVIX returns. RVIX is the excess returns of VIX strategy return over the benchmark long-short portfolio return. The benchmark portfolio is to long the sentiment-prone decile (P) and short the sentiment-immune decile (I), and that the timing strategy is to hold the sentiment-prone decile after low VIX and hold the sentiment-immune decile after high VIX. VIX-based trading strategy is to buy and hold the sentiment-immune decile following a high VIX trading day and to buy and hold the sentiment-prone decile otherwise. A high VIX trading day is defined as current VIX is at least 10% higher than its prior 25-day average. Last column, the success ratio (Success), is the percentage of non-negative RVIX return. All the average returns are annualised and are in percentages. ***and ** indicates the t-test significance at 1% and 5% level, respectively. The sample period is from 1990/01/01 to 2008/12/31.

		Panel A Original Long-Short Portfolio				Panel B VIX Strategy Return				Panel C RVIX			
		Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	Success
ME	1-10	15.80***	13.97	-0.54	1.13	34.96***	15.92	0.15	2.2	19.15***	23.08	1.16	0.53
Age	1-10	-2.46	15.23	0.47	-0.16	13.58***	20.42	0.01	0.67	15.98***	17.74	0.47	0.53
Sigma	10-1	3.44	26.36	0.39	0.13	16.49***	26.9	0.02	0.61	13.14***	19.93	-0.6	0.53
E/BE	1-10	-1.33	13.48	0.4	-0.1	13.37***	20.95	-0.13	0.64	14.68***	19.7	0.3	0.53
D/BE	1-10	1.52	17.98	0.84	0.08	13.10***	21.28	0.06	0.62	11.59***	19.27	-0.53	0.53
PPE/A	1-10	-2.07	19.58	0.82	-0.11	10.07**	22.04	-0.01	0.46	12.16**	22.67	0.17	0.52
RD/A	10-1	3.95	16.6	-0.08	0.24	8.95*	23.6	0.02	0.38	5.05	21.03	0.03	0.53
BE/ME	10-1	6.03*	14.92	0	0.4	23.59***	19.14	0.17	1.23	17.55***	23.3	0.9	0.53
EF/A	10-1	7.49**	14.16	-0.93	0.53	15.10***	20.12	0.2	0.75	7.56	28.21	0.98	0.53
GS	10-1	0.91	13.72	-0.28	0.07	12.61**	21.69	0.13	0.58	11.69*	27.44	0.44	0.54
BE/ME	1-5	-1.93	11.88	0.35	-0.16	5.74	19.99	0.22	0.29	7.70*	20.19	0.38	0.53
EF/A	10-5	-7.07**	12.98	0.53	-0.54	5.26	22.19	0.07	0.24	12.39***	17.6	0.52	0.54
GS	10-5	-2.79	13.11	0.06	-0.21	9.56*	22.79	0.04	0.42	12.36***	18.27	0.19	0.53
BE/ME	10-5	4.09*	10.48	0.01	0.39	19.84***	18.85	0.11	1.05	15.76***	19.72	0.9	0.54
EF/A	1-5	0.42	8.14	-0.09	0.05	15.02***	17.8	0.12	0.84	14.61***	18.31	0.46	0.54
GS	1-5	-1.88	11.26	-0.07	-0.17	11.90***	19.81	-0.06	0.6	13.77***	19.11	0.37	0.53

Table E.24 Returns and BETCs with Different Thresholds to Define High VIX

This table reports the returns and break-even transaction costs of VIX-based trading strategies if I choose alternative horizons to compare the VIX with its past average. For instance, I define a high VIX day if current VIX is higher than x% its prior 25-day average. In this table, I show the results when x equals 0, 5, 10, 15, 20. Panel A reports the returns of my VIX-based trading strategies when using different horizon average to define high VIX, and the returns are in percentages. Panel B reports the corresponding break-even transaction costs and the costs are in basis points. The sample period is from 1990/01/01 to 2016/04/30.

Panel A. Profitability on different trading signal horizons							
	P	I	0%	5%	10%	15%	20%
ME	1	10	39.47	43.43	42.38	40.43	39.59
Age	1	10	30.03	30.95	28.35	27.8	27.25
Sigma	10	1	40.28	41.34	38.25	37.4	36.38
E/BE	1	10	32.7	34.34	33.41	32.87	32.88
D/BE	1	10	31.28	33.02	30.83	30.16	29.75
PPE/A	1	10	24.05	22.76	22.38	22.35	22.72
RD/A	10	1	34.19	34.22	31.43	30.95	31.21
BE/ME	10	1	34.4	37.43	40.49	40.4	40.38
EF/A	1	10	23.34	26.53	29.67	30.8	31.14
GS	1	10	27.83	30.59	31.82	32.14	32.83
BE/ME	1	5	25.11	24.49	22.05	22.25	21.92
EF/A	10	5	27.38	26.14	23.02	22.04	21.53
GS	10	5	27.1	25.35	22.73	21.52	20.71
BE/ME	10	5	38.27	40.69	41.31	41.42	41.07
EF/A	1	5	30.96	32.91	32.93	33.08	32.9
GS	1	5	35.48	36.48	35.11	34.21	34.09
Panel B. BETC on different trading signal horizons							
ME	1	10	89.54	112.07	137.66	192.55	258.67
Age	1	10	68.11	79.86	92.1	132.4	178.08
Sigma	10	1	91.36	106.68	124.25	178.13	237.71
E/BE	1	10	74.18	88.62	108.53	156.54	214.83
D/BE	1	10	70.95	85.21	100.16	143.65	194.42
PPE/A	1	10	54.55	58.73	72.68	106.43	148.44
RD/A	10	1	77.54	88.31	102.09	147.4	203.92
BE/ME	10	1	78.03	96.6	131.51	192.41	263.87
EF/A	1	10	52.94	68.48	96.37	146.69	203.49
GS	1	10	63.12	78.93	103.37	153.04	214.54
BE/ME	1	5	56.95	63.2	71.64	105.97	143.23
EF/A	10	5	62.11	67.47	74.79	104.96	140.65
GS	10	5	61.46	65.41	73.84	102.5	135.32
BE/ME	10	5	86.82	105	134.18	197.25	268.36
EF/A	1	5	70.22	84.94	106.96	157.52	214.99
GS	1	5	80.47	94.16	114.04	162.92	222.78

Table E.25 VIX Timing Strategy on Cross-Sectional Long-Short Portfolios

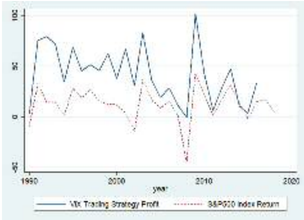
This table reports average returns (Avg Ret), the standard deviation (Std Dev), skewness (Skew) and the Sharpe ratio (SRatio) for the long-short portfolios, VIX timing strategy on long-short portfolio, and the RVIX returns. RVIX is the excess returns of VIX strategy return over original long-short portfolio return. The first three columns indicate the construction of the long-short portfolio. The benchmark portfolio is to long the sentiment-prone decile and short the sentiment-immune decile. In this table, VIX Timing Strategy is to buy (short) sentiment-immune decile and short (long) sentiment-immune decile following a high (low) VIX trading day. A high VIX trading day is defined as current VIX is at least 5% higher than its prior 25-day average. Last column, the success ratio (Success), is the percentage of non-negative RVIX return. All the average returns are annualised and are in percentages. ***and ** indicates the t-test significance at 1% and 5% level, respectively. The sample period is from 1990/01/01 to 2016/04/30.

		Panel A Original Long-Short Portfolio				Panel B VIX Strategy Return				Panel C RVIX			
		Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	SR	Avg Ret	SD	Skew	Success
ME	1-10	23.12***	13.95	-0.53	1.66	40.40***	13.8	0.65	2.93	17.28***	17.88	2.45	0.87
Age	1-10	10.93***	11.21	-0.2	0.98	23.95***	11.13	0.26	2.15	13.02***	13.74	1.28	0.87
Sigma	10-1	18.80***	15.55	-0.2	1.21	32.89***	15.46	0.03	2.13	14.09***	19.87	0.64	0.86
E/BE	1-10	13.37***	7.91	-0.03	1.69	19.57***	7.86	0.4	2.49	6.20***	9.35	1.25	0.86
D/BE	1-10	11.57***	8.85	-0.26	1.31	21.85***	8.77	0.24	2.49	10.28***	11.24	1.22	0.86
PPE/A	1-10	-3.18	10.12	-0.12	-0.31	-3	10.12	-0.05	-0.3	0.17	12.43	0.16	0.86
RD/A	10-1	9.23***	12.58	-0.05	0.73	14.63***	12.56	0.01	1.17	5.40*	15.48	0.24	0.86
BE/ME	10-1	17.57***	12.04	-0.24	1.46	14.83***	12.06	0.43	1.23	-2.74	15.25	1.27	0.85
EF/A	10-1	-11.85***	8.55	0.24	-1.39	-1.68	8.58	-0.14	-0.2	10.17***	10.42	-0.53	0.87
GS	10-1	-12.37***	7.56	0.17	-1.64	-9.90***	7.58	-0.12	-1.31	2.47	8.98	-0.59	0.86
BE/ME	1-5	10.39***	13.41	-0.02	0.77	15.19***	13.39	-0.31	1.13	4.8	18.18	-0.41	0.85
EF/A	10-5	8.59***	13.6	-0.24	0.63	19.26***	13.55	-0.08	1.42	10.68***	18.12	0.42	0.85
GS	10-5	8.07***	13.88	-0.22	0.58	17.05***	13.85	-0.06	1.23	8.98**	18.38	0.4	0.86
BE/ME	10-5	27.96***	9.2	0.2	3.04	30.01***	9.17	0.49	3.27	2.06	10.84	0.77	0.85
EF/A	1-5	20.44***	9.24	-0.53	2.21	20.95***	9.24	0.18	2.27	0.51	11.93	1.34	0.85
GS	1-5	20.44***	10.81	-0.42	1.89	26.96***	10.75	0.2	2.51	6.51**	13.76	1.33	0.85

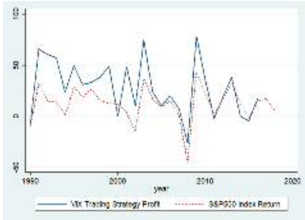
Table E.26 Summary Statistics of VIX Timing Decile Portfolios

This table reports summary statistics for the decile portfolios, VIX timing strategy on decile portfolio, and the RVIX returns. Panel A and for all the most sentiment-immune deciles in Panel B. The first two column show the choice of decile portfolios as original portfolios. The first column shows the characteristics used to form the decile portfolio. The second column reports the decile rank. VIX Timing Strategy is to buy (short) original decile following a high (low) VIX trading day. A high VIX trading day is defined as current VIX is at least 5% higher than its prior 25-day average. Success is the percentage of non-negative RVIX return. All the average returns are annualised and are in percentages. ***and ** indicates the t-test significance at 1% and 5% level, respectively. The sample period is from 1990/01/01 to 2016/04/30.

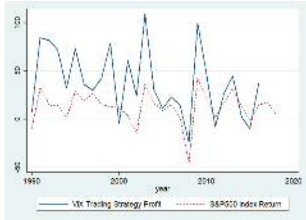
		Panel A Original Long-Short Portfolio				Panel B VIX Strategy Return				Panel C RVIX			
SP	Decile	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	SD	Skew	SRatio	Avg Ret	SD	Skew	Success
Panel A													
ME	1	34.79***	13.18	-0.64	2.42	38.57***	13.14	0.2	2.72	3.78	17.58	1.46	0.84
Age	1	24.44***	17.23	-0.48	1.25	30.30***	17.2	-0.02	1.6	5.87	22.85	0.84	0.85
Sigma	10	34.29***	21.14	-0.39	1.49	41.32***	21.09	-0.03	1.82	7.03	28.05	0.67	0.85
E/BE	1	31.24***	17.76	-0.44	1.6	35.02***	17.73	0	1.81	3.78	23.62	0.79	0.84
D/BE	1	27.88***	17.57	-0.44	1.42	29.73***	17.56	-0.03	1.53	1.85	23.61	0.69	0.85
PPE/A	1	22.67***	15.07	-0.2	1.31	19.57***	15.09	-0.12	1.11	-3.1	20.03	0.08	0.84
RD/A	10	31.52***	21.97	-0.28	1.3	34.57***	21.95	-0.04	1.44	3.05	29.07	0.44	0.85
BE/ME	1	38.80***	15.44	-0.33	2.33	39.14***	15.44	0.18	2.35	0.34	19.75	0.98	0.85
BE/ME	10	21.23***	20.71	-0.22	0.89	24.31***	20.7	-0.17	1.04	3.08	28.11	0.11	0.85
EF/A	1	19.76***	20.33	-0.31	0.83	28.36***	20.29	-0.08	1.26	8.59	27.34	0.45	0.85
EF/A	10	31.62***	16.19	-0.54	1.78	30.04***	16.2	0.04	1.68	-1.58	21.45	0.98	0.84
GS	1	31.82***	17.08	-0.52	1.7	35.52***	17.05	0.08	1.92	3.7	22.48	1.09	0.85
GS	10	19.45***	20.39	-0.29	0.81	25.61***	20.36	-0.07	1.12	6.16	27.32	0.41	0.85
Panel B													
ME	10	11.67***	19.19	0.17	0.46	-1.83	19.2	-0.4	-0.24	-13.50***	26.64	-0.96	0.84
Age	10	13.50***	16.13	-0.16	0.66	6.35**	16.15	-0.26	0.22	-7.15*	22.02	-0.22	0.84
Sigma	1	15.49***	9.19	-0.32	1.37	8.43***	9.23	-0.24	0.6	-7.06***	12.66	0	0.84
E/BE	10	17.87***	17.69	-0.3	0.85	15.46***	17.7	-0.08	0.71	-2.42	24.08	0.32	0.85
D/BE	10	16.31***	15.8	-0.13	0.85	7.87**	15.82	-0.13	0.32	-8.43**	21.22	-0.09	0.84
PPE/A	10	25.85***	17.67	-0.29	1.3	22.57***	17.69	-0.11	1.11	-3.28	23.46	0.26	0.84
RD/A	1	22.29***	15.49	-0.37	1.25	19.94***	15.5	-0.11	1.1	-2.35	20.78	0.4	0.84
BE/ME	5	21.68***	17.31	-0.31	1.09	18.26***	17.32	-0.08	0.89	-3.43	22.82	0.37	0.85
EF/A	5	22.36***	15.83	-0.27	1.23	18.19***	15.85	-0.1	0.97	-4.16	20.85	0.26	0.85
GS	5	22.75***	15.36	-0.22	1.29	17.11***	15.39	-0.05	0.93	-5.63	20.37	0.21	0.84



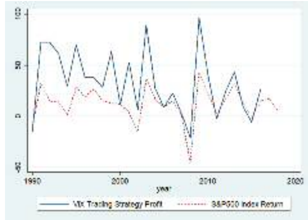
(a) ME(L-H)



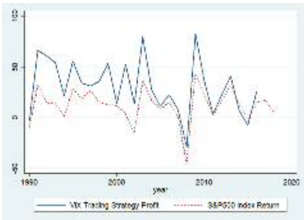
(b) Age(L-H)



(c) Sigma(H-L)



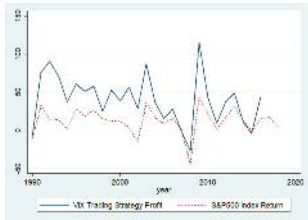
(d) E/BE(L-H)



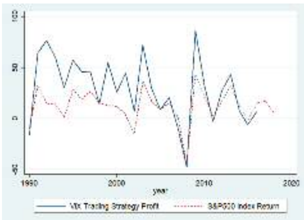
(e) D/BE(L-H)

(f) PPE/A(L-H)

(g) RD/A(H-L)



(h) BE/ME(H-L)

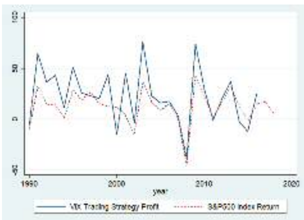


(i) EF/A(H-L)

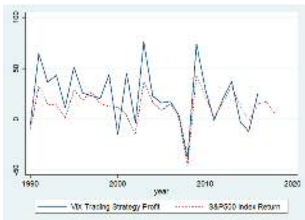
(j) GS(H-L)

(k) BE/ME(L-M)

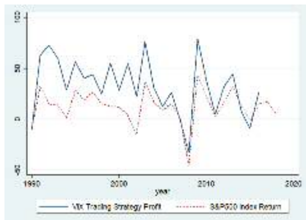
(l) EF/A(H-M)



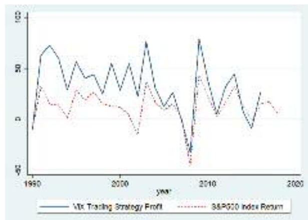
(m) GS(H-M)



(n) BE/ME(H-M)



(o) EF/A(L-M)



(p) GS(L-M)

Annual Profits of VIX Trading Strategy and S&P 500 Returns The solid line is the annual returns of VIX trading signal. The dashed line is the annual S&P 500 returns. The sample period is from 1990 to 2016.

Fig. E.3 VIX Trading Strategy Profit Compared with S&P 500 Index Returns