Investor Sentiment and Asset Pricing:
Empirical Evidence from an Enhanced Investor Sentiment Index

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Abstract

This thesis covers three interconnected topics that investigate the impact of investor sentiment on stock returns. Given that investor sentiment is the central theme of this thesis, an accurate measure of investor sentiment is of great importance, and it is this theme which the thesis starts by exploring. With a new investor sentiment index which is superior to others currently available, the question of whether sentiment or fundamental factors play a more important role in driving stock returns is then explored. Finally, the thesis explores in greater depth channels through which investor sentiment drives stock returns as well as the pricing of rational and irrational risk factors.

The first substantive chapter proposes an enhanced investor sentiment index, uniquely accounting for time-varying components in its construction. The poor time-series forecasting power of the often-used Baker and Wurgler (2006) investor sentiment index has long been a puzzle, and this study demonstrates that it is largely due to its implicit assumption that contributions of its individual index components to the aggregate sentiment index are time-invariant. By capturing time-varying contributions of those components, the enhanced investor sentiment index not only demonstrates the basic property of a good sentiment measure (*i.e.* sentiment today predicts negatively the future aggregate stock returns), but also represents a superior measure of investor sentiment as compared to other sentiment indexes given that it is the only investor sentiment measure that has its sustained predictive power across different forecast horizons. Cross-sectionally, the new index also predicts significantly the time series of cross-sectional stock returns for portfolios sorted based on firm size, book-to-market ratio and momentum.

The relative importance of investor sentiment to stock market fluctuations is explored in the second substantive chapter. Whilst most studies can be split into two distinct branches of the forecasting literature – forecasting power of investor sentiment versus fundamental return predictors – this chapter performs a battery of forecasting tests in evaluating the forecasting power of the enhanced investor sentiment index against a host of widely applied economic predictors in order to determine the main driver of stock market fluctuations. The results show that investor sentiment exerts a stronger influence on stock market movements, manifested by the superior forecasting power of the new index relative to the economic predictors, in both the statistical and economic sense.

The third, and final, substantive chapter examines the channels through which investor sentiment affects stock market returns, i.e. the cash flow or discount rate channel, in light of the predictive ability of investor sentiment on stock market returns. This chapter constructs a four-beta model that separates the cash flow beta and the discount rate beta of Campbell and Vuolteenaho (2004) into rational and irrational components. The results show that the irrational beta in the cash flow channel receives a relatively greater weight than that in the discount rate channel, implying that the predictive power of investor sentiment is going through the cash flow channel. The findings also do not support the assumptions made in Campbell, Polk and Vuolteenaho (2010) that cash flow (discount rate) is mainly fundamental (sentiment) driven. Comparing the asset pricing performance of the four-beta model against alternative asset pricing models reveals that the four-beta model has a better model fit with a lower pricing error. The documented negative (positive) risk premia of irrational (rational) betas implies that investors are willing to pay a price (require a risk premium) for stocks that are sensitive to the irrational risk factors (rational risk factors).

To my parents and husband, who are the pillars of my life.

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Declaration

I declare that this thesis is my own work conducted under the supervision of Professor Bartosz Gebka and Dr. Robert D.J. Anderson. All information retrieved from others' work have been acknowledged appropriately. I certify that this thesis has not been previously submitted for a degree or other qualification in this or any other University.

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List of Abbreviations

10IND	10 Industry sorted portfolios
10MOM	10 Momentum sorted portfolios
2B	Two-beta model
4B	Four-beta model
AAII	American Association of Individual Investor
ACC	Accruals
Adj-R2	Adjusted R-squared
AF	Analysts' forecasts
BE/ME	Book-to-market ratio for individual stocks
BEst	Bloomberg Estimates
BETA	Market beta
BM	Book-to-market ratio for the Down Jones Industrial Average
BV	Book value
BW	Baker and Wurgler
CAGR	Compounded Annual Growth Rate
CAPM	Capital Asset Pricing Model
CAY	Consumption-wealth ratio
CCI	Consumer Confidence Index
CEFD	Closed-end fund discount
CER	Certainty equivalent gain
CF	Cash flow
CMA	Conservative minus aggressive investment factor
CPV	Campbell, Polk and Vuolteenaho
CRSP	Center for Research in Security Prices
CV	Campbell and Vuolteenaho
D	Dividend
DDM	Dividend discount model
DE	Dividend payout ratio
DFR	Default return spread
DFY	Default yield spread
DP	Dividend price ratio
DR	Discount rate
DY	Dividend yield ratio
E	Earnings
EMH	Efficient Market Hypothesis
ENC	Forecast encompassing test
EP	Earnings-price ratio
EPS	Earnings per share
EQ	Share of equity issues
FDPS	Forecasts of dividend per share
FEPS	Forecasts of earnings per share

FF	Fama and French
FF25	Fama-French 25 size and *BE/ME* sorted portfolios
FF-3	Fama and French (1993) three factors
FF-5	Fama-French (2015) five factors
FFC-4	Fama-French-Cahart four factors
FGLS	Feasible Generalised Least Square
FMB	Fama-Macbeth
FROE	Forecasts of return on equity
GAAP	Generally Accepted Accounting Principles
HAC	Heteroscedasticity and autocorrelation consistent
HML	High minus low value factor
HMM	Historical mean model
IBES	Institute of Broker Estimates System
II	Investor Intelligence
INFL	Inflation
IPO	Initial Public Offerings
IVOL	Idiosyncratic volatility
LTG	Long-term EPS growth rate
LTR	Long-term return
LTRVS	Long-term reversal
LTY	Long-term yield
M	Momentum
MDM	Modified Diebold-Mariano test statistic
ME	Market capitalization or market equity
MPE	Mean-pricing-errors
MS	University of Michigan Consumer Sentiment Index
MSFE	Mean squared forecasts error
NBER	National Bureau of Economic Research
NI	Net issuance
NIPO	Number of IPOs
NTIS	Net equity expansion
NW	Newey-West
OG	Output gap
OLS	Ordinary Least Square
OOS	Out-of-sample
PCA	Principal component analysis
PC-ECON	First principal component of economic predictors
PDND	Dividend premium
PLS	Partial Least Square
RESVAR	Variance of risk-adjusted returns
RIPO	Average first-day returns of IPOs
RMRF	Market
RMSPE	Root-mean-squared-pricing-errors
RMW	Robust minus weak profitability factor

ROE	Return on equity
S^{BW}	Baker-Wurgler investor sentiment index
SCR	Surplus consumption ratio
SKEW	Idiosyncratic skewness
SMB	Small minus big size factor
S^{PLS}	Aligned investor sentiment index
SR	Sharpe ratio
STR	Short-term reversal
S^{TV}	Time-varying weighted investor sentiment index
SVAR	Stock return variance
SVI	Google Search Volume Index
TBL	Treasury bill rate
TMS	Term yield spread
TV-VAR	Time-varying Vector Autoregression
UMD	Winners minus losers momentum factor
VAR	Vector Autoregression
VARR	Variance of returns
VIX	Chicago Board Option Exchange's Volatility Index

Chapter 1. Introduction

1.1 Motivations

Market efficiency has been theorised since 1960s, but empirical evidence on market efficiency have actually been documented much earlier. The earliest version of market efficiency documented empirically is associated with the random walk theory, i.e. subsequent price changes (i.e. stock returns) are independent and unpredictable (see Fama, 1965b; 1970 for a review). The accumulated evidence on the random walk pattern in stock prices led to the formal development of the efficient market hypothesis (EMH), pioneered by Fama (1965b) and Samuelson (1965). Fama (1965b) suggests that, in an efficient market, chartists and fundamental analysts will not be able to consistently beat the investor who adopts a buy-and-hold strategy since stock prices will always converge to their fundamental values. Meanwhile, Samuelson (1965) argues that price changes, on average, will be zero in an efficient market as stock prices fully reflect all information used in forming the expectations. In a simple statement, the EMH states that all available information has already been incorporated into current stock prices in an efficient market (Fama, 1970). Later, Jensen (1978) defines the EMH as investors being unable to systematically make any risk-adjusted profits based on the given information set if the market is efficient.

Fama (1970) further distinguishes the information set and defines three different forms of market efficiency, i.e. weak-, semi-strong- and strong-form EMH, based on the degree to which stock prices efficiently reflect a particular set of information. Although Fama (1970) hypothesises a constant expected return in the weak-form test, this was later relaxed in Fama (1991), who re-interprets the EMH[1] and extends the weak-form test to include the time-varying expected return[2].

Whilst the definition and the test of market efficiency could have changed, proponents of EMH tend to assume that investors are collectively rational and the role played by irrational investors is immaterial. Nevertheless, Fama (1991) poses the following question: "Does return predictability reflect rational variation through time in expected returns,

[1] The weak-form test covers the test of return predictability, the semi-strong-form test is called as event studies and the strong-form test is replaced by the test for private information.

[2] Timmermann and Granger (2004) and Rapach and Zhou (2013) also argue that time-varying return predictability is not an evidence against EMH.

irrational deviations of price from fundamental value, or some combination of the two?". Even though Fama (1991) tends to believe it is the variation in rational expectations, the theory has been increasingly challenged by empirical studies since 1980s (e.g. Banz, 1981; DeBondt and Thaler, 1985; Jegadeesh and Titman, 1993; Poterba and Summers, 1988). This growing body of evidence against the EMH has laid the path to the emergence of behavioural finance.

Unlike the EMH, behavioural finance acknowledges that the irrationality of investors does matter in asset pricing. The advocates of EMH argued that any deviation of a stock's price from its intrinsic value is merely a short-lived event and would be self-corrected by rational arbitrageurs. However, unforecastable sentiment of noise (or irrational) traders can impede the willingness of arbitrageurs to take a position against the noise traders. De Long, Shleifer, Summers and Waldmann (1990) claim that noise traders with correlated misperceptions[3] induce a systematic risk that affects the asset price. Therefore, the mispricing may not be fully corrected and the effect of noise trading could last longer, resulting in price reversal in the long run. In fact, this theory is clearly manifested in the stock market: the optimistic sentiment creates 'irrational exuberance' during expansion periods, which builds up until the 'bubble burst' and the stock market rapidly corrects, as evidenced from the 1990s dot-com bubble and the 2007/08 financial crisis.

Hence, investor sentiment has a dominant role in the formation of stock prices. Being able to measure sentiment accurately provides useful and valuable information for stock return prediction. Nevertheless, the unobservable nature of investor sentiment presents a challenge to researchers to accurately quantify sentiment. In view of this, a better measure of sentiment is consistently sought-after in the literature, and this is the main objective of Chapter 3. The theory proposed by De Long et al. (1990) and the empirical evidence documented by Brown and Cliff (2005) and Huang, Jiang, Tu and Zhou (2015) concur that investor sentiment has a strong presence in the aggregate stock market. However, the market-wide sentiment index developed by Baker and Wurgler (2006) is found to have weak predictive power for stock returns at the aggregate level (Baker and Wurgler, 2007; Baker, Wurgler and Yuan, 2012), which is perplexing. Therefore, Chapter 3, building on the basis of the BW index, aims to construct an enhanced investor sentiment index that can substantially improve the predictive power of the Baker and Wurgler (BW) index for stock market returns.

[3] Their misperception represents the bullishness and bearishness of noise traders.

The validity of the new index in being a good measure of investor sentiment index is also tested.

Although investor sentiment does affect the evolution of stock market prices, previous literature has also revealed that stock market returns are predictable based on various fundamental factors (e.g. Fama and French 1989, Campbell and Yogo, 2006; Cochrane, 2011). As both types of return predictors have their own proponents, there is a question to ponder: which predictor – investor sentiment or fundamental economic predictors – has a stronger predictive power and therefore, plays a relatively more important role in stock market movements? This question is central to Chapter 4. The answer to this question is derived by performing a series of forecast evaluation tests, which do not involve the perfect foresight assumption, on the return forecasts produced by different predictors, from both statistical and economic viewpoints.

The present value formula indicates that stock prices change as a result of the variations of expectations about future cash flows and/or discount rates. If investor sentiment has a strong predictive power for stock market returns, then through which channel – cash flow (CF) or discount rate (DR) – is the sentiment effect transmitted to asset returns? The controversial claim held in previous studies that the cash flow channel is purely rational calls for further investigation (see Campbell, Polk and Vuolteenaho, 2010; Huang et al., 2015) and insights into this question are discussed in Chapter 5. The two-beta model of Campbell and Vuolteenaho (2004) serves as the building block in Chapter 5, given their model decomposes the market beta into cash flow and discount rate betas. The sentiment-induced CF and DR betas are extracted by further disentangling the two-beta model into a four-beta model, accounting for both the rational and irrational components in each channel. This four-beta model acts as a device to evaluate the relative importance of changes in the irrational expectations of cash flows versus discount rates. The question of whether the four resulting factors are systematic risks that are priced across different stocks is also addressed in Chapter 5.

1.2 Contributions

This thesis contributes to the literature in behavioural finance as well as asset pricing, and is of relevance to practitioners. The main contribution of Chapter 3 is the construction of an enhanced investor sentiment index that addresses the weaknesses of the BW index and thereby improves the time-series return predictability of the BW index. Not only is the new index of relevance to future empirical studies that require a good proxy of investor sentiment for the U.S. stock market, but the method used to capture the investor sentiment over time as proposed in this thesis also provides a reference for future academic research that consider constructing accurate investor sentiment measures for other stock markets. Furthermore, the findings provide insights into the root cause of the weak return predictability by investor sentiment in the time-series context.

Chapter 4 contributes mainly to the literature on return predictability. Previous studies, such as Welch and Goyal (2008) and Campbell and Thompson (2008), examined only the predictive power of fundamental predictors. Extending their works, the chapter considers investor sentiment as another return predictor that competes with fundamental predictors in forecasting stock market returns. The findings of this chapter provide a deeper understanding towards the underlying driving force of stock market fluctuations, which is relevant to the intense debate between rational and behavioural proponents. The economic value analysis also provides an indication to practitioners as to which type of return predictor – sentiment or fundamental – should be employed in forecasting stock returns in order to enhance their returns on investment.

Chapter 5 contributes to the literature in behavioural finance and asset pricing by developing a four-beta model that integrates the expectations formed by rational and sentiment traders on the future CF and DR into one model. Based on the four-beta model, the chapter reveals the underlying source of the predictive power of investor sentiment on the stock market returns (i.e. CF or DR). The findings in Chapter 5 complements the conclusion of Huang et al. (2015) that cash flow channel is the transmission medium for investor sentiment to affect the stock market movements. However, the analysis in this thesis is conducted within a direct examination framework, which is in contrast to the indirect approach of Huang et al. (2015). Second, this study calls for academic attention to the appropriateness of assuming cash flow (discount rate) is mainly fundamentals (sentiment) driven. Third, the four-beta model provides a view on the pricing properties of each of the four betas in a more comprehensive model that considers the rational and irrational expectations in both CF and DR channels.

1.3 Structure of the thesis

The remainder of this thesis is organised as follows. Chapter 2 reviews the literature on investor sentiment and return predictability. The chapter starts by exploring different definitions of investor sentiment and provides justification for the definition adopted throughout this thesis. The second section reviews the theory of noise traders and how their presence impedes the arbitrage activities. This section discusses the role that investor sentiment plays within the stock market. Subsequently, different measures of investor sentiment employed in the literature and the predictive power of each of these measures on the stock returns are reviewed. Finally, the chapter discusses the return predictability using different fundamental economic predictors and considers some of the potential issues associated with the out-of-sample forecasting.

Chapter 3 constructs an enhanced investor sentiment index after discussing the weaknesses of the BW index and providing evidence to support the construction of a new index. To establish the validity of the new index in being a good proxy of investor sentiment, this chapter evaluates whether the new index delivers the negative sentiment-return relationship. At the same time, the superior predictive power of the new index is tested by evaluating its in-sample predictive power for stock market returns against other sentiment measures. The closing section of this chapter concentrates on the predictive power of the new index on the time-series of portfolio returns.

Chapter 4 analyses the relative importance of investor sentiment to stock market fluctuations. This chapter begins by comparing the out-of-sample forecasting performance of the new index relative to other sentiment measures, providing further support to the in-sample findings documented in Chapter 3 that the new index is a superior measure of investor sentiment. The chapter then provides empirical results on the out-of-sample predictive performance of the enhanced investor sentiment index against the fundamental economic predictors in order to assess the role of sentiment versus economic predictors in the stock market movements. The robustness check on the predictive performance of various return predictors and analysis over different business cycle periods are presented in the next section.

Chapter 5 examines the transmission channels the sentiment effect on the stock market returns is going through and the pricing of the four-beta model. First, the chapter reviews the literature on the expectations formed regarding future cash flows and discount rates, highlighting the need of considering both rational and irrational expectations of the cash flows and discount rates in a model. Then, a section is dedicated to the construction of the four-beta model, followed by the examination on the key research questions of this chapter: (1) Is the sentiment effect going through the CF or DR channel? (2) are the assumptions that CF (DR) is fundamentals- (sentiment-) driven, as argued in previous studies, appropriate? (3) Do the four betas represent systematic risks that are priced at the cross-sectional level? The robustness check on the asset pricing test of the four-beta model and the use of the four-beta model in explaining a set of anomalies are presented in two separate sections.

The last chapter provides the summary of findings and discusses the policy and practical implications of the empirical investigations of this thesis. Finally, the recommendations for future research are proposed in the last section.

Chapter 2. Literature Review

2.1 Definition of investor sentiment

Previous literature offers more than one definition for investor sentiment. De Long, Shleifer, Summer and Waldmann (1990) define investor sentiment as the belief about asset returns that cannot be explained by fundamentals. Shleifer (2000, p.12) mentions that "investor sentiment reflects the common judgment errors made by a substantial number of investors, rather than uncorrelated random mistakes." In Barberis, Shleifer and Vishny (1998, p.332), investor sentiment can be referred as "how investors form expectations of future earnings". Brown and Cliff (2004, p.2) define investor sentiment as "expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever ''average'' may be". They also referred investor sentiment as excessively optimism or pessimism in their paper published in 2005. Meanwhile, Baker and Wurgler (2006) mention that investor sentiment can be broadly defined as "optimism or pessimism about stocks in general" (Baker and Wurgler, 2006, p. 1649). A year later, Baker and Wurgler (2007) define investor sentiment as "a belief about future cash flows and investments risks that is not justified by the facts at hand".

The definition used by Baker and Wurgler (2006) and Brown and Cliff (2005), in which investor sentiment refers to optimism or pessimism about the stock market, is mainly used in this thesis. The reasons for this choice of definition is twofold. First, as Chapter 3 aims to enhance the way the sentiment captured by S^{BW}, for fairness, same definition adopted in Baker and Wurgler (2006) has been used here. Second, this definition is consistent with the concept of market-wide investor sentiment, which its effect on aggregate stock market returns is evaluated in this thesis. As a complement to the above definition, Chapter 5 also employs the definition given by Baker and Wurgler (2007) since the chapter focuses on the irrational expectations about future cash flows and discount rates. Investors could form optimistic or pessimistic expectations about these two elements, which then affect the stock returns.

2.2 Noise traders theory and limit to arbitrage

Noise trader theory, first established in the early 1980s, has resulted in it being widely accepted in the finance literature that some investors behave irrationally. Black (1986) argues that investors do not share common beliefs and information, which violate the assumptions of the EMH – homogeneous expectations. The consequence of these information asymmetries is the presence of noise traders in the markets. Black (1986) claim that some investors trade on noise[4] as if the erroneous beliefs were information, and these traders are termed as 'noise traders'. He further predicts that "[t]he influence of noise traders will become apparent" (Black, 1986, p.530). Despite Black (1986) outlining and acknowledging the profound effect of the noise traders, De Long et al. (1990) is the first paper that proposes a model to demonstrate the role of noise traders or irrational investors in the stock market. In their model, noise traders are assumed to act collectively and their misperceptions are correlated. This, in turn, creates a force in the stock market that could not be easily be cancelled out by arbitrageurs within a short period. As such, the implication of their models is that asset prices tend to revert to mean only in the long run.

The traditional asset pricing model claims that the existence of noise traders can be ignored as their impact on the stock prices is trivial even though EMH does not deny the fact that not all investors are rational. The proponents of classical finance theory believe that the deviation of stock prices from their 'correct' values caused by noise traders will be fully swept away by arbitrageurs. However, this perfect arbitrage argument is impractical since close substitutes of stocks are unavailable in the market, and hence the riskless arbitrage does not exist in the stock markets, arbitrageurs are reluctant to trade aggressively in the presence of arbitrage risk (Wurgler and Zhuravskaya, 2002) since EMH assumes that all rational investors (including arbitrageurs) are risk-averse. As such, the argument that arbitrage activity will always correct the dispersion of stock prices from their fundamental values is dubious. Arbitrageurs are also likely to have short horizons due to the liquidity constraint faced by them (Shleifer and Vishny, 1997). As mentioned in Shleifer and Vishny (1997), most arbitrageurs in the real world act as an agent to wealthy investors (i.e. principal) and the liquidity constraint does matter in this agency context. The principal tends to evaluate the competency of an arbitrageurs based on their past performance, which has been called as performance-based arbitrage in Shleifer and Vishny (1997). Principals may refuse to channel additional capital or withdraw their capital if the investment position seems to be deteriorating due to widening mispricing. In this case, full arbitrage could be hard to achieve.

Apart from the arbitrage risk stemming from imperfect stock substitutes, risk-averse arbitrageurs also encounter two main sources of risk, namely fundamental risk and noise

[4] Noise is the pseudo-signals obtained from technical analysis, sentiment indexes and financial gurus' advices, that do not carry any reliable information (De Long et al., 1990).

trader risk, which reduce their willingness to bet against noise traders. Fundamental risk, as Shleifer and Summers (1990) explain, is the risk that the stock price moves against the arbitrageur's initial bet due to unexpected news. For instance, if a particular stock is believed to be overvalued, an arbitrageur will short sell the stock. If the stock price returns to the value as expected in the future, the arbitrageur is making profit by buying back the stock later at a price lower than the selling price. However, the arbitrageur is at risk if the stock subsequently increases in value as a consequence of favourable fundamental news arrives unexpectedly. Aversion to the loss due to fundamental risk limits the arbitrage trading (Mitchell, Pulvino and Stafford, 2002).

'Noise trader risk', as introduced by De Long et al. (1990), also demonstrates that perfect riskless arbitrage does not exist in the stock markets. Unpredictable noise traders' beliefs create unforecastable variations in future stock prices when the sentiment of irrational investors are correlated. It is possible for the noise traders to become even more optimistic or pessimistic and hence causes stock prices to drift further from their fundamental values. If this is the case, arbitrageurs who initially bet against noise traders' beliefs would face a huge loss. This phenomenon has been termed as 'noise trader risk'. For instance, an arbitrageur who initially takes a short sell position would hope for stock price to reduce and revert to its mean. However, the mispricing caused by noise traders might persists for a long-term period as a result of the beliefs of noise trader persistently move towards one extreme direction, causing stock prices to be even more overvalued. Owing to the liquidity constraint and the higher transaction costs in the long-term, arbitrageurs may have to liquidate and close their positions at a loss. Thus, fear of having such a loss may deter arbitrageurs from betting against noise traders and the effect generated by noise traders might persist for a long time. This argument has been discussed in several other studies as well (Campbell and Kyle, 1993; De Long, Shleifer, Summers and Waldmann, 1990; Shleifer and Vishny, 1997; Shleifer and Summers, 1990).

Abreu and Brunnermeier (2002, 2003) offer a new type of risk, termed as 'synchronization risk'. Although the synchronization risk does not originate from the aggressive noise traders' activity, nonetheless, it is important to understand how an increase in this risk can limits the arbitrage activity in the short-term. Synchronization risk arises when an arbitrageur is unable to coordinate with other rational investors in eliminating the mispricing since he or she is uncertain about when other arbitrageurs will also exploit the arbitrage opportunity. Huge losses could be incurred if the arbitrageur trades alone since the force from a single arbitrage is unable to counteract the noise traders' activity. Thus, this synchronization risk delays and limits arbitrage activity.

The rationale underlying the limit to arbitrage is not confined to different types of risks faced by arbitrageurs, but the inability of arbitrageurs in distinguishing the fundamental information from the noise also contributes to the 'limit to arbitrage' (Shleifer and Summers, 1990). If the deviation of price is excessively large and follows a 'random walk' behaviour persistently, then it would be hard for arbitrageurs to correctly identify the fundamental value of the stocks and the risk involved in the arbitrage activity. Hence, the arbitrage activity is limited in this case. In fact, irrational investors with erroneous beliefs have exerted an effect that can persist for a long period of time, regardless of their long-run survival (Kogan, Ross, Wang and Westerfield, 2006), since investor sentiment is highly persistent in the stock market (Brown and Cliff, 2005).

The discussions above clearly depict that noise traders, who based their decision making on their beliefs or investor sentiment, creates the risk that form the basis for the 'limit to arbitrage'. As such, investor sentiment plays a key role in the variations of stock prices that cannot be justified under the classical finance theory. As mentioned in Baker and Wurgler (2007, p.130), "the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects." Since investor sentiment is a latent variable, researchers have strived hard to produce accurate measure of investor sentiment. The next section provides a discussion of various investor sentiment measures and their predictive power on the stock returns.

2.3 Measures of investor sentiment and returns predictability by sentiment

Since investor sentiment has a profound impact in the stock market, constructing an accurate measure of investor sentiment is of high importance and is an ongoing task among the researchers in behavioural finance. Different measures have been continuously sought in past studies and a range of investor sentiment measures used in extant studies can be categorised into three main groups: survey-, market-, and textual-based measures. Although different measures have been proposed in the literature, these measures have the same purpose: to predict the stock returns. As discussed in the previous sub-section, noise trader risk curtails arbitrage activities in the short-term, and hence price reversal tends to occur in the long-term. This proposition has been supported by empirical evidence that high (low) sentiment predicts a high (low) contemporaneous return, followed by low (high) future return as the overpricing (underpricing) is eventually corrected (e.g., Ben-Rephael, Kandel and Wohl, 2012; Da, Engelberg and Gao, 2011; Tetlock, 2007). Despite the fact that the negative relationship between sentiment and future stock returns is regularly documented in the literature, there are also studies which find a positive relationship between investor sentiment and future stock market returns (see Beaumont, Daele, Frijns, Lehnert and Muller, 2008; Gebka, 2014; Lutz, 2016).

Survey-based measures reveal the optimistic or pessimistic view of market participants by gathering the responses of people regarding their expectation of stock market and general economic conditions. Popular survey-based measures include, but are not limited to, Investor Intelligence (II), American Association of Individual Investors (AAII), Consumer Confidence Index (CCI), and University of Michigan Consumer Sentiment Index (MS)[5]. II, which is constructed by categorising newsletters into a bearish, bullish or neutral perspective, can be viewed as institutional investor sentiment since investment newsletters are mainly written by professionals (Brown and Cliff, 2004). Contrarily, AAII collect the responses of market participants about the stock market perspective.

Studies which have used the survey-based sentiment measures as discussed above have employed these in different ways to uncover the underlying investor sentiment. Fisher and Statman (2000) use a simpler way by calculating the percentage of optimistic investors as measured by AAII and II; whereas some studies have instead constructed the bull-bear spread based on the percentage of bullish and bearish investors reported in AAII and/ or II. (Brown and Cliff, 2004; 2005; De Bondt, 1993; Greenwood and Shleifer, 2014; Verma, Baklaci and Soydemir, 2008; Verma and Soydemir, 2006). The consistent feature of all these studies is that a negative sentiment-return relationship, i.e. an increase in AAII and/ or II is followed by a lower future stock returns, has been documented, with the only exception being Brown and Cliff (2004).

The CCI and MS are monthly survey-based measures of individual investor sentiment that have been used concurrently in many studies since both indices reveal the level of consumer confidence with respect to the overall conditions of the economy. Since these two indexes have been found to correlate positively with contemporaneous returns (Fisher and

[5] These survey-based measures are the barometers of the investor sentiment in US. II and AAII are published on a weekly basis, whereas MS and CCI are published on a monthly basis. To match the data frequency of other sentiment measures and economic predictors, this study opts for MS and CCI in the forecast comparison.

Statman, 2003; Qiu and Welch, 2004), many studies have adopted these two measures as a proxy for investor sentiment in studying the fluctuation of stock prices. Fisher and Statman (2003) and Lemmon and Portniaguina (2006) find that both MS and CCI predict negatively the future return on small-cap stocks. Meanwhile, Coakley, Dotsis, Liu and Zhai (2014) find that MS has significant impact on the option prices of large firm and growth stock indices. In contrast, Kalotay, Gray and Sin (2007) reveal that MS does not have any predictive power on the quarterly equity risk premium for US stock market. Ho and Hung (2012) also claim that CCI does not generate significant impact on US next month stock market returns. Likewise, Coakley et al. (2014) does not find any significant relationship between MS and the option price of S&P 500 index[6].

Studies that focus on the stock markets outside the US prefer to use a consumer confidence index as a proxy to investor sentiment since this type of measure is readily available in many countries. For instance, Bathia and Bredin (2013), Ho and Hung (2012) and Schmeling (2009) find a negative relationship between consumer confidence indicators and future stock market returns across different developed countries. Recently, Ferrer, Salabera and Zalewska (2016) reveal that EU and US stock markets Granger-cause consumer confidence indicators, but the reverse direction was either not observed or weak. This finding is in line with Fisher and Statman (2003), Jansen and Nahuis (2003) and Otoo (1999) who also find that changes in stock prices seem to lead the consumer confidence indicators. Adding insult to injury, Ferrer, Salabera and Zalewska (2016) find that consumer confidence indexes do not even hold the basic property of investor sentiment given that there is no universally significant support to the positive relationship between contemporaneous stock returns and consumer confidence. Furthermore, they found that consumer confidence measures are shaped based on macroeconomic condition, which is also shown in Acemoglu and Scott (1994) and Lemmon and Portniaguina (2006). Hence, the mixed findings on the use of consumer confidence indicators as an investor sentiment measures calling for more research to prove its predictive power on the stock market returns.

Market-based measures, on the other hand, rely on market data that correlate with investor sentiment. Chicago Board Option Exchange's Volatility Index (VIX) is a commonly used market-based measure. It is the implied volatility computed from S&P 500 index option prices and is often known as 'investor fear gauge' (Whaley, 2000). Kaplanski and Levy (2010)

[6] They documented the same findings by using S^{BW} as an alternative investor sentiment measure.

who use the VIX as a proxy for investor sentiment find that VIX increases while stock prices declines following an aviation disaster, and this effect is generally stronger on the firms that face the difficulty to arbitrage as suggested in Baker and Wurgler (2006). Similarly, Smales (2017) reveal that VIX, which they claim is the preferred measure of investor sentiment, affect significantly the price movements of not only the aggregate stock market, but also small firms and technology firms. Since high value of VIX represents 'fear' and pessimism, Smales (2017) find that VIX has a negative relationship with contemporaneous return but a positive relationship with future return. Other studies that documented the similar findings include Ben-Rephael, Kandel and Wohl (2012) and Lutz (2016).

Other than VIX, various market-based single proxies have been proposed and used in past studies, these include closed-end fund discount (Bathia and Bredin, 2013; Doukas and Milanos, 2004; Gemmill and Thomas, 2002; Lee, Shleifer and Thaler, 1991; Neal and Wheatley, 1998); IPO-related measures (Brown and Cliff, 2004; Baker and Wurgler, 2006); derivative variables (Sheu and Wei, 2011b; Spyros, 2012; Wang, Keswani and Taylor, 2006); share of equity issues (Baker and Wurgler, 2000); dividend premium (Baker and Wurgler, 2004; Baker and Wurgler, 2007).

Since single market-based sentiment proxies as mentioned above are imperfect measures, Baker and Wurglr (2006) combine several single market-based proxies into a composite sentiment index, S^{BW}. They documented that S^{BW} predict negative future stock returns significantly in subgroups of stocks with stocks that are hard to value and difficult-to-arbitrage[7] tend to suffer a lot following the high sentiment period. Gradually, other studies also followed their path, constructing investor sentiment indexes using the same approach and/ or proxies for other stock markets in order to investigate the potential effect of investor sentiment on other stock market returns (see Chen, Chong and Duan, 2010, for Hong Kong stock market; Finter, Niessen-Ruenzi and Ruenzi, 2012, for German stock market; Hu and Wang, 2012, for Chinese stock market; Li, 2015, for Chinese stock market; Ryu, Kim and Yang, 2017, for Korean stock market; Yang and Zhou, 2015; 2016, for Chinese stock market).

Besides that, S^{BW} index has been widely employed as an investor sentiment measure in different financial applications, ranging from stock market anomalies (Antoniou, Doukas and Subramanyam, 2013; Stambaugh, Yu and Yuan, 2012; 2014); mean-variance relation (Yu and

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[7] Stocks that fulfil these characteristics are small stocks, younger stocks, stocks at the two extreme quintiles of book-to-market ratio, highly volatile stocks, unprofitable stocks and non-dividend-paying stocks.

Yuan, 2011), pricing of macro-risk (Shen, Yu and Zhao, 2017), to high-beta low-return puzzle or downward sloping security market line (Antoniou, Doukas and Subramanyam, 2016). All of the above studies excluding Yu and Yuan (2011) mainly focused on cross-sectional stock returns and concluded that S^{BW} successfully explains the cross-sectional asset pricing puzzles. The empirical evidences of sentiment effect at the cross-sectional level is supported by the theoretical model proposed recently by Ding, Mazouz and Wang (2019). Ding et al. (2019) further find that the short- (long-) run component of investor sentiment predicts positively (negatively) the contemporaneous (future) returns of long-short portfolios.

One drawback of the Baker and Wurgler (2006) approach has been that empirical evidence for its performance in capturing sentiment for the aggregate stock market has been rather mixed; as epitomised by its weak forecasting power for future aggregate stock returns. Baker and Wurgler (2007) themselves observe that, when forecasting the aggregate market using S^{BW}, "the statistical significance is modest" (p. 148). To address this shortcoming, Huang et al. (2015) construct an improved investor sentiment index using the same components as in S^{BW} but employing a different methodological approach. They find that their aligned investor sentiment index (S^{PLS})[8] significantly predicts short-term future aggregate stock market returns, where S^{BW} has been found to have no predictive power in the same sample. Arif and Lee (2014) also confirm the fact that S^{BW} has weak or no predictive power over the aggregate stock market returns, and produces a prediction that is in the wrong direction (i.e. positive slope coefficient). A more extreme result on the predictive performance of S^{BW} and S^{PLS} is documented in Bekiros, Gupta and Kyei (2016). Given the parameter instability and the non-linear structure in the relationship between investor sentiment and stock market returns, they employ a nonparametric causality test to examine the predictive ability of S^{BW} and S^{PLS}. Surprisingly, using a non-linear approach, both S^{BW} and S^{PLS} are not able to predict future stock market returns nor volatility.

Recently, a new branch of literature focuses on the textual-based investor sentiment measures, which can be further split into media-based and search-based sentiment measures. Media-based sentiment measures are computed by analysing the content published on traditional and social media such as newspaper columns, internet stock message boards, and Twitter. These measures are believed to shape investor sentiment as investors follow the news

[8] S^{PLS} is constructed by disentangling the information embedded in the proxies that are related to the stock market returns from common approximation errors.

or the opinions, and react accordingly even if those information could be misleading or false. Tetlock (2007), the seminal paper which uses news media content to construct an investor sentiment measure, finds that the media pessimism, i.e. the proportion of negative words in a *Wall Street Journal* (*WSJ*) column, predicts a long-run reversal in the stock market returns, supporting the hypothesis of the noise model instead of information theory. Instead of counting only on the negative words, Garcia (2013) accounts for both positive and negative words in the financial columns of the *New York Times* (*NYTimes*) in his sentiment measure. Similarly, the price reversals happened in the later period and the heightened trading volume associated with extreme positive or negative news are in line with the behavioural model. He found that his sentiment measure predicts well the next day stock returns during recessionary periods. While their findings are built on the basis of daily sentiment measures, Sun, Najand and Shen (2016) find that the intraday investor sentiment measure, the Thomson Reuters MarketPhysc index, contains textual information from both traditional and social media, and strongly predicts intraday stock market returns.

Investor sentiment extracted from social media has also been found to statistically significantly predict stock returns (see Chen, De, Hu and Hwang, 2014 (extract the sentiment information from *SeekingAlpha.com*); Bollen and Mao, 2011 (extract investor sentiment from Twitter posts)). Contrarily, Das and Chen (2007) find that the daily small investor sentiment constructed utilising the positive and negative opinions posted for each technology stock on the stock message boards does not have strong statistical predictive power over individual stock prices, but their aggregate investor sentiment index does have statistical predictive power on the stock market returns. Similarly, Kim and Kim (2014) find that investor sentiment extracted from internet message postings does not predict future stock returns at both aggregate and individual stock levels. Meanwhile, Antweiler and Frank (2004) claim that this type of sentiment measure produces return forecasts that is not economically justifiable.

As for search-based sentiment measures, they are constructed mainly based on the Google Search Volume Index (SVI). One of the most popular search-based sentiment measures is the FEARS index of Da et al. (2015). The index is formed by aggregating the number of searches for the words that express household concerns, *e.g.* “unemployment”, “recession” and “bankruptcy”, and revealed that a high FEARS value, which represents investor pessimism, is associated with a low contemporaneous returns but predicts a higher future returns in few days later. Another study by Joseph, Wintoki and Zhang (2011) constructed the sentiment measure based on the number of searches for stock tickers also found that investor sentiment predicts the returns reversal in longer horizons (i.e. beyond two weeks) for stocks that are hard-to-arbitrage and of high volatility. Despite SVI has been used as a proxy to investor sentiment measure in these studies, other studies using it as a measure to investor attention (see Bank, Larch, Peter, 2011; Da, Engelberg and Gao, 2011; Vozlyublennaia, 2014)[9]. Even though Dimpfl and Jank (2016) mention that the number of searches for stock index is mainly driven by noise traders, Da et al. (2011) claim that an increase in investor attention could also be caused by investors paying attention to genuine news. They found that the SVI is weakly correlated to other media-based sentiment measures.

The review of literature above shows that most investor sentiment measures do not consistently perform well in predicting (1) positive contemporaneous returns, and (2) negative future returns. Therefore, there is room for further investigation on a better investor sentiment measure that predicts stock returns well. Chapter 3 and Chapter 4 focus mainly on the prediction of the latter case, i.e. investor sentiment predicts negatively future stock returns. The former case is not the focus of this study since contemporaneous sentiment-return relationship has the endogeneity issue (Smales, 2017). It is also more realistic to test on the predictive power of investor sentiment on future stock returns instead of contemporaneous returns as any potential gains could be offset by the trading costs having to rebalance the portfolio within a month. For the interest of comparison, this study uses only the survey- and market-based sentiment measures. The textual-based sentiment measure is not considered in this study as the data frequency of the textual-based measure, which is at daily, weekly or even intraday level, does not match the monthly data frequency of this study.

2.4 Predictability of stock returns by economic predictors

Having reviewed the association of return predictability and investor sentiment, this sub-section reviews the previous literature working on the return predictability using fundamental factors. A vast amount of fundamental economic predictor variables have been proposed since late 1980s, starting with the financial valuation ratios, such as dividend yield and earnings yield. The literature has then expanded to include other valuation ratios and financial market variables, such as dividend payout ratio and net equity issuance. Fama and French (1989) argue that the predictability of stock returns stemmed from the ability of predictor variables in tracking the variations in the business cycle. In particular, expected

[9] These three studies, except Vozlyublennaia (2014), find that increased in search queries leads to a short-run increased in the stock returns, which is then reversed in a longer prediction horizon.

returns covary negatively with the business cycle, and any variable moves along with the upswings and downswings of the business cycle should be able to predict the expected stock returns. Nevertheless, there is no economic risk underlying the relationship between expected return and these business cycle indicators. Therefore, a few variables that link the return predictability to the macroeconomics factor, such as consumption, aggregate wealth, and production have been proposed since late 1990s. Accordingly, reviews of the literature on return predictability by widely employed economic predictors can be categorised into (a) financial indicators: dividend price ratio, dividend yield ratio, earnings-price ratio, book-to-market ratio, dividend payout ratio, stock return variance, and net equity expansion; (b) business cycle indicators: treasury bill rate, term yield spread, default yield spread, and inflation; (c) macroeconomics indicators: output gap, consumption wealth ratio, surplus consumption ratio.

Dividend price ratio (DP) and Dividend yield ratio (DY). The present-value identity of Campbell and Shiller (1988a; 1988b) shows that DP, which measures the fundamental value relative to the current stock prices, deviates from its mean whenever there is a change in expected dividend growth and/ or expected returns. This implies that return is predictable from DP. The expected returns is forecasted to be lower when the stocks are overpriced as compared to fundamentals, i.e. low DP or DY[10], and vice versa. Studies that provide support to the predictive power of DP and DY include Cochrane (1992; 2008; 2011), Hodrick (1992), Koijen and van Nieuwerburgh (2011), Lewellen (2004), and Rozeff (1984).

Furthermore, most studies find that the predictive power of these ratios improves with the forecast horizon. For instance, Hodrick (1992) reports a dramatic increase of R^2 from a 6% at next-month forecast to a 39% at 4-year-ahead forecast for the predictive power of DY. Similarly, the in- and out-of-sample forecasts of Fama and French (1988b) show that the DP ratio explains the monthly return variability for less than 7%, but account for up to 64% of the return variance for four-year forecasts. In contrast, Ang and Bekaert (2007) find that the predictive power of DP on the stock market returns forecasted from next-month to 60-month horizon is unseen[11], consistent with Goetzman and Jorion (1993) whose findings are

[10] The difference of DP and DY ratios is that the former (latter) divides the current dividend with the contemporaneous (lagged) stock prices. Fama and French (1988b) mention that the DY is a rather conservative measure, avoiding the potential of overly reject the null that no predictability from dividend yield but understating its out-of-sample predictive power as compared to the DP, which is a more timely measure.

[11] Ang and Bekaert (2007) find that DP can only predict next-month stock market returns when three-month Treasury bill rates in included as another predictor in post-1952.

documented from one- to four-year horizons. Goetzman and Jorion (1995) and Nelson and Kim (1993) report that the predictive power of these ratios could be driven by the survivorship bias and small sample bias, respectively.

Earnings-price ratio (EP). Similar to the dividend yield ratios, EP ratio should positively predict expected returns. A high EP ratio implies that the stock is undervalued, so will have higher expected returns in the future. Nevertheless, Fama and French (1988b) find that the explanatory power of EP ratio on future stock market returns is weaker than that of the dividend yield ratio even though the predictive power of EP ratio is strengthened with the forecast horizon. A similar conclusion is presented by Lamont (1998) for quarterly returns forecasts, and by Lewellen (2004) who find that the predictive power of EP ratio depends on the definition of asset returns (nominal vs. excess returns). Campbell and Yogo (2006), however, reveal the opposite findings that EP ratio consistently predicts the stock returns from monthly to annual frequency whereas DP ratio can only predict annual returns.

Book-to-market ratio (BM). BM is another valuation ratio that is expected to have positive impact on the future stock returns. The use of BM ratio as one of the factors in the three-factor model proposed by Fama and French (1992; 1993) has motivated researchers to investigate its ability to predict the stock market returns. Kothari and Shanken (1997) reveal that the predictive power of BM ratio are sensitive to the sample period as well as the returns definition (equal-weighted vs. value-weighted). They found that BM strongly predicts the returns even after accounting for the small sample bias over the entire sample period (1926-1991) but not for the period in post-1962. The disappearance of the predictive ability of BM ratio post-1960 is further verified by Pontiff and Schall (1998), who find that both DJIA and S&P 500 BM ratios lose their ability to predict the respective stock market returns. Their findings are dissimilar to that reported in Lewellen (2004), where he found that BM ratio reliably predicts the next-month stock market returns. However, only the equal-weighted returns are predictable by BM ratio, a finding that is consistent with Kothari and Shanken (1997).

Dividend payout ratio (DE). As mentioned by Lamont (1998), DE predicts returns because (1) dividends, which signal future cash flows, forecast future returns in a positive direction, and (2) earnings, which covary positively with the business cycle, negatively predict future returns. Combining both effects, DE positively predicts future stock returns. Its predictive ability is, however, limited to the short-horizon forecasts (i.e. quarterly and annual frequencies).

Stock return variance (SVAR). The risk-return trade-off suggests a positive relation between risk and expected returns. Although this hypothesis has long been proposed in the literature, empirical findings are mixed, depending on the risk measure. French, Schwert and Stambaugh (1987) confirm that expected excess market returns are positively related to the market returns volatility when GARCH-in-mean instead of realized volatility is employed to estimate the market volatility. Furthermore, the documented negative relationship between the realized excess market returns and the contemporaneous shocks in the market volatility further support their findings on the positive risk-return trade-off.

Guo (2006), however, find that the effect of the market volatility on future stock market returns is unveiled only when the regression is augmented by consumption-wealth ratio (CAY), which is a proxy for the liquidity premium. The author further revealed that the market volatility has strong out-of-sample forecasting power when both volatility and CAY are employed in the forecasting exercise, implying that the liquidity premium proxied by CAY could be the explanation for the failure of risk-return trade-off.

In contrast, Goyal and Santa-Clara (2003) shows that market volatility fails to predict stock market returns. They found that idiosyncratic risk, which is the cross-sectional average of stock risks, reliably forecasts the future stock market returns and brings economic benefit to investors based on the out-of-sample trading strategy.

Net equity expansion (NTIS). Empirical studies generally found that stock issuers deliver low average returns in the long-run after the equity issuance. Ritter (1991) find that initial public offerings (IPOs) stocks underperform the matching firms' stocks by about 29% three years after the IPOs. His result is supported by Loughran, Ritter and Rydqvist (1994) and Purnanandam and Swaminathan (2004) which find that IPOs stocks earn negative market-adjusted abnormal returns of up to five years after the IPOs. Not only do IPOs stocks experience the long-run underperformance relative to comparable non-issuers, firms conducting seasoned equity offerings (SEOs) also deliver negative adjusted returns in the long run. Loughran and Ritter (1995) find that the average five-year holding period return that is 60 percentage point lower than of non-issuers; whereas Spiess and Affleck-Graves (1995) reveal that the median returns over five-year period that is 32% percentage point lower than the non-issuers.

Rather than focusing on the returns of IPOs stocks, Baker and Wurgler (2000) provide evidence on the predictive power of equity issuance on the future stock market returns. They showed that stock market returns are positive (negative) following the years with low (high) equity issue, and demonstrated that new equity issuance predicts the future stock market returns significantly and negatively even after controlling for other aggregate return predictors. Butler, Grullon and Weston (2005) reveal contradictory findings that future expected returns is not predictable by the net equity issuance.

Treasury bill rate (TBL). Campbell (1987) reveals that one-month TBL can be used to predict the excess stock returns, where a low TBL predicts high future returns, since TBL is the state variable of the term yield spread that predicts the excess stock returns. Indeed, its predictive power becomes stronger in the second sub-sample period (*i.e* post-1979). Besides that, Hodrick (1992) also find that TBL strongly predicts the future stock returns in their late sample period. However, Pontiff and Schall (1998) who also employ the three-month TBL show that TBL does not predict significantly the next-month and annual stock market returns across different sample periods even though its coefficient sign is generally consistent with the literature. A similar finding is documented in Baker and Wurgler (2000); contradictory finding can be found in Ang and Bekaert (2007) and Campbell and Yogo (2006).

Term yield spread (TMS). The changes in yield curve reflects the different phases of business cycle, and hence, TMS, which is the spread in yields of long-term bond and short-term bond, capture the information about business cycle. TMS tend to be higher (lower) at the trough (peak) of the business cycle, suggesting a better (poor) prospects for the future of the economy. Since the business cycle is countercyclical with expected stock returns, TMS positively predicts expected future returns. This intuition is confirmed by Fama and French (1989) who reveal that TMS predicts positively and significantly for monthly and quarterly returns, a finding supported by Campbell and Yogo (2006) at the aggregate level. Campbell and Hamao (1992) and Campbell and Ammer (1993) also show that TMS has a positive relation with the next-month stock returns across different subperiods within the time frame of Fama and French (1989). On the other hand, Baker and Wurgler (2000) find that TMS is unable to predict the next-year stock market returns from 1928 to 1997. Similarly, Pontiff and Schall (1998) show that TMS predicts neither the next-month returns nor next-year returns at the aggregate level over almost the similar sample period.

Default yield spread (DFY). Apart from TMS, Chen, Roll and Ross (1986) and Fama and French (1989) argue that DFY, that is, the yield spread between lower- and higher-grade bonds, is closely related to the business cycle. The default yield premium tends to be higher near the trough, and hence predicts higher expected returns in the future, and the converse holds. Fama and French (1989) find that the predictive power of the DFY increases with the forecast horizon as the statistical significance of its slope coefficient increases from the next-month forecast up to the 4-year forecast. The increasing predictive power of DFY with the forecast horizon also evident in Fama (1990).

Keim and Stambuagh (1986), although incorporating the DFY as one of the *ex-ante* predictor variables, their measure also has the element of TMS since they consider the yield spread between the low-grade corporate bond and one-month TBL. They generally found that the predictive ability of DFY is seen only on the large stocks and over the full sample period, but the predictive power disappears at all over the sub-sample periods. In contrast, Amihud (2002) does not only find that the DFY has a strong positive effect on the expected excess market returns, but also notice that its effect decreases with firm size.

Inflation (INFL). Although stocks are commonly viewed as a hedge against the inflation, i.e. the parameter estimates of inflation should be positive, in the past, literature generally found that stock market returns correlate negatively with the INFL (Fama and Schwert, 1977[12]; Jaffe and Mandelker, 1976; Lintner, 1975; Kaul, 1987). Nelson (1976) also find that INFL predicts negatively the future stock market returns at short-horizons. Despite the negative relation between these two variables, the author revealed that the trading strategies using the return forecasts estimated from the inflation variable indeed generates higher returns than a simple buy-and-hold strategy in an out-of-sample context. Besides that, Kim and In (2005) find that the negative relationship exists at the intermediate horizon. A few studies, however, documented a positive relationship between stock returns and INFL at long-horizons (Jaffe and Mandelker, 1976, Boudoukh and Richardson, 1993).

Output gap (OG). The use of OG as a returns predictor is introduced by Cooper and Priestley, 2009). OG, a measure of divergence of the log industrial production from a time trend, is a business cycle indicator that tracks the variation in stock prices. The expected returns are predicted to be low (high) when the output gap is high (low) during the expansion

[12] They employed the Treasury bill rate as the proxy for the expected inflation rate.

(recession). Since this measure does not possess the information of the asset price, they argued that the predictive power of OG merely reflects the time-varying risk, avoiding the return predictability stemmed from the stock mispricing. Cooper and Priestley (2009) claim that OG is a strong stock market returns predictor at short-horizon and long-horizon, evaluated in both in- and out-of-sample contexts. Vivian and Wohar (2013) further extend the evidence on the predictive power of OG to the cross-section of stock returns. Their findings that all size and value sorted portfolio returns are predictable by OG appear to support the predictive ability of OG documented at the aggregate level.

Consumption-wealth ratio (CAY). CAY measures the transitory deviation of log consumption from the shared trend derived from the log assets and log labour income. Based on the present-value identity, Lettau and Ludvigson (2001a) show that consumption-wealth ratio can be expressed as a function of expected stock returns and expected consumption growth. If the expected consumption growth is rather constant, then the consumption-wealth ratio can be a good return predictor[13]. To smooth the consumption pattern over time, investors would reduce (increase) their consumption when the expected returns are low (high) in the future, resulting in consumption falling below (above) the long-term trend, i.e. low (high) CAY. The in- and out-of-sample forecasts conducted by Lettau and Ludvigson (2001a) shows that the predictive power of CAY on the quarterly excess market returns is particularly strong at short- and intermediate-horizons, further supported by Cochrane (2011). Meanwhile, their in-sample results further depict that the variable alone can predict the excess market returns at long-horizon of up to six years. The superior out-of-sample performance of CAY over the historical mean model has also been confirmed in Guo (2006).

Surplus consumption ratio (SCR). SCR proposed by Campbell and Cochrane (1999) argue that the expected returns is inversely related to the ratio of consumption relative to the external habit[14]. In particular, low surplus consumption, i.e. consumption level in excess of the habit decreases, in cyclical downswing predicts the high expected returns as the risk aversion increases and current stock prices drop. The simulated data produced from their model matches the long-horizon stock returns prediction. Engsted, Hyde and Møller (2010)

[13] Indeed, they found that only the coefficient of CAY on the growth of asset wealth is significant, suggesting that only the asset wealth (i.e. asset returns) that will adjust to ensure the log consumption aligns with the shared trend. Therefore, the trend deviation signals the variation in the expected returns.

[14] The external habit formation specifies that the habit level is determined based on the history of total consumption in the economy.

and Møller (2009) provide empirical in-sample evidences on the ability of SCR in predicting the annual excess market returns.

Although the above cited literature provide the rationale and the direction to which each variable predicts the stock returns, majority of these studies are primarily in-sample and studied either a particular variable or a limited set of return predictors. The most influential study by Welch and Goyal (2008) has contributed greatly towards the understanding of the return predictability by considering the predictive power of a more comprehensive set of predictors, including the ones reviewed above[15], in both the in- and out-of-sample contexts. They cast doubt about the forecast ability of economic predictors since most of the predictors considered fail to survive from the in-sample and out-of-sample tests. Whilst the predictors like BM and NTIS perform well in-sample, their out-of-sample predictive power is hard to unfold. Their findings reconcile with the work of Bossaerts and Hillion (1999), Marquering and Verbeek (2004) which concerns on the economic value of the return forecasts by market volatility.

The poor out-of-sample forecasting performance of economic predictors could be originated from the parameter instability as Welch and Goyal (2008) reveal that all predictors perform badly after the oil shock recession. Other studies which also reveal the break in the relationship between expected returns and economic predictors include Paye and Timmermann (2006), Pesaran and Timmermann (2002). Accordingly, different strategies have been proposed in the literature with an aim to improve the out-of-sample forecasts of economic predictors.

First, Campbell and Thomson (2008) restrict either the coefficient's sign to be consistent with the theory or the return forecasts to be non-negative. The sum-of-parts (SOP) approach of Ferreira and Santa-Clara (2011) can be viewed as a restrictive model in that the intercept of DY predictive model is restricted to be the long-run average of the past earnings growth and the slope coefficient of DY is one[16]. Second, some studies evaluate the predictive performance of economic predictors across different regimes (*e.g.* Dangl and Halling, 2012;

[15] They also included long-term yield (LTY), long-term returns (LTR) and default return spread (DFR) in their set of predictors.

[16] The SOP method forecasts the components stock market returns separately from the expected values of DY and earnings growth as well as the price-earnings multiple growth rate (PEG). The expected earnings growth is estimated as the long-run average, representing the intercept in the model; the PEG is assumed to be zero, leaving the DY to follow a random walk process.

Henkel, Martin and Nardari, 2011; Pesaran and Timmermann, 1995). Third, a diffusion index that retrieves the common (latent) factor underlying a broad range of predictors is constructed based on either the principal component analysis (Ludvigson and Ng, 2007; Neely, Rapach, Tu and Zhou, 2014) or the partial least square method (Kelly and Pruitt, 2013, Huang, Jiang, Tu and Zhou, 2015). Fourth, Rapach, Strauss and Zhou (2010) combining the forecasts of individual predictors. All of these studies together with Rapach and Zhou (2013) acknowledge the usefulness of these strategies in improving the forecasting performance of the economic predictors, and reached at a conclusion contradicting Welch and Goyal (2008). Along this line, there are studies echoed the suggestion of Welch and Goyal (2008) by introducing the new predictors, such as short interest (Rapach, Ringgenberg and Zhou, 2016) and technical indicators (Neely et al., 2014), and by using a more advanced method (Gebka and Wohar, 2019).

Apart from the poor out-of-sample forecasting performance, the other issue concerning many researchers is the striking forecasting performance of economic predictors in the long-horizon, where some studies, as reviewed above, revealed that the measure of linear fit, e.g. R^2 statistics, of long-horizon prediction are much higher than that of the short-horizon prediction. This phenomenon could be attributable to the highly persistent and endogenous return predictors, *e.g.* ratios of fundamental relative to price, (see Ferson, Sarkissian and Simin, 2003; Nelson and Kim, 1993; Stambaugh, 1999). Stambaugh (1999) argues that small sample bias exists when the stock returns are regressed on a highly persistent predictor and the return innovations is correlated with the innovation in the stochastic predictor. As a result, the estimated slope coefficient is biased. Therefore, bias-adjusted estimator has been proposed for single-predictor model (Lewellen, 2004) and multiple-predictor model (Amihud, Hurvich and Wang, 2009). Whilst Lewellen (2004) find that the long-horizon predictability stands up even after accounting for the Stambaugh bias, other studies remain doubtful about the long-horizon predictability (*e.g.* Ang and Bakaert, 2007; Boudoukh, Richardson and Whitelaw, 2008; Kostakis, Magdalinos and Stamatogiannis, 2015; Lanne, 2002, Maynard and Ren, 2019; Torous, Valkanov and Yan, 2004).

The literature reviews on the return prediction using economic predictors reveals that the research in this line remains controversial in view of the mixed results on the in-sample findings, the structural instability of the parameter estimates, the presence of the statistical bias, and the poor out-of-sample forecasting performance. Correspondingly, the conclusion on the predictive power of any return predictor should be carefully assessed not only in the in-sample context, but also in the out-of-sample framework. The findings on the predictive power of the economic predictors and the enhanced investor sentiment index in Chapter 4 are, therefore, drawn mainly from the out-of-sample evaluation. This study also guards against the potential Stambaugh bias by considering the Feasible Generalised Least Square (FGLS) approach proposed by Westerlund and Narayan (2012) in order to produce reliable out-of-sample forecasts[17]. A few forecasting strategies as discussed above are employed to derive a more robust results that stands up with the alteration in the specification.

[17] FGLS procedure will be discussed in detailed in Section 4.2.1

Chapter 3. Constructing a Superior Investor Sentiment Index

3.1 Introduction

Investor sentiment is well established in the behavioural finance literature as having a pivotal impact on asset price fluctuations. De Long, Shleifer, Summers and Waldmann (1990, DSSW henceforth), for example, demonstrate how prices can be driven away from their fundamental values by ‘sentiment’, also called ‘noise’, traders. They suggest that where such unpredictable traders dominate, they deter arbitrage activities in the short-term, leading to price reversals (towards their fundamental values) in the long-term[18]. Crucially, this implies that investor sentiment has predictive power for stock returns, and thus, an accurate measure of investor sentiment is of great empirical importance: for instance, portfolio managers would benefit from availability of an empirical measure which captures a well-known risk factor (sentiment, or noise risk) in asset pricing (e.g., Antoniou et al., 2016), while, given that investor sentiment induces mispricing especially in the environment of lacking transparency and weak corporate governance of firms (e.g., Firth et al., 2015), policy makers, regulators and accounting professionals would gain an improved instrument to gauge the severity of such distortions and to guide them towards appropriate reforms.

A key issue with the measurement of investor sentiment is that it is a latent (unobservable) factor in investor decisions. Survey-based measures have sought to directly quantify sentiment but have been found to perform poorly empirically (e.g. Ferrer, Salabera and Zalewska, 2016; Otoo, 1999), whereas market-based measures have attempted to approximate sentiment based on observable market variables. The seminal paper of Baker and Wurgler (2006) fits into and builds upon this second class of measures, as their index (S^{BW} hereafter) combines six market-based sentiment proxies, using constant time-invariant weights, into a single sentiment index. The BW index successfully predicts high (low) future returns for small stocks, young stocks, distressed stocks, and extreme growth stocks when current sentiment is low (high), i.e. at the cross-sectional level.

It might be expected that S^{BW} would also perform well at the market level given that investor sentiment is a market-wide phenomenon (see Baker and Wugler, 2006; 2007; Brown

[18] De Bondt and Thaler (1985) and Chopra, Lakonishok and Ritter (1992) demonstrate that stock prices experience price reversal over 3- to 5- year horizons. Fama and French (1988a) and Poterba and Summers (1988) also shows that stock returns are negatively correlated over long-horizon.

and Cliff, 2004; DSSW, 1990; Lee, Jiang and Indro, 2002; Stambaugh, Yu and Yuan, 2012) and that S^{BW} seeks to capture market-wide sentiment. However, numerous studies demonstrate that S^{BW} fails to exhibit strong statistically significant predictive power for future aggregate stock market returns in the time-series context (Arif and Lee, 2014; Baker and Wurgler, 2007; Huang, Jiang, Tu and Zhou, 2015).

The novelty of the approach of this chapter is to propose that one possible reason for the failure of S^{BW} to significantly forecast future aggregate stock returns could be the fixed nature of the original index's components weights, which is based on an implicit assumption that the ability of each component to capture latent sentiment is time-invariant[19]. Crucially, all these proxies are driven by both sentiment and market fundamental factors. Thus, changes in these imperfect measures of investor sentiment could reflect a change in investor sentiment or/and fundamental factors, e.g., equity issuance varies with investor sentiment, but issuing equities depends also on the investment opportunities (Jung, Kim and Stulz, 1996). As such, the degree to which each proxy captures the investor sentiment may vary over time[20]. In other words, not every proxy captures the unobserved investor sentiment to the same degree at all times, an observation which casts doubt on the constant weight being applied to every component in the original S^{BW} index.

An enhanced investor sentiment index, which would address this shortcoming and which could consequently establish the time-series forecasting power of the BW approach, is therefore required. Furthermore, it might be argued that a more stringent test of any sentiment index is how it performs in the time-series rather than cross-sectional domain, given that Baker and Wurgler (2007) observe that the forecasting ability of investor sentiment for aggregate stock market is less apparent than its cross-sectional performance, which suggest that the former feature is harder to capture.

For the cross-sectional predictive performance, Baker and Wurgler (2006) find that their market-wide sentiment measure generates different effects on the cross-section of stock

[19] The proxies used include: dividend premium (PDND); average first-day returns of IPOs (RIPO); the number of IPOs (NIPO); the closed-end fund discount (CEFD); market turnover (TURN) and the share of equity issues (EQ).

[20] Excluding NYSE share turnover from the construction of the latest series of S^{BW} exemplified the importance or contribution of each sentiment proxy to the sentiment index could have changed over time. In Jeffrey Wurgler's latest data file, he mentioned that "Turnover does not mean what it once did, given the explosion of institutional high-frequency trading and the migration of trading to a variety of venues". Therefore, a sentiment proxy which was once potentially reflect the investor sentiment may no longer capture the sentiment well. Similarly, other sentiment proxies could also have their contributions to the sentiment index increased or reduced over time.

returns with stocks that are hard to arbitrage and value, such as, small, distressed, and extreme growth stocks, affected most by the wave of investor sentiment. Even though the main aim of this chapter is to improve the time-series return predictability of S^{BW} at the aggregate level, this study also concerns on whether an index that can predict the aggregate stock market returns predicts also the returns of different portfolios across time.

This chapter therefore seeks to address the following key research questions: (1) Can the predictive ability of S^{BW} in the time series context be improved by allowing the contribution of each index component to vary over time? (2) Is the newly constructed investor sentiment index a good proxy for investor sentiment (i.e. high sentiment today predicts low future returns and vice versa)? (3) If it is, does the new index stand out to be the superior investor sentiment index that outperforms other sentiment measures in predicting the stock market returns? (4) Does the newly constructed investor sentiment index predict equally well the returns of different portfolios across time?

To briefly review the main results, this chapter finds that S^{TV} appears to be a good measure of investor sentiment and generally outperforms competitor variables. In particular, S^{TV} is found to have the required negative and significant relationship with future stock returns, even after having controlled for economic fundamentals in the in-sample evaluations. Furthermore, the new index predicts significantly the stock market returns from a prediction horizon of 3-month up to 60-month, a strong predictive power unobserved in other sentiment measures. Furthermore, S^{TV} index continues to predict well the time-series of characteristics portfolio returns. It predicts significantly the returns of most portfolios sorted based on size, book-to-market (BM) ratio and momentum across time with differential impacts have been detected within cross-section, such that greater effect of sentiment is seen on small stocks, past losers and value stocks.

This study contributes to the existing literature as follow. First, this chapter constructs a new investor sentiment index, S^{TV}, expanding on the work of Baker and Wurgler (2006): the new index does not suffer from look-ahead bias, and permits dynamic time-varying features of sentiment components to be captured. This study is different from previous studies (e.g. Chen, 2011; Chung et al., 2012; Garcia, 2013[21]) in that the dynamic feature of investor

[21] These studies examined the asymmetry effect of investor sentiment on stock returns in different market states. Therefore, they focused on the changes of the slope coefficient associated with the investor sentiment in the return predictive regression without considering on the time-varying ability of each sentiment component in capturing the investor sentiment optimally.

sentiment is first modelled through the time-varying weights of index components *prior to* evaluating the predictive power of investor sentiment in a time-varying sentiment-return relation framework, thus avoiding look-ahead bias. Empirically, S^{TV} outperforms other sentiment measures statistically at the aggregate level, justifying the benefits of accounting for the dynamic structure in the weights of sentiment components. The enhanced sentiment index also does equally well at predicting cross-sectional portfolio returns across time. Overall, this study proposes a superior measure of unobservable investor sentiment.

The remainder of this chapter is organised as follows: Section 3.2 presents the data employed for the empirical analyses and the descriptive statistics of data. Section 3.3 describes the construction of the time-varying weighted investor sentiment index (S^{TV}) and the return predictive regression. Section 3.4 discusses the empirical findings and Section 3.5 concludes.

3.2 Data and descriptive statistics

The following sub-sections provide details of various types of data, which include investor sentiment indexes, aggregate stock market return cross-sectional portfolio returns and economic predictors. The sample period of this study spans for forty-nine full calendar years (in order to avoid biases potentially induced by seasonal or month of the year effect in variables) from January 1966 through December 2014.

3.2.1 Investor sentiment Indexes

Five investor sentiment proxies: dividend premium (PDND), average first-day returns of IPOs (RIPO), the number of IPOs (NIPO), the closed-end fund discount (CEFD), and the share of equity issues (EQ), along with five macroeconomic variables: growth of industrial production ($\Delta INDPRO$), real growth of durable consumption ($\Delta CONSDUR$), real growth of nondurable consumption ($\Delta CONSNON$), real growth of services consumption ($\Delta CONSSERV$), growth in employment ($\Delta EMPLOPY$) are employed in this study. Data for these variables and S^{BW} index are obtained from Jeffrey Wurgler's website[22]. This study also uses other market-based sentiment measures, namely S^{PLS}, which is available from Guofu Zhou's website[23], and Chicago Board Options Exchange's volatility index (VIX)[24], which is

[22] http://people.stern.nyu.edu/jwurgler/

[23] http://apps.olin.wustl.edu/faculty/zhou/

retrieved from Datastream. Two most popular survey-based investor sentiment indexes, which are the University of Michigan Consumer Sentiment Index (MS), obtained from Michigan directly[25], and the Conference Board Consumer Confidence Index (CCI), retrieved from Bloomberg, are also used.

3.2.2 Aggregate stock market returns and cross-sectional portfolio returns

In line with other studies[26], the excess market return (R_m) is used as a measure of aggregate stock market return. It is computed as monthly stock market return minus the risk-free rate (i.e. 3-month annualized Treasury-bill rate divided by 12). The stock market return is the monthly value-weighted S&P 500 index returns (inclusive of dividends) computed by the Center for Research in Security Price (CRSP). The data for stock market returns is obtained from Amit Goyal's website[27]. The data for cross-sectional portfolio returns can be obtained from Kenneth R. French's data library[28].

3.2.3 Descriptive statistics of data

Table 3.1 summarises the descriptive statistics for the six investor sentiment indexes in panel A; the excess market return (R_m), risk-free rate (R_f), the cross-sectional portfolio returns in panel B, from January 1966 to December 2014.

Panel A shows that all sentiment indexes are positively skewed, except MS, and have no excess kurtosis, and are mesokurtic (kurtosis value of close to 3), except S^{PLS} and VIX which are highly leptokurtic with positive excess kurtosis (kurtosis value > 3). Among all investor sentiment measures, CCI has the highest standard deviation. First-order autocorrelation, denoted as $\rho(1)$, suggests that sentiment indexes have a relatively long

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[24] VIX is only available from January 1990.

[25] http://www.sca.isr.umich.edu/tables.html. MS was first published on a quarterly basis for months February, May, August and November and only became available on a monthly basis after 1978. Similarly, the series of CCI gathered by the Conference Board are published once every two months prior to June 1977. To be consistent with the data frequency of other variables (i.e. monthly frequency), the 'missing values' of these two indexes are filled with the latest observation until the next observation becomes available following the procedure adopted by Lemmon and Portniaguina (2006) and Ho and Hung (2009).

[26] Campbell (1987), Campbell and Shiller (1988a; 1988b), Campbell and Thompson (2008), Huang et al. (2015), Kim, Ryu and Seo (2014), Lee, Jiang and Indro (2002), Welch and Goyal (2008), and Yu and Yuan (2011), for example.

[27] http://www.hec.unil.ch/agoyal/

[28] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 3.1: Summary statistics of data from January 1966 to December 2014

	Mean	*SD*	Skewness	Kurtosis	*Min*	*Max*	*ρ(1)*
	Panel A: Investor sentiment index						
S^{TV}	-0.022	2.198	0.113	2.619	-5.442	6.650	0.723
S^{BW}	0.020	0.994	0.147	3.645	-2.325	3.076	0.983
S^{PLS}	0.016	0.964	1.363	4.516	-1.701	3.249	0.977
MS	84.816	12.408	-0.324	2.488	51.700	112.000	0.950
VIX	19.837	8.250	2.223	11.678	10.020	70.330	0.824
CCI	93.406	24.989	-0.042	2.448	25.300	144.710	0.967
	Panel B: Risk-free returns and stock returns						
R_f	0.004	0.003	0.527	3.726	0.000	0.014	0.988
R_m	0.005	0.044	-0.417	4.714	-0.221	0.162	0.043
ME1	0.011	0.065	-0.137	5.266	-0.289	0.295	0.240
ME2	0.011	0.065	-0.241	5.087	-0.305	0.284	0.150
ME3	0.012	0.062	-0.423	4.851	-0.290	0.257	0.132
ME4	0.011	0.059	-0.485	4.984	-0.296	0.243	0.135
ME5	0.011	0.057	-0.494	5.030	-0.279	0.248	0.122
ME6	0.011	0.054	-0.513	4.845	-0.263	0.209	0.124
ME7	0.011	0.053	-0.460	5.247	-0.262	0.224	0.123
ME8	0.010	0.051	-0.447	4.723	-0.243	0.191	0.090
ME9	0.010	0.047	-0.433	4.894	-0.223	0.181	0.101
ME10	0.008	0.043	-0.335	4.602	-0.197	0.181	0.020
BM1	0.008	0.052	-0.195	4.350	-0.227	0.230	0.084
BM2	0.009	0.047	-0.426	4.795	-0.248	0.196	0.073
BM3	0.010	0.047	-0.457	5.101	-0.257	0.171	0.073
BM4	0.010	0.048	-0.493	5.400	-0.236	0.185	0.079
BM5	0.009	0.045	-0.424	5.442	-0.235	0.176	0.071
BM6	0.011	0.044	-0.372	5.198	-0.231	0.184	0.037
BM7	0.010	0.047	-0.351	5.865	-0.243	0.222	0.095
BM8	0.011	0.047	-0.598	6.839	-0.249	0.227	0.103
BM9	0.013	0.050	-0.336	4.740	-0.194	0.223	0.084
BM10	0.013	0.062	-0.145	7.188	-0.264	0.348	0.154
M1	0.002	0.082	0.645	7.248	-0.261	0.455	0.156
M2	0.007	0.063	0.208	6.012	-0.249	0.355	0.105
M3	0.009	0.054	0.290	6.534	-0.233	0.338	0.105
M4	0.009	0.049	-0.128	4.987	-0.187	0.217	0.108
M5	0.008	0.045	-0.278	5.097	-0.215	0.208	0.107
M6	0.009	0.046	-0.392	5.334	-0.238	0.167	0.078
M7	0.009	0.044	-0.451	5.579	-0.243	0.189	-0.008
M8	0.011	0.045	-0.319	4.795	-0.204	0.189	0.052
M9	0.011	0.049	-0.531	5.658	-0.263	0.218	0.039
M10	0.015	0.063	-0.384	4.743	-0.267	0.231	0.050

Notes: *SD* denotes standard deviation, *Min* is the minimum value, *Max* is the maximum value and *ρ(1)* is the first-order autocorrelation. The descriptive statistics of investor sentiment indexes and returns data are reported in panel A and B, respectively. For the cross-sectional portfolio returns, each portfolio is labelled with a combination of text and number: the text represents the characteristics used to form the portfolio and the number represents the decile from 1 to 10. ME denotes the market capitalization, BM denotes the book-to-market ratio, and M represents momentum (i.e. prior returns). The sample period spans for 588 months, from January 1966 until December 2014.

Table 3.2: Correlations of investor sentiment indexes

	S^{TV}	S^{BW}	S^{PLS}	VIX	MS	CCI
S^{TV}	1.000					
S^{BW}	0.073*	1.000				
S^{PLS}	0.024	0.552***	1.000			
VIX	-0.124**	-0.130**	0.379***	1.000		
MS	0.085**	0.320***	0.045	-0.248***	1.000	
CCI	0.246***	0.297***	0.158***	-0.139**	0.810***	1.000

Notes: This table reports the correlations of investor sentiment indexes: time-varying weighted investor sentiment index (S^{TV}), Baker and Wurgler investor sentiment index (S^{BW}), aligned investor sentiment index (S^{PLS}), Chicago Board Options Exchange's volatility index (VIX), University of Michigan Consumer Sentiment Index (MS), and Conference Board Consumer Confidence Index (CCI). *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The sample period covers from December 1968 to December 2014.

memory, with all but S^{TV} and VIX having a value for $\rho(1)$ greater than 0.95. S^{TV} is the least persistent in the set of sentiment indexes which would therefore, suggest that the estimated predictive regression model from this sentiment measure will be subject to the least Stambaugh bias. Yet, as shown in next section, the predictive performance of S^{TV} at long forecast horizons (i.e. 3 – 5 years) is not scarified and has optimal performance amongst the full set of sentiment indexes.

Panel B shows that the excess market return has a mean of 0.47% and standard deviation of about 4.40%. The returns of small stocks (i.e. ME1), value stocks (i.e. BM10), growth stocks (i.e. BM1), stocks with lowest prior returns (i.e. M1) are more volatile than their counterparts sorted based on similar characteristics. The statistics show the stylized facts of return series – return series are negatively skewed and exhibit leptokurtic distribution. In contrast to investor sentiment indexes, returns series are less persistent.

Table 3.2 presents the correlations of S^{TV} and other sentiment measures. S^{TV} positively correlates with all sentiment indexes except VIX[29]. Other sentiment indexes also display the similar pattern, except S^{PLS} which covaries positively with VIX. Meanwhile, S^{TV} is highly significantly correlated with sentiment indexes that are free from look-ahead bias and employ relatively recent information in the index construction, such as VIX, MS and CCI. The correlation between S^{TV} and CCI is especially strong, i.e. 0.246, and highly significant at 1%

[29] Ben-Rephael, Kandel and Wohl (2012) and Kurov (2010) find that the changes in VIX is negatively correlated with the changes in other sentiment measures. VIX measures the expectation of market participants about the stock market volatility. High VIX value represents 'fears' and investor pessimism, of which is reflected by a lower value in other investor sentiment indexes. Therefore, VIX should be negatively correlated with other investor sentiment measures.

level[30]. On the other hand, S^{TV} is weakly correlated with S^{BW} and S^{PLS}, which are 0.073 and 0.024, respectively, suggesting that S^{TV} extract latent sentiment information that is not captured by S^{BW} and S^{PLS} after accounting for the dynamic contribution of each sentiment component to the sentiment index.

3.3 Methodology

This section describes the methodology underlying the S^{BW} and presents the time-varying weighted investor sentiment index, S^{TV}, designed to address underlying issues of S^{BW}. The return predictive regression used to assess the sentiment-return relationship is then described after the construction of S^{TV}.

3.3.1 Baker and Wurgler investor sentiment index (S^{BW})

Baker and Wurgler (2006) construct S^{BW} using principal component analysis (PCA) to extract the common sentiment component from six investor sentiment proxies: dividend premium (PDND), average first-day returns of IPOs (RIPO), the number of IPOs (NIPO), the closed-end fund discount (CEFD), market turnover (TURN), and the share of equity issues (EQ). PCA identifies the latent common factor from the group of interrelated variables. It redefines the data set by transforming it into new variables, which are termed principal components (PCs), and the first principal component (PC1) is the linear combination of the variables that explain the maximum variation from the sentiment proxies. PC1 is then used as S^{BW}.

Prior to employing PCA, fundamental components related to business cycle are removed from sentiment proxies. This is achieved by orthogonalising each proxy by regressing it on a set macroeconomic variables: $\Delta INDPRO$, $\Delta CONSDUR$, $\Delta CONSNON$, $\Delta CONSSERV$, $\Delta EMPLOPY$ and NBER-dated recession (*RECESS*).

There are two features of this process of construction of S^{BW} which might affect its ability to capture sentiment. Firstly, as PC1 is extracted using the entire sample period, each component within PC1 is implicitly assumed to have fixed affect (or weight) across all time periods in the sample. This is equivalent to an assumption that each component's ability to capture sentiment, relatively, i.e. as compared to the remaining components, is constant over

[30] Further analysis in Section 3.4.1 shows that both S^{TV} and CCI have strong effect on future stock market return across all forecast horizons. However, the strong predictive performance of CCI is driven mainly by the fundamental economic factors.

time. As this assumption might not be correct, S^{BW} may not optimally capture the dynamic contributions of those sentiment proxies to the aggregate sentiment index, given that each sentiment proxy might better capture the unobserved sentiment in some periods while being largely affected by fundamental factors in others. This chapter proposes to relax this implicit assumption and allow contributions of each index component to vary over time.

Second, as discussed by Chung et al. (2012), S^{BW} is constructed with a look-ahead bias, due to PC1 being extracted utilising data for the entire sample (i.e. July 1965 to December 2010). This poses an issue when evaluating the forecasting power of any variable, as forecasts formed at any time *t* should not rely on information which would have only become available in the future (*t+1* and beyond). For example, the value of sentiment in January 2000 should not be drawn from information after this date, yet the value of S^{BW} estimated using the entire sample period would be employing information which is in the future to January 2000. All sentiment values prior to the last period in the sample suffer therefore from this look-ahead bias. To put differently, when applying such an index for return forecasting, investors are assumed to have had access to future information, i.e. future, to them, values of sentiment proxies. This is clearly not realistic. To address this issue, one should construct an investor sentiment index utilising only information available up to time *t,* in order to avoid any look-ahead bias in the return prediction implied by the sentiment model for time $t+k$[31].

Recently, Huang et al. (2015) proposed a new investor sentiment index (S^{PLS}) that aims at improving the short-term return predictive power of S^{BW}. They argued that a more accurate sentiment index can be constructed by using the partial least squares (PLS) rather than PCA approach. They suggested that the lack of forecasting power in the original S^{BW} index is stemmed from its inability to factor out common approximation errors, which are irrelevant to the expected stock market returns, from the sentiment element common among the index's individual proxy variables, and argued that the PLS method is an appropriate approach to remove that common noise component. However, the Huang et al. (2015) approach of employing the PLS estimation methodology in the context of six sentiment proxies involves running regressions with only six observations in the cross-section, at each point in time. This is concerning given that Kelly and Pruitt (2015) demonstrate that large time and cross-section dimensions are required to ensure that the PLS produces consistent forecasts from the latent factor. Despite this issue, Huang et al. (2015) demonstrate that their

[31] Antoniou et al. (2016) also urge that alternative sentiment measure based solely on the historical information should be sought in future research.

index has an improved performance at the aggregate time-series level compared to S^{BW} for short-term horizons. However, their index can also suffer from look-ahead bias: a solution they use is to estimate the index values recursively, but this suffers from potentially employing very outdated information, as compared to a rolling window estimation which only utilises most recent values of relevant variables.

While Huang et al. (2015) attribute the sub-optimal forecasting power of the original BW index to the existence of common approximation errors contained in sentiment proxies, this study investigates a different, maybe complementary, proposition, namely the fluctuating relative ability of those proxies to capture unobservable sentiment and the resulting need to model their contributions to the investor sentiment index as time-varying. This study also aims at avoiding look-ahead bias and mitigating employment of outdated, irrelevant information by estimating the new index in the rolling window framework rather than recursively. The findings of this study reveal that the issue this study addresses here (i.e., of time-varying ability components' to capture sentiment) seems to be more relevant empirically than that of common errors, given that the new time-varying weighted investor sentiment index (S^{TV}) outperforms S^{PLS}, on average, in forecasting stock market returns.

3.3.2 Evidence on the time-varying performance of investor sentiment components

This section motivates the construction of an improved investor sentiment index accounting for a time-varying ability of sentiment index components to accurately capture the unobserved sentiment. As a starting point, consider the basic sentiment-return regression model below:

$$\begin{gathered} R_{m,t+h} = \alpha + \beta Sent\_Proxy_{i,t} + \varepsilon_{t+h} \\ \text{where } R_{m,t+h} = \left(\tilde{R}_{m,t+1} + \ldots + \tilde{R}_{m,t+h}\right) / h \\ Sent\_Proxy_{i,t} = \left\{S_t^{BW}, PDND_t, RIPO_t, NIPO_t, CEFD_t, EQ_t\right\} \end{gathered} \tag{3.1}$$

$\tilde{R}_{m,t+h}$ is the h-month-ahead excess market return and $Sent\_Proxy_{i,t}$ is one of the different sentiment proxies at time t, which, for comparison, also includes the Baker and Wurgler (2006) sentiment index, S_t^{BW}, which combines these individual proxies into a single investor sentiment index.

Table 3.3: Predictive performance of S^{BW} and individual investor sentiment proxies on excess market return across different horizons

	Prediction horizons							
	h = 1	*h = 3*	*h = 6*	*h = 9*	*h = 12*	*h =24*	*h = 36*	*h = 60*
	β (%)	β (%)	β (%)	β (%)	β (%)	β (%)	β (%)	β (%)
S^{BW}	-0.1723	-0.1489	-0.1670	-0.1580	-0.1311	0.0186	0.1109	0.0441
	[-0.7780]	[-0.7032]	[-0.8233]	[-0.8402]	[-0.7374]	[0.1403]	[1.2621]	[0.5389]
PDND	-0.0045	-0.0015	-0.0007	0.0019	0.0037	0.0011	-0.0033	-0.007
	[-0.2618]	[-0.0863]	[-0.0398]	[0.1140]	[0.2256]	[0.0908]	[-0.3979]	[-1.2992]
RIPO	-0.0186*	-0.0214**	-0.0247***	-0.0285***	-0.0309***	-0.0292***	-0.0186***	-0.0088***
	[-1.5930]	[-1.8787]	[-2.3549]	[-2.9755]	[-3.7141]	[-5.3598]	[-3.3223]	[-2.6308]
NIPO	-0.0001	0.0000	0.0001	0.0001	0.0002	0.0005	0.0007	0.0003
	[-0.0641]	[-0.0169]	[0.0793]	[0.1435]	[0.2639]	[1.0332]	[1.6773]	[0.8487]
CEFD	0.0051	0.0081	0.0142	0.0151	0.0137	0.0031	-0.0074	0.0043
	[0.1960]	[0.3406]	[0.5768]	[0.6240]	[0.5954]	[0.1707]	[-0.6809]	[0.4250]
EQ	-3.8859**	-3.3964*	-2.6574	-2.1917	-1.7820	-0.2685	0.6198	0.1617
	[-1.7837]	[-1.5706]	[-1.2292]	[-1.0111]	[-0.8452]	[-0.1700]	[0.5015]	[0.1629]

Notes: This table presents the estimated coefficients of S^{BW} and individual proxies from the predictive regression $R_{m,t+h} = \alpha + \beta Sent\_Proxy_{i,t} + \varepsilon_{t+h}$ where $R_{m,t+h}$ is the *h*-period-ahead excess market return and $Sent\_Proxy_{i,t}$ denotes the S^{BW} or individual investor sentiment proxies. S^{BW} is the Baker and Wurgler investor sentiment index constructed from six proxies: dividend premium (PDND), average first-day returns of IPOs (RIPO), number of IPOs (NIPO), closed-end fund discount (CEFD), and share of equity issues (EQ). The Newey-West (automatic bandwidth selection) *t*-statistics are shown in brackets. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The sample period covers from January 1966 to December 2014.

The results shown in Table 3.3 for S_t^{BW} are consistent with the literature, in that β is insignificant, hence S^{BW} is unable to predict future excess market returns across all prediction horizons (Arif and Lee, 2014; Huang et al., 2015). Furthermore, for longer prediction horizons the sign of S^{BW}, in being positive (yet still insignificant), is inconsistent with the theory that investor sentiment should negatively influence future stock returns due to return reversals.

For individual sentiment proxies, the appropriate sign of β depends on each sentiment proxy given that sentiment proxies are either negatively or positively correlated with sentiment. As such, it is appropriate to test the null hypothesis of $\beta = 0$ against the alternate hypothesis of $\beta > 0$ for CEFD and PDND, yet $\beta < 0$ in the alternate hypothesis for RIPO, NIPO and EQ. Table 3.3 clearly shows that RIPO performs best in predicting future excess market returns over the entire sample given that it predicts significantly and negatively the excess market return across all forecast horizons, justifying the use of RIPO as the benchmark in the construction of S^{TV} as shown in the next sub-section. In contrast, the predictive power of EQ can only be seen to be significant over shorter forecast horizons. Likewise, other sentiment proxies have a greater or lesser effect depending on the time-horizon, demonstrating that those proxies contain different information potentially useful in forecasting.

To show the time-varying ability of each sentiment proxy to capture sentiment, as mirrored by its performance in predicting excess market returns, the equation (3.1) is estimated on a rolling-window basis, using a fixed window of three years[32].Specifically, the first window runs from January 1966 to December 1968 and the window will then be rolled over to incorporate the following month's data and drop the first month's observation from previous estimation period. The graphical evidence on the time-varying effect of investor sentiment is shown in Figure 3.1.

Panel A of Figure 3.1 shows that the estimated coefficients vary considerably over time, clearly demonstrating the time-variability in these sentiment proxies' abilities to capture sentiment and hence predict future stock market returns. Much clearer illustration on the significant effect of investor sentiment is shown by the rolling *p*-values and rolling *R*-squared

[32] Pesaran and Timmermann (2002) mention that a rolling window approach instead of a recursive window is used if "parameters … are not believed to be constant over time". Since the impact of investor sentiment is expected to change over time, a rolling window approach is used in this study.

in Panel B and C, respectively. Panel B depicts that investor sentiment proxies predict future excess market returns differently across time[33]. For example, dividend premium (PDND), the number of IPOs (NIPO) and the share of equity issues (EQ) are shown to have a very significant effect on future excess market return during 1982-1983, whereas the influence of closed-end fund discount (CEFD) is far more modest, while average first-day returns of IPOs (RIPO) does not have any effect during this period. Yet, in the 2001-2002 period, only CEFD has any predictive power.

This evidence shows that S^{BW}, which assumes constant weights on each investor sentiment proxy over the entire sample, may not be able to optimally capture the dynamic contribution of each sentiment proxy over time. Instead, an index which allows these weights to vary over time should be able to capture far better the overarching sentiment component.

3.3.3 Construction of the time-varying weighted investor sentiment index (S^{TV})

Single market-based variables might individually be poor proxies for general investor sentiment, due to inherent idiosyncratic noise. Therefore, this thesis combines several single market-based proxies into a composite sentiment index in order to "iron out the remaining idiosyncracies" (Baker and Wurgler, 2007, p.139). Following Baker and Wurgler (2006, 2007), PCA approach is employed to extract the common latent sentiment component from imperfect sentiment measures (i.e. PDND, RIPO, NIPO, CEFD and EQ) in the construction of the time-varying weighted investor sentiment index, S^{TV}. To capture the time-varying contribution of each of these proxies, this study differs from BW in that S^{TV} is constructed on a rolling window basis. This approach allows us to utilise only the most up-to-date, hence the most relevant, information at each point in time, and has an additional benefit of avoiding any look-ahead bias in the construction of the index. Furthermore, following Baker, Wurgler and Yuan (2012) and Finter, Niessen-Ruenzi and Ruenzi (2012), the contemporaneous proxies are adopted in the construction of S^{TV}[34]. Following reviews of each sentiment proxy also provide further support to the use of contemporaneous proxies.

[33] The predictive power of each sentiment proxy remains fluctuated over time even after controlling for macroeconomic factors. The graphs are shown in Figure A. 1 (refer to Appendix).

[34] The use of contemporaneous rather than lagged values is more practical when applied in the forecasting context since, at any point in time *t* prior to sample's end, a forecaster would not possess information from the entire sample to determine the optimal in-sample lag for each proxy. The robustness check also confirms that the parsimonious model does not lose its power in *h*-horizon return predictions. Indeed, it performs better than sentiment index constructed using lagged proxies.

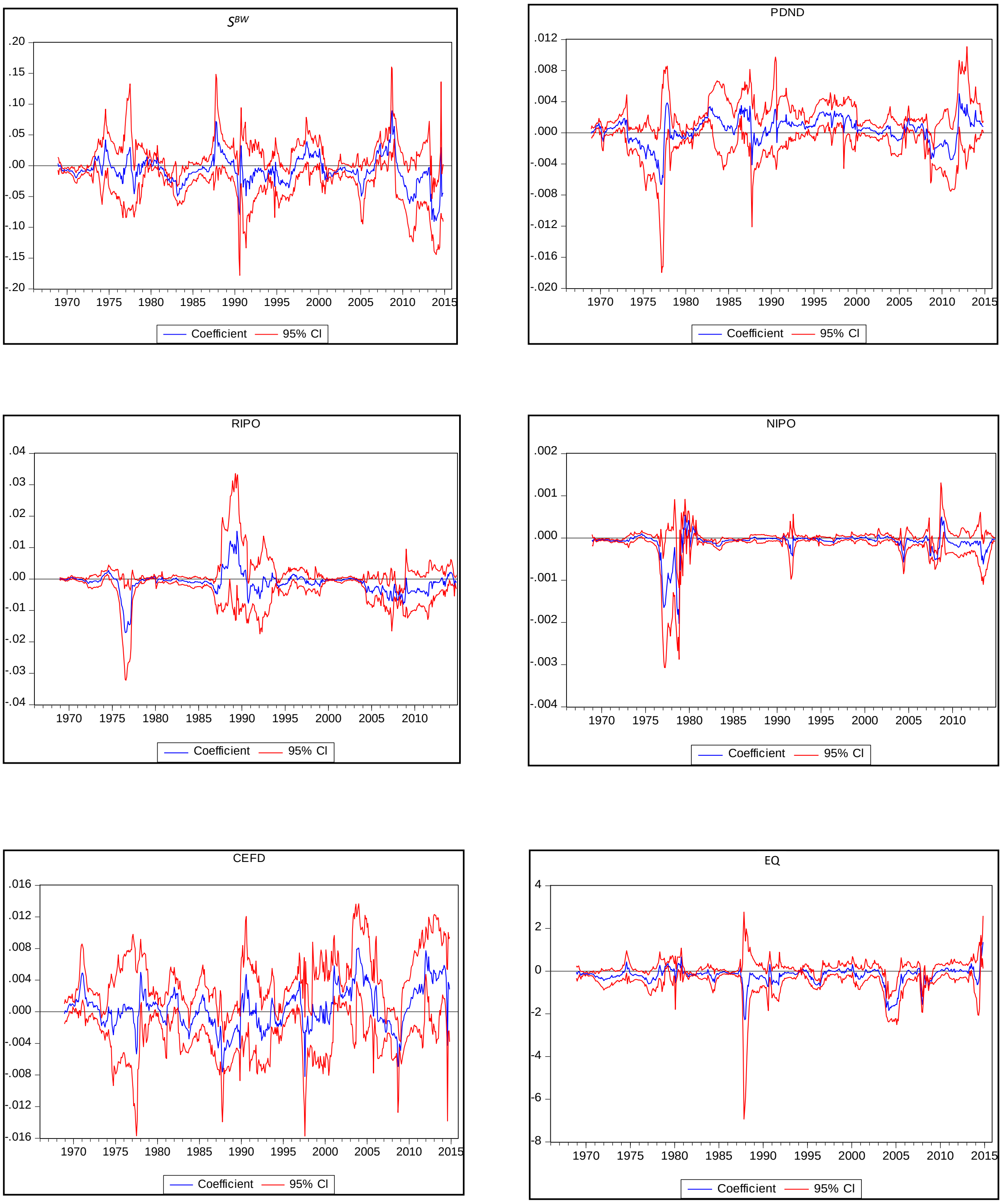
Figure 3.1: 36-month rolling regression estimates for S^{BW} and individual investor sentiment proxies

The predictive regression model used to plot these figures:

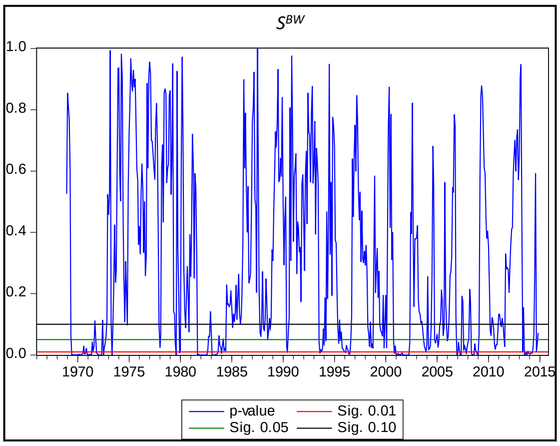
$$R_{m,t+1} = \alpha + \beta Sent\_Proxy_{i,t} + \varepsilon_{t+1}\ , \qquad Sent\_Proxy_{i,t} = \{S_t^{BW}, PDND_t, RIPO_t, NIPO_t, CEFD_t, EQ_t\}$$

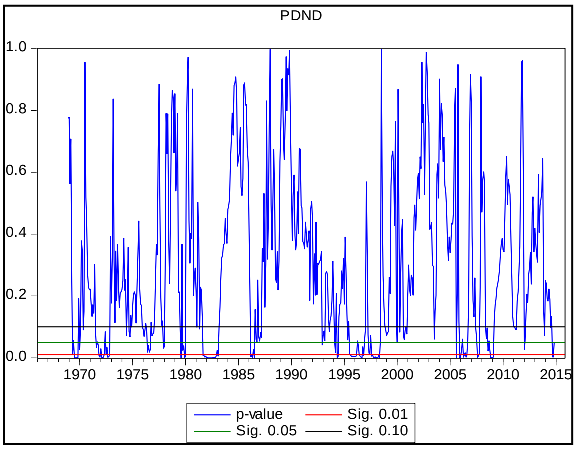
Panel A shows the rolling slope coefficients (blue lines) associated with the confidence intervals (red lines) for Baker and Wurgler investor sentiment index (S^{BW}), dividend premium (PDND), average first-day returns of IPOs (RIPO), number of IPOs (NIPO), closed-end fund discount (CEFD), and share of equity issues (EQ). Panel B shows the rolling *p*-values of the slope coefficients. The dark, green and red lines denote the significance level of 10%, 5% and 1%, respectively. Panel C exhibits the rolling *R*-squared. The sample period covers from January 1966 to December 2014.

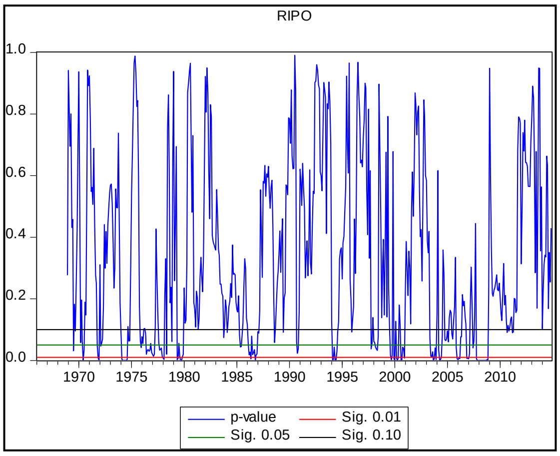
Panel A: Rolling Coefficient Estimates

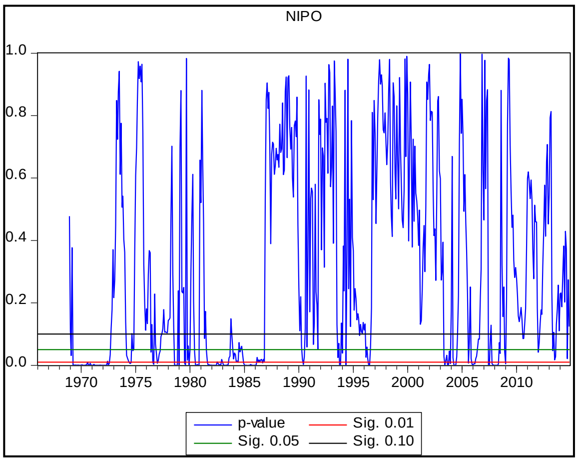


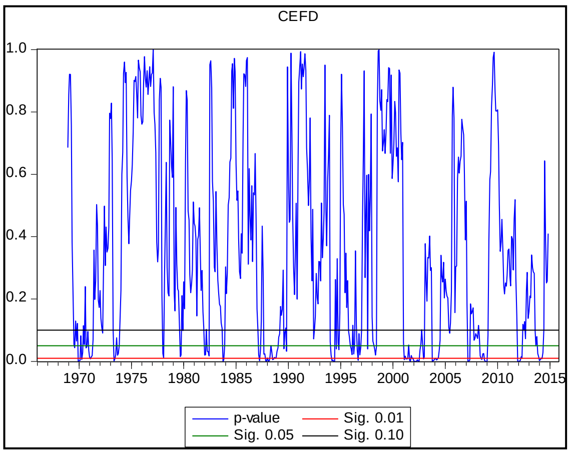
Panel B: Rolling *p*-values

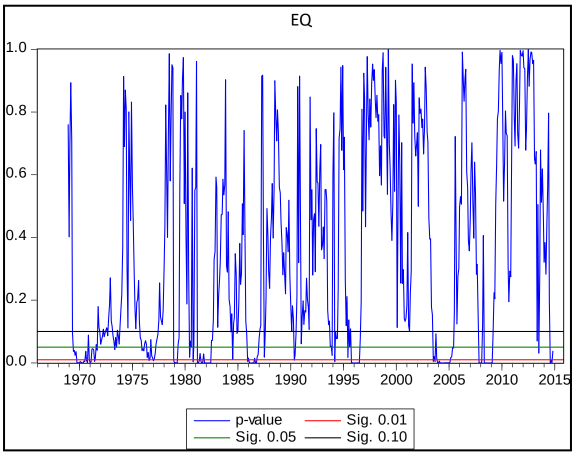




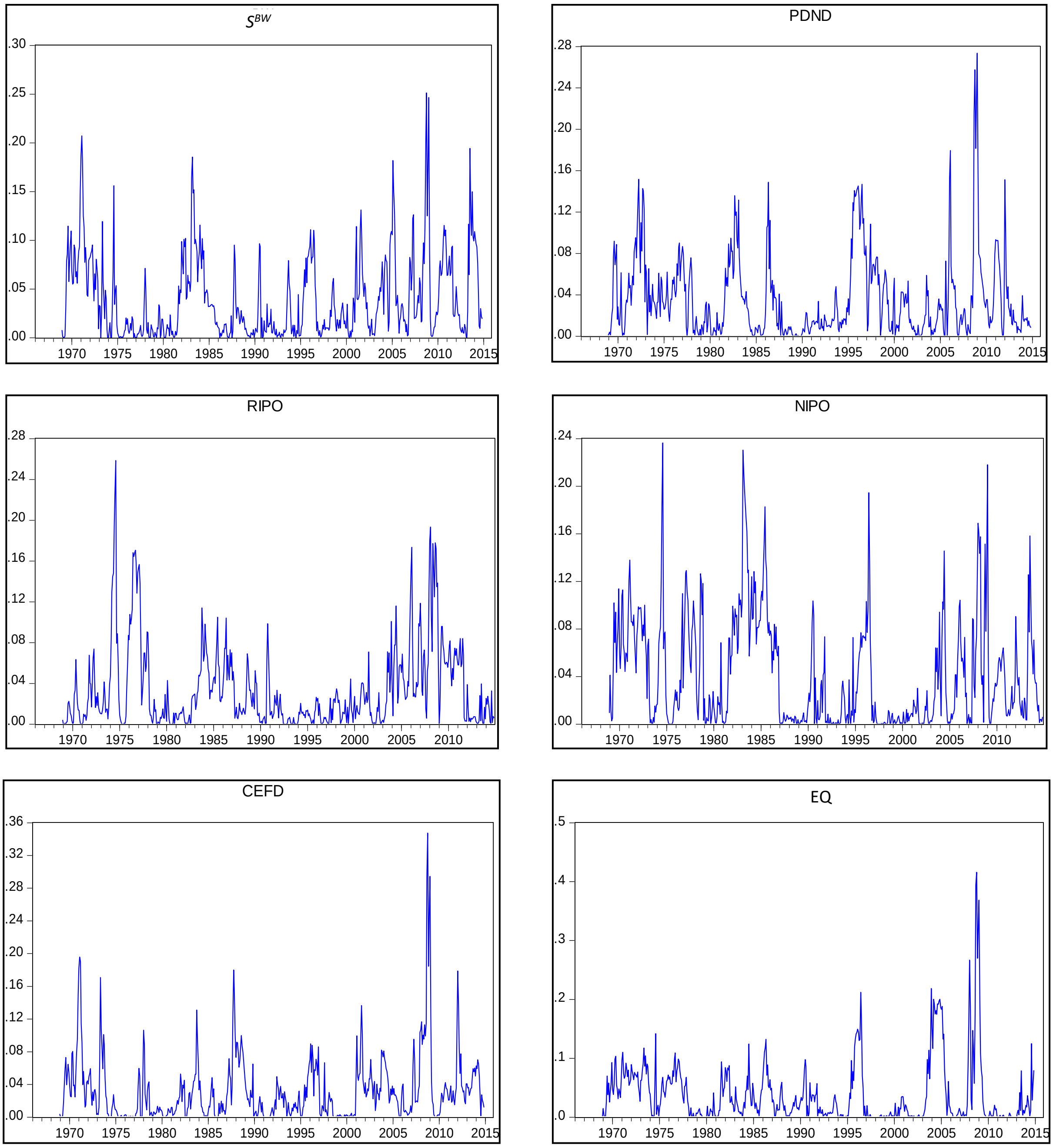








Panel C: Rolling *R*-squared



Dividend Premium (PDND). Based on the dividend catering theory (Baker and Wurgler, 2004), firms tend to pay dividends when investors' demand on dividend-paying stocks is high. The predictable cash flow stream from dividend payers gives a feel of safety to investors, inducing investors to place more emphasize on the dividend distribution during the market downturn (i.e. low sentiment period). Therefore, a 'flight-to-safety' phenomenon could be observed during declining market, whereby investors demand more on, or switching from non-dividend-paying stocks to, dividend-paying stocks. This, in turn, widens the dividend premium – the valuations between dividend-paying stocks and non-dividend-paying stocks. As such, a negative contemporaneous relationship between investor sentiment and dividend premium could be seen.

Initial Public Offerings (IPOs) Market. It has long been a puzzle for IPOs 'underpricing' that stems from positive **average first-day returns on IPOs (RIPO)**. Previous studies have documented that high level of first-day returns is 'corrected' subsequently, especially when high volume of IPOs is observed (Ritter, 1991)[35]. Derrien (2005) and Ljungqvist, Nanda and Singh (2006) confirm that the optimism of noise traders push the IPO stock prices more than it should be, leading to high initial returns but a subsequent poor long-run performance when investor sentiment fades away. Therefore, there is a positive contemporaneous relationship between RIPO and investor sentiment, where high initial returns of IPOs are observed during the high sentiment period. The monthly RIPO series is computed as the NIPO-weighted average of RIPOs over the previous 12 months.

Not only does the over-optimism of sentiment traders affect initial returns of IPO stocks, their periodic bullish sentiments also offer windows of opportunity to issuers. Ritter (1991) proposes that firms 'time' their stock offering during which investor sentiment is high. Later, Loughran, Ritter and Rydqvist (1994) demonstrate a contemporaneous positive relationship between market valuation and IPOs volume on a yearly basis. They claimed this phenomenon as the successful timing of firms' offerings in matching the market overvaluation period, during which investors could be excessively optimistic. Other studies that documented the same finding include Loughran and Ritter (1995), Ibbotson, Sindelar and Ritter (1994), and Ljungqvist et al. (2006). Hence, an increase in the number of **IPOs (NIPO)** is commonly observed during high sentiment periods. Whist one may contend that RIPO tends to lead NIPO (see Ibbotson and Jaffe, 1975; Lowry and Schwert, 2002) and their relationship with investor sentiment should enter with different timings (Baker and Wurgler, 2006; 2007), this study argues that the high NIPO and RIPO could happen at the same time when sentiment is high.

IPOs in US typically take an average of three to four months from the beginning of filing date to their first trading day (see Boeh and Dunbar, 2016). Despite previous initial returns bear some role on a firm's decision to go public, the success of an IPO still depends

[35] Ritter and Welch (2002) provide detailed review on the pricing and long-run performance of IPOs.

on investors' perception towards the market condition close to the issuing date. Owing to the book building process of IPOs, in which 'road shows' have been conducted in order to elicit investors' interest on the offerings, firms in US have an option to withdraw their offerings before issue date (Busaba, Benveniste and Guo, 2001). After the marketing process, underwriter proposes an offer price by taking into consideration of investors' interests. At this stage, the firm may opt out from an IPO if the firm viewed the proposed offer price as 'undervalued'. This could happen when market participants irrationally undervalued the firm (see Boeh and Dunbar, 2014). In other words, firms may withdraw the IPO if investors are pessimistic, and the reverse holds. As a result, actual NIPO depends on current investor sentiment, and a contemporaneous relationship between NIPO and investor sentiment is deemed appropriate. The monthly NIPO data is simply the sum of NIPO over the prior 12 months.

Share of Equity (EQ). Share of equity computed as the equity issues over the total new issues is one of the proxies for investor sentiment. The main difference between share of equity and IPOs is that share of equity consists of all seasoned and non-seasoned equity offerings. Baker and Wurgler (2000) reveal that future stock market returns can be predicted by the share of equity. They discovered that firms tend to finance their companies with more equity than debt prior to the period of low returns and vice versa. Hence, in a similar logic to the IPOs market, firms have been claimed to 'time' their equity issuing when their stocks are overvalued by market participants, resulting in a significantly poor performance in the long-run which contradicts the efficient market hypothesis. This is a manifestation of the contemporaneous effect of investor sentiment on the firms' equity financing activities.

Closed-End Fund Discount (CEFD). Closed-end funds are publicly traded at the stock exchange with a specified number of shares issued during IPOs. Therefore, unlike the open-end funds, prices of close-end funds fluctuate with the supply and demand in the market, and are potentially different from their net asset value (NAV). CEFD, which is computed as the difference between the NAV of a closed-end fund and its market price, has been employed as a measure of investor sentiment (Neal and Wheatley, 1998; Zweig, 1973; Gemmil and Thomas, 2002). Large discount on closed-end funds reflects investor pessimism; investors are bullish otherwise. Since investor demand, which depends partly on investors' mood, directly affects the CEFD, a contemporaneous relationship between CEFD and investor sentiment can be assumed.

The window length chosen for the rolling-window is three years[36], with the first window running from January 1966 until December 1968. As in Baker and Wurgler (2006, 2007), each proxy is first orthogonalised against a set of macroeconomic variables to remove any business cycle related (fundamental) components. The macroeconomic variables used are: growth of industrial production ($\Delta INDPRO$), real growth of durable consumption ($\Delta CONSDUR$), real growth of nondurable consumption ($\Delta CONSNON$), real growth of services consumption ($\Delta CONSSERV$), growth in employment ($\Delta EMPLOPY$). The resulting orthogonalised sentiment components are standardized to have a zero mean and unit variance before being applied in the principal component analysis. As with S^{BW}, the value of S^{TV} in each window is defined as the first principal component, PC1, or more precisely, the summation of the products of standardized investor sentiment proxies and their respective component loadings. Finally, the value of S^{TV} is taken as the last observation in each window[37]. As such, S^{TV} can be viewed as a series of updated investor sentiment proxies utilising only the most relevant and updated information in every window. Figure 3.2 clearly depicts the construction of the new index.

It is noteworthy that the signs generated by PCA are arbitrary for each PC vector and hence the signs of PC1 component loadings could be inconsistent with theory (Fenn, Porter, Williams, McDonald, Johnson and Jones, 2011). Hence, the sign of an eigenvector can be flipped (Narsky and Porter, 2013; Bro, Acar and Kolda, 2008) to ensure a theoretically relevant index is constructed. As long as the sign of every variable is flipped, their relative contributions and hence the optimal variance of the principal component is preserved. In view of this, the sign of the eigenvector is flipped whenever the sign of RIPO is inconsistent with the theory in each window[38]. Previous literature shows a positive relation between investor

---

[36] The period of three years roughly corresponds to a half of the average duration of a business cycle in the U.S. for the sample period employed in this study, the rationale being that the sentiment impact on stock market varies across phases of the business cycle (see Chung et al., 2012; Garcia, 2013; Huang et al., 2015).

[37] The average proportion of variance explained by first principal component across different windows is about 50%, which is higher than the proportion of variance explained by first principal component from the entire sample (i.e. about 41%).

[38] RIPO has been used as a benchmark component since Baker and Wurgler (2006, 2007) mention that IPO variables (i.e. NIPO and RIPO) capture well the demand of stocks that are sensitive to investor sentiment. As RIPO directly links to the investor demand, it can better reflect investor sentiment on a theoretical basis. This is confirmed in Huang et al. (2015), which show that RIPO receives the greatest weight in their aligned investor sentiment index. Empirically, Chu et al. (2017) reveal that RIPO is least affected by macroeconomic factors as compared to other sentiment proxies of S^{BW}. Thus, RIPO truly reflects a greater proportion of investor sentiment component as compared to other proxies. As shown in the analysis over the whole sample period (refer Table 3.3), RIPO consistently predicts the equity premium across all forecast horizons, implying that RIPO could have the component that is most sensitive to investor sentiment and hence predicts future stock market returns well.

sentiment and RIPO, as investor over-optimism generates high RIPO (e.g. Cornelli, Goldreich and Ljungqvist, 2006; Derrien, 2005). Therefore, the sign of whole vector will be flipped if RIPO received a negative initial loading; otherwise, the signs of component loadings remain unchanged.

Figure 3.2: The construction of time-varying weighted investor sentiment index (S^{TV})

This figure depicts the construction of S^{TV}, which is computed on a rolling window basis with a fixed window length of 36 months. The first window spans from January 1966 to December 1968, and is subsequently rolled over to the next window by eliminating the observation in January 1966 and adding a new observation from January 1969 into the series. The principal component analysis is performed in every window and only the last observation in each window is retained. The same estimation process is repeated until the end of the data series, which gives a total of 553 observation in the S^{TV} index.

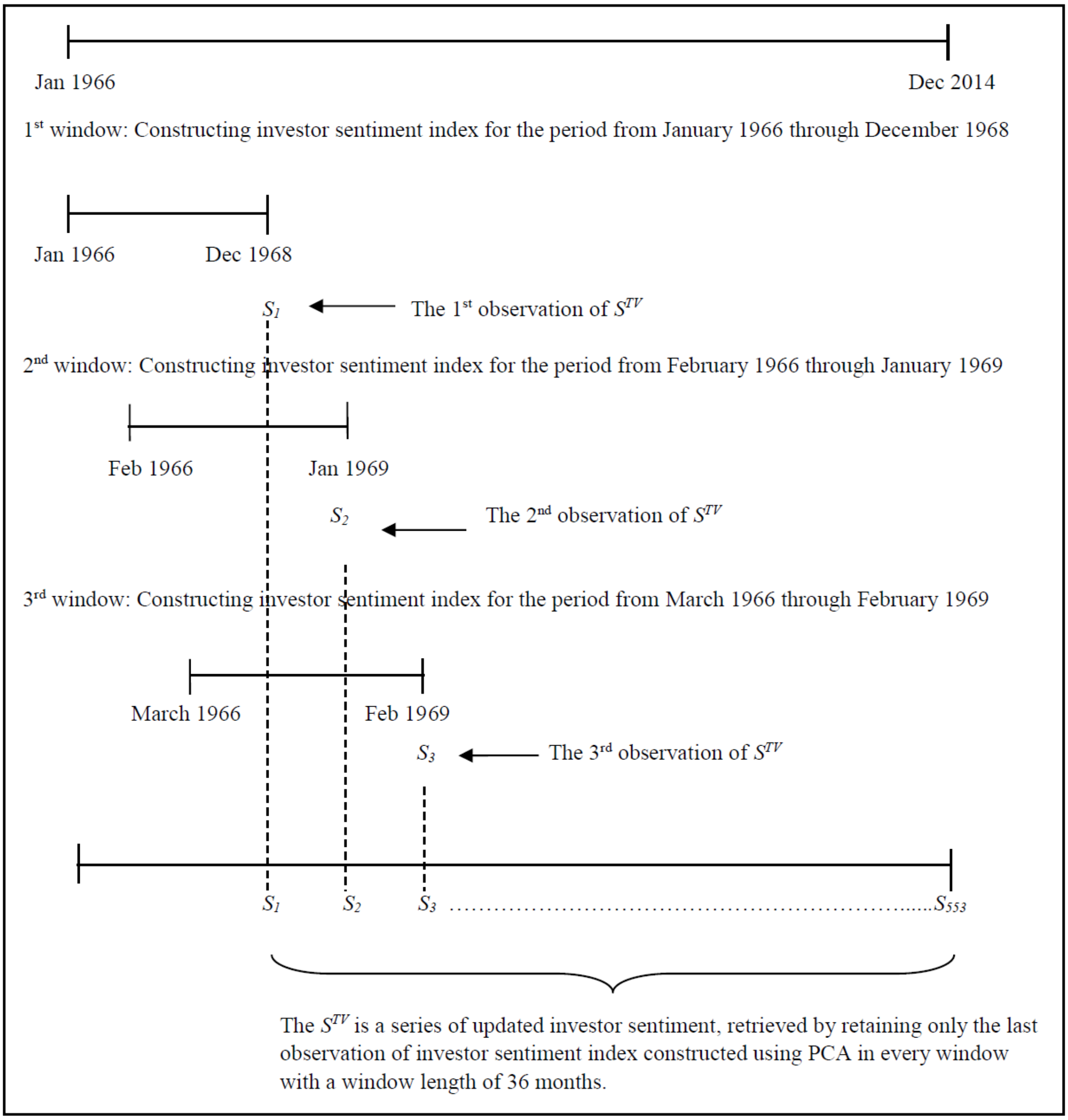


Figure 3.3: Investor sentiment indexes

This figure depicts the investor sentiment indexes over three sub-periods: December 1968 to November 1982, December 1982 to March 2001, and April 2001 to December 2014. The blue line is the time-varying weighted investor sentiment index (S^{TV}), the green colour line is the aligned investor sentiment index (S^{PLS}) retrieved from Guofu Zhou's website, and the dotted line is the Baker and Wurgler investor sentiment index (S^{BW}) retrieved from Jeffrey Wurgler's website. Orthogonal investor sentiment indexes are used in this figure. The shaded bars represent the recession period as dated by NBER.

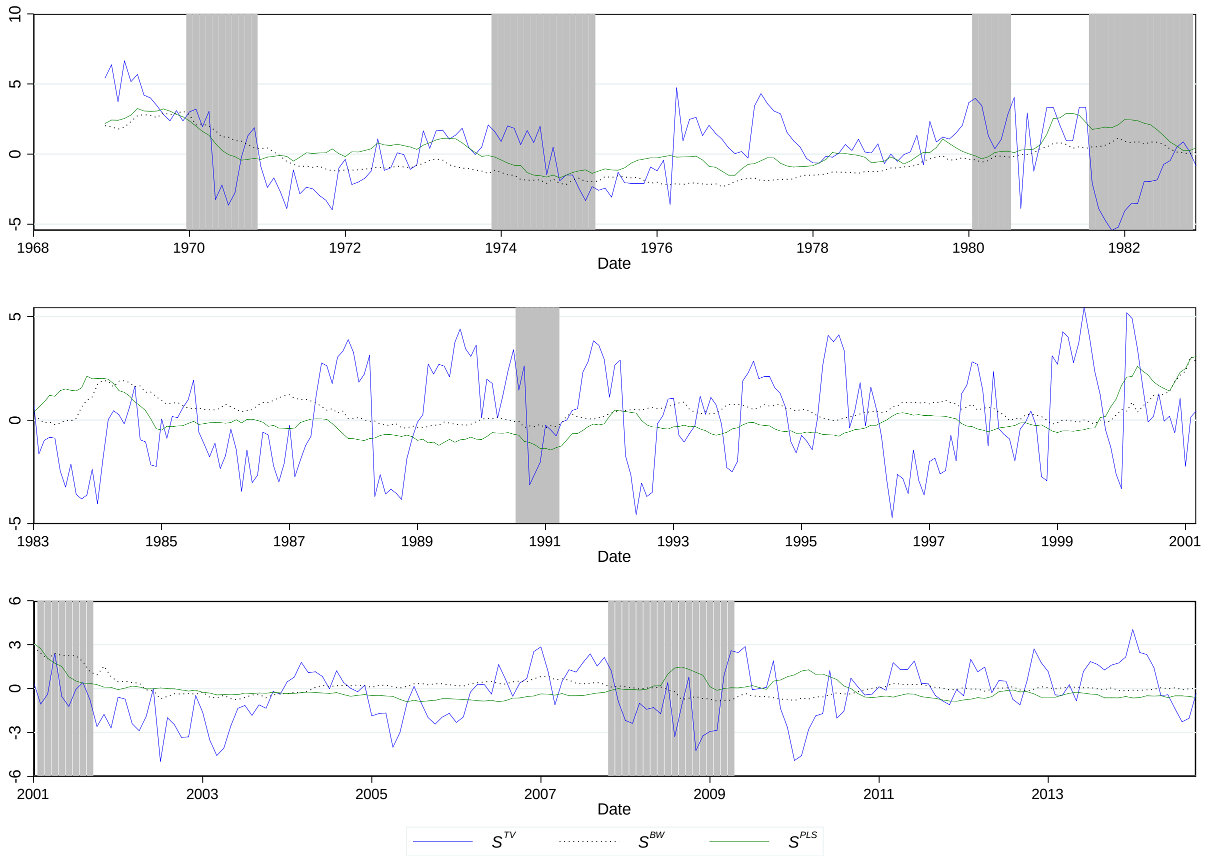


Figure 3.4: Principal component loadings of each investor sentiment proxy for S^{TV}

The figures show the weights of investor sentiment proxies, which are dividend premium (PDND), average first-day returns of IPOs (RIPO), number of IPOs (NIPO), closed-end fund discount (CEFD), and share of equity issues (EQ), for the time-varying weighted investor sentiment index (S^{TV}) from December 1968 to December 2014. The weights of sentiment proxies in month t are retrieved from the first principal component on a rolling window basis with a window length of 36 months. The shaded bars represent the recession period as dated by NBER.

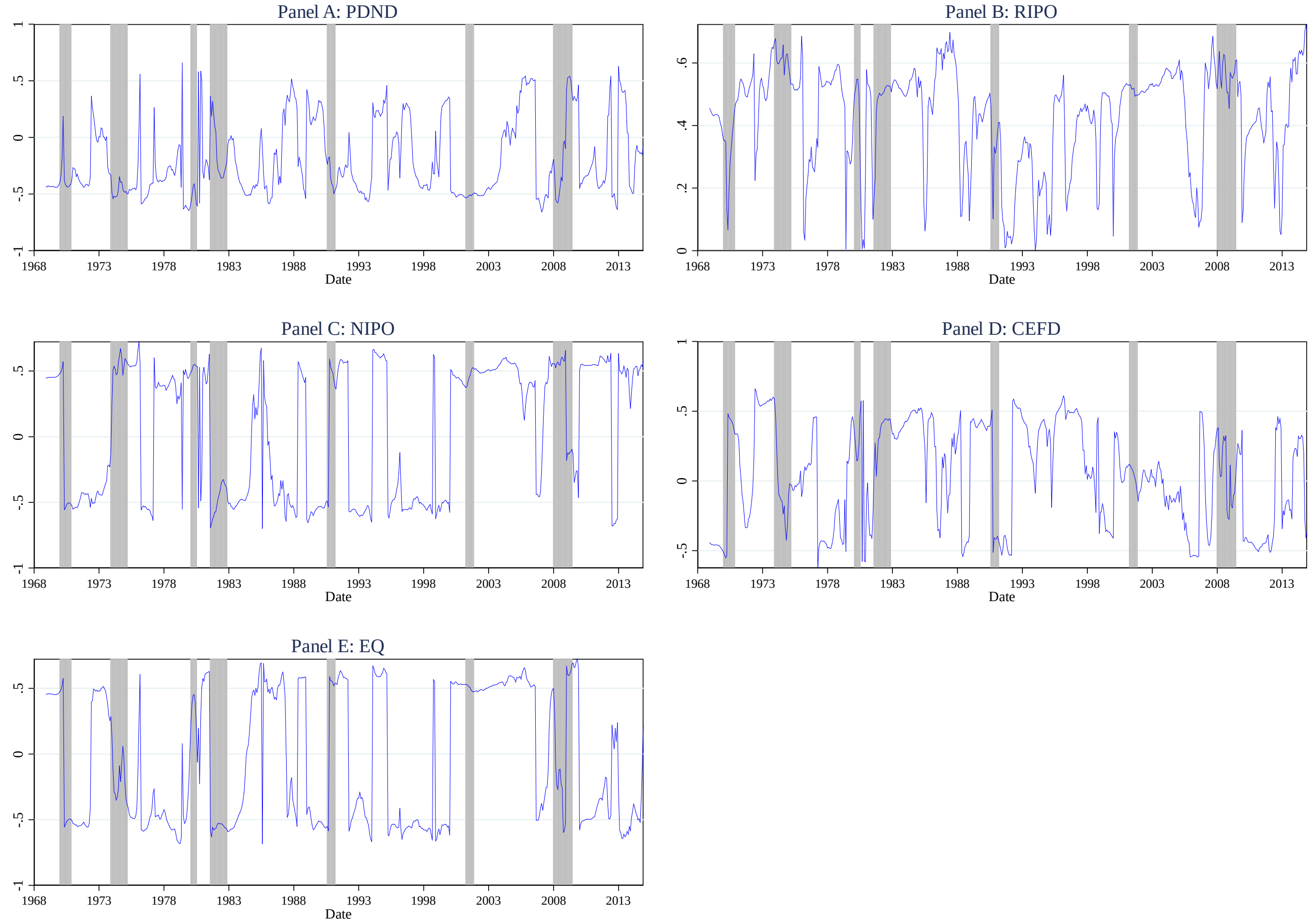


Figure 3.3 presents the enhanced investor sentiment index, S^{TV}, as well as those of BW, S^{BW}, and of Huang et al. (2015), S^{PLS}, from December 1968 to December 2014 split, for clarity, into three sub-periods: December 1968 to November 1982, December 1982 to March 2001, and April 2001 to December 2014. It can be observed that S^{TV} evolves in line with the overall trend of S^{BW} and S^{PLS}. Although the initial glance shows that S^{TV} is more volatile than S^{BW} and S^{PLS}, its movements correspond to the peaks and the troughs of business cycle. The surge in investor sentiment as shown by S^{TV} is parallel with the speculative periods, for instance, the young growth stocks bubble in 1968, the speculative period of the late 1970s, the early 1980s biotech bubble, the technology boom of the late 1990s, and the housing speculation before 2007. S^{TV} also clearly shows a drop in investor sentiment during the historic bear market periods, such as, the 1968-1970 recession, the stock market crash of 1973-1974, the 1981-1982 recession, the burst of biotech bubble in mid-1983, the Black Monday 1987, post-dot-com bubble period of 2000-2002, and the subprime crisis of 2008-2009.

To provide further evidence for the initial hypothesis that individual components of the BW index exhibit a time-varying ability to capture sentiment, the behaviour of estimated weights of index components is inspected and depicted in Figure 3.4. Their visible fluctuations over time further support the new approach of constructing the aggregate sentiment index on a rolling-window basis.

3.3.4 Return predictive regression

To assess whether S^{TV} can predict negatively future stock market returns and to compare its predictive power against other investor sentiment indexes over the entire sample period, this study estimates the standard return predictive regression model:

$$\begin{aligned} &R_{m,t+h} = \alpha + \beta Sent_{i,t} + \varepsilon_{t+h} \\ &\text{where } R_{m,t+h} = \left(\tilde{R}_{m,t+1} + \ldots + \tilde{R}_{m,t+h}\right)\big/ h \\ &\qquad Sent_{i,t} = \left\{S_t^{TV}, S_t^{BW}, S_t^{PLS}, VIX_t, MS_t, CCI_t\right\} \end{aligned} \tag{3.2}$$

where, as previously, $\tilde{R}_{m,t+h}$ denotes the h-month-ahead excess market return and $Sent_{i,t}$ represents one of different investor sentiment indexes. As discussed in Section 2.3, in general, current sentiment is negatively correlated with future stock returns. Thus, this study tests the null hypothesis of $\beta = 0$ against the alternative of $\beta < 0$. The only exception is VIX where the alternative is $\beta > 0$ given that high VIX values represent investor pessimism. To account for autocorrelation in the error terms caused by the overlapping forecast horizons and possible heteroscedasticity, a robust covariance matrix (Newey and West, 1987) is employed when estimating (3.2).

To examine if the predictive power of S^{TV} is not driven by fundamental factors, this study also estimates the "kitchen sink" (Welch and Goyal, 2008) regression model[39], directly controlling for all potential fundamental predictors. This chapter includes all but two of the economic fundamental proxies suggested by Welch and Goyal (2008)[40]: dividend price ratio (DP), dividend yield (DY), earnings-price ratio (EP), stock return variance (SVAR), book-to-market ratio (BM), net equity expansion (NTIS), treasury bill rate (TBL), long-term return (LTR), term yield spread (TMS), default yield spread (DFY), default return spread (DFR), lagged inflation (INFL), and consumption-wealth ratio (CAY). This study also includes another two economic predictors, namely the lagged output gap (OG) as suggested by Cooper and Priestley (2009) and the log surplus consumption (SCR) as proposed by Campbell and Cochrane (1999)[41]. Hence, the following model is estimated, with the same hypothesis tests on β as outlined previously:

$$
\begin{aligned}
& R_{m,t+h} = \alpha + \beta Sent_{i,t} + \sum_{j=1}^{15} \phi_j Z_{j,t} + \varepsilon_{t+h} \\
& \text{where } R_{m,t+h} = \left(\tilde{R}_{m,t+1} + \ldots + \tilde{R}_{m,t+h}\right) \big/ h \\
& \qquad Sent_{i,t} = \left\{ S_t^{TV}, S_t^{BW}, S_t^{PLS}, VIX_t, MS_t, CCI_t \right\} \\
& \qquad Z_{j,t} = \begin{Bmatrix} DP_t, DY_t, EP_t, SVAR_t, BM_t, NTIS_t, TBL_t, LTR_t, \\ TMS_t, DFY_t, DFR_t, INFL_t, CAY_t, OG_t, SCR_t \end{Bmatrix}
\end{aligned}
\tag{3.3}
$$

The S^{TV} is considered to be a good measure of investor sentiment if its slope coefficient in equation (3.3) remains significant and negative across different forecast horizons.

[39] Kitchen sink regression include all possible predictors and is found to perform well in the in-sample analysis of Welch and Goyal (2008).

[40] The multiple regression suffers from the multicollinearity issue if all economic fundamental proxies are included at once. Therefore, this study excludes dividend payout ratio (DE) and long-term yield (LTY) since DP, DE and EP are inter-correlated, and TMS is a linear combination of LTY and TBL. First, DE is dropped for three reasons: (i) Welch and Goyal (2008) find that DE does not significantly predict the equity premium over the in-sample period, (ii) Welch and Goyal (2008) find that DP significantly predicts monthly equity premium in both in-sample and out-of-sample forecasts, (iii) Campbell and Thomson (2008) also confirm the predictability of EP for both the in-sample and out-of-sample forecasts. Second, LTY is excluded because (i) Campbell and Thompson (2008) and Welch and Goyal (2008) depict that TBL and TMS are good equity premium predictors for monthly stock market return for both in-sample and out-sample analyses, (ii) Ang and Bekaert (2007) even conclude that TBL is the most robust predictor in predicting excess return.

[41] The construction of all economic predictors is described in Section 4.3.

To evaluate the predictive performance of S^{TV} on the time-series of cross-sectional portfolio returns, this study performs the following regression model:

$$\begin{aligned} &R_{j,t+h} = \alpha_j + \beta_j Sent_{i,t} + \varepsilon_{j,t+h} \\ &\text{where } R_{j,t+h} = \left(\tilde{R}_{j,t+1} + ... + \tilde{R}_{j,t+h}\right)\big/ h \\ &\qquad Sent_{i,t} = \{S_t^{TV}, S_t^{BW}, S_t^{PLS}\} \end{aligned} \tag{3.4}$$

where $R_{j,t+h}$ is the h-month ahead excess portfolio returns and $Sent_{i,t}$ denotes one of the investor sentiment measures. The cross-sectional portfolios employed here is the value-weighted returns for portfolios sorted into ten deciles based on market capitalization (ME), book-to-market (BM) ratio, and prior returns (i.e. momentum). For investor sentiment measure, the predictive performance of S^{TV} is evaluated against S^{BW} and S^{PLS}[42]. As usual, the null hypothesis of $\beta_j = 0$ against the alternative hypothesis of $\beta_j < 0$ is tested. This study hypothesizes that S^{TV} could explain all stocks to some extent if S^{TV} has improved predictive power at the aggregate stock market level as compared to S^{BW}, yet, the enhanced sentiment index is able to show that investor sentiment does affect certain types of stocks to a greater extent.

3.4 Empirical results

This section presents the results in two parts. The first part reviews the predictive performance of S^{TV} against other investor sentiment indexes in order to determine if our index is a good measure of investor sentiment, in both absolute (i.e., does it behave like a sentiment proxy?) and relative (i.e., is it superior to alternative sentiment proxies?) terms. The second part examines the predictive power of S^{TV} relative to other market-based sentiment measures on the time-series of characteristics-sorted portfolios.

3.4.1 Predictability of S^{TV} on the stock market returns

As discussed previously, the goodness of a sentiment measure can be empirically assessed by testing if high values of that measure today predict lower stock returns in the future, and vice versa. To that end, Table 3.4 presents the parameter estimates, *t*-statistic and R^2 values for different investor sentiment indexes across different forecast horizons estimated based on equation (3.2). First, it is apparent that S^{TV} produces negative and significant β

[42] Only S^{BW} and S^{PLS} are used in the comparison since S^{TV} is constructed with an aim to improve the time-series predictability of S^{BW}, and S^{PLS} is another index computed with the same intention as ours and performs well after S^{TV} at the aggregate stock market level (see Section 3.4.1).

Table 3.4: Predictive performance of different investor sentiment indexes without controlling for economic predictors

	Prediction horizons							
	h = 1	h = 3	h = 6	h = 9	h = 12	h = 24	h = 36	h = 60
S^{TV}								
β (%)	-0.1242*	-0.1571**	-0.1474**	-0.1572***	-0.1765***	-0.0834***	-0.0485**	-0.0484**
t-statistic	[-1.4467]	[-2.1766]	[-2.4268]	[-3.2009]	[-4.2541]	[-3.1310]	[-1.7278]	[-2.2747]
R^2	0.0039	0.0178	0.0291	0.0487	0.0810	0.0384	0.0217	0.0390
S^{BW}								
β (%)	-0.2221	-0.1868	-0.1982	-0.1673	-0.1276	0.0240	0.1008	0.0354
t-statistic	[-0.9677]	[-0.8525]	[-0.9339]	[-0.8464]	[-0.6816]	[0.1715]	[1.1092]	[0.4169]
R^2	0.0025	0.0050	0.0105	0.0111	0.0086	0.0006	0.0192	0.0044
S^{PLS}								
β (%)	-0.6595***	-0.6285***	-0.5632***	-0.4741***	-0.4168***	-0.2154**	-0.0640	-0.0614
t-statistic	[-3.8154]	[-4.3985]	[-4.2856]	[-3.5050]	[-3.0248]	[-1.6680]	[-0.6693]	[-0.7022]
R^2	0.0209	0.0548	0.0819	0.0855	0.0876	0.0499	0.0073	0.0123
CCI								
β (%)	-0.0172**	-0.0167**	-0.0153**	-0.0138**	-0.0146**	-0.0129***	-0.0115***	-0.0134***
t-statistic	[-1.7883]	[-1.8568]	[-1.9096]	[-1.9322]	[-2.2640]	[-2.4899]	[-2.9798]	[-6.7987]
R^2	0.0087	0.0235	0.0369	0.0444	0.0663	0.1079	0.1422	0.3163
MS								
β (%)	-0.0061	-0.0072	-0.0052	-0.0055	-0.0090	-0.0114	-0.0092	-0.0134**
t-statistic	[-0.3186]	[-0.3827]	[-0.3111]	[-0.3648]	[-0.6661]	[-1.0097]	[-0.9947]	[-2.3093]
R^2	0.0003	0.0012	0.0012	0.0019	0.0069	0.0233	0.0250	0.0923
VIX								
β (%)	0.0077	0.0216	0.0290	0.0201	0.0146	0.0152	0.0056	-0.0016
t-statistic	[0.1399]	[0.5049]	[1.1575]	[0.9211]	[0.7166]	[0.8070]	[0.3160]	[-0.0884]
R^2	0.00004	0.0043	0.0143	0.0099	0.0068	0.0126	0.0026	0.00004

Notes: This table reports the estimates obtained from equation (3.2) for the time-varying weighted investor sentiment index (S^{TV}), the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the Chicago Board Options Exchange's volatility index (VIX), the University of Michigan Consumer Sentiment Index (MS) and the Conference Board Consumer Confidence Index (CCI) across different prediction horizons. The Newey-West (automatic bandwidth selection) t-statistics are shown in brackets. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The sample period covers from December 1968 to December 2014, except for VIX which starts from January 1990.

Table 3.5: Predictive performance of different investor sentiment indexes after controlling for economic predictors

	Prediction horizons							
	h = 1	h = 3	h = 6	h = 9	h = 12	h = 24	h = 36	h = 60
S^{TV}								
β (%)	-0.0657	-0.1213**	-0.1032*	-0.1166**	-0.1447***	-0.0681***	-0.0294**	-0.0307***
t-statistic	[-0.7219]	[-1.6637]	[-1.5261]	[-2.0510]	[-3.3058]	[-3.0538]	[-1.8098]	[-2.6665]
R^2	0.0465	0.0741	0.1709	0.2338	0.2982	0.4741	0.663	0.7521
S^{BW}								
β (%)	-0.2464	-0.172	-0.1714	-0.1253	-0.0622	0.0944	0.1532	0.0179
t-statistic	[-1.0240]	[-0.7194]	[-0.7928]	[-0.6600]	[-0.3539]	[0.9254]	[2.8386]	[0.3663]
R^2	0.0474	0.0675	0.1633	0.2142	0.2518	0.4579	0.6832	0.7391
S^{PLS}								
β (%)	-0.5702***	-0.6884***	-0.6499***	-0.5367***	-0.4355***	-0.1495*	0.0541	-0.0275
t-statistic	[-2.4466]	[-2.9705]	[-4.0204]	[-4.3064]	[-3.9922]	[-1.4991]	[1.0251]	[-0.6130]
R^2	0.0552	0.1056	0.2262	0.2786	0.3104	0.4667	0.6593	0.7399
CCI								
β (%)	0.0049	0.002	0.0049	0.0078	0.003	-0.0008	-0.001	-0.0101***
t-statistic	[0.2678]	[0.1251]	[0.3546]	[0.6757]	[0.2872]	[-0.2691]	[-0.2491]	[-6.6245]
R^2	0.0457	0.0649	0.1594	0.2139	0.2512	0.4518	0.6563	0.7879
MS								
β (%)	0.0400	0.0340	0.0396	0.0325	0.0196	0.004	0.0018	-0.0152***
t-statistic	[1.0786]	[1.3894]	[1.4054]	[1.2287]	[0.8866]	[0.4401]	[0.2556]	[-4.2265]
R^2	0.049	0.0721	0.1767	0.2285	0.2593	0.4524	0.6563	0.7693
VIX								
β (%)	0.3454***	0.2706***	0.1419***	0.0633**	0.0359	0.0293	0.0096	-0.0313
t-statistic	[7.0084]	[6.7112]	[4.6042]	[2.2991]	[1.2153]	[1.2470]	[0.8093]	[-3.4529]
R^2	0.1419	0.3120	0.3881	0.4140	0.4503	0.6175	0.7993	0.8590

Notes: This table reports the estimates obtained from equation (3.3) for the time-varying weighted investor sentiment index (S^{TV}), the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the Chicago Board Options Exchange's volatility index (VIX), the University of Michigan Consumer Sentiment Index (MS) and the Conference Board Consumer Confidence Index (CCI) across different prediction horizons. The Newey-West (automatic bandwidth selection) t-statistics are shown in brackets. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The sample period ranges from December 1968 to December 2014, except for VIX which starts from January 1990.

values across different forecast horizons, hence meeting the requirement that a good investor sentiment measure should predict statistically significant negative future excess market returns[43]. Apart from S^{TV}, only S^{PLS} and CCI produce such a result. Both S^{TV} and CCI are strong return predictors across all horizons whilst S^{PLS} can only predict the excess market return up to the 24-month forecast horizon. Nevertheless, S^{PLS} is a strong predictor for next-month stock market returns since its slope coefficient is highly significant at 1% level. In contrast, MS and VIX perform poorly in predicting excess market returns given that β values are insignificant for these indexes.

Next, this sub-section establishes whether S^{TV} continues to be a significant predictor of future excess market returns after controlling for a set of economic predictors by using equation (3.3). Results in Table 3.5 further confirm the previous findings regarding the strength of S^{TV}. The predictive power of S^{TV} continues to hold across all forecast horizons as the slope coefficient of S^{TV} remains negative and significant in the presence of a set of economic predictors, the only small difference being at the 1-month horizon[44]. The lack of predictability for 1-month forecast horizon is consistent with Brown and Cliff (2005) and Yu and Yuan (2011) who claim that predictive power of investor sentiment in the short run is weaker since investor sentiment is highly persistent and arbitrage activity is limited within the short run. As such, one should not expect the mispricing at the aggregate level to be completely eliminated within the next-month period[45]. Rather, longer-term price reversals, and therefore the ability of a sentiment measure to predict stock market returns over the intermediate and long-run periods is more indicative of the sentiment effect.

As for S^{PLS}, it continues to predict future stock market returns for short-horizons,

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[43] Robustness check, as in Table A. 1 (refer to Appendix), conducted using different widow sizes demonstrates that the period of three years is optimal to capture the time-varying ability of proxy variables to mirror sentiment, as measured by performance of model (3.2).

[44] The bivariate regression which regresses the excess market return on investor sentiment and a single economic predictor is also conducted. The results are reported in Table A. 2 (refer to Appendix). In brief, S^{TV} is found to robustly predict future stock market returns across all forecast horizons for most of the regressions. In contrast, only 7 out of 17 economic predictors predict significantly future stock market returns across different forecast horizons.

[45] For instance, Lamont and Thaler (2003a) show that mispricing is corrected slowly (i.e. requires at least two months) even when the mispricing occurred between the market value of a parent company and its subsidiary (i.e. disaggregate level) is unambiguous. In addition, mispricing at individual stock level should be eliminated quicker than at the aggregate stock market level, given the scale of arbitrage and the capital required to restore the value of the total stock market are relatively greater.

including at the next-month forecast horizon. The stronger predictive ability of S^{PLS} over the short run could be a reflection of the dominance of a short-run component of investor sentiment in that index. As shown in Ding et al. (2019), the short-run sentiment is a temporary deviation of investor sentiment from its long-run trend. Hence, when the transitory deviation of sentiment reverts back to its long-run mean within a short-term period, the mispricing due to this short-run deviation of sentiment will disappear as well. Table 3.5 shows that the predictive power of S^{PLS} over longer horizons is weaker whereas our index performs best in the medium-to-longer run, implying that whilst S^{PLS} mainly captures the short-term component of sentiment, S^{TV} manages to empirically incorporate longer term sentiment features.

The CCI, on the other hand, does not predict the excess market return across most horizons after controlling for fundamental effects. This finding suggests that the prominent result for CCI in Table 3.4 is likely driven by fundamental factors which are irrelevant to investor sentiment. In contrast, VIX predicts significantly and positively future stock market returns for forecast horizons of less than a year once the fundamental information has been controlled for. Again, MS does not have significant effect on future excess market returns across most forecast horizons. The result for CCI and MS is consistent with Ferrer, Salaber and Zalewska (2016) who argue that consumer confidence indicators, such as MS and CCI, are inferior measures of investor sentiment, since they reflect how consumers perceive the future economic condition instead of their prospects for the future of the stock market[46].

Overall, the in-sample results confirm that S^{TV} is a superior investor sentiment measure amongst the main competitors tested in this study, since its high (low) values today predict low (high) future values of market returns, its predictive power is not driven by fundamental information, and it performs better than competitors including both the original BW index as well as the amended index proposed by Huang et al. (2015).

3.4.2 Predictability of S^{TV} on the time-series of the characteristics portfolios returns

The results are split into eight panels in Table 3.6, with each panel corresponds to the predictive performance at a particular forecast horizon. All investor sentiment indexes considered here, except S^{BW} beyond 24-month forecast horizon, continue to be the contrarian

[46] See also Chung, Hung and Yeh (2012, p.234) which found limited predictive power of orthogonalised consumer confidence across different portfolios.

predictors (i.e. generate negative slope coefficient) of future stock returns across different forecast horizons at the first glance. This result again confirms that high (low) sentiment today predicts low (high) future stock returns of different characteristics portfolios.

S^{TV} predicts most of the portfolio returns significantly across different forecast horizons, i.e., β_j associated with S^{TV} is significantly lower than zero at 10% level. The insignificant slope coefficients associated with the S^{TV} for the size-sorted portfolios, especially the small stocks, beyond one-year forecast indicating that small stocks have their prices revert to fundamental values within a year. Similar finding can also be seen from the results of S^{PLS} in longer prediction horizons. Besides that, S^{TV}, on average, improves the explanatory power of investor sentiment on future stock returns, as measured by R^2 statistic, relative to S^{BW}. For instance, the R^2 of S^{TV} is 2.53% for value stocks at 3-month horizon; whereas the R^2 of S^{BW} for the same portfolio is only 0.97%.

In contrast, S^{BW} produces statistically insignificant effect on future returns in about half of the characteristics portfolios across all forecast horizons considered. Among three characteristics portfolios, the best return prediction produced by S^{BW} is on the portfolios sorted based on firm size where it significantly predicts all portfolios of different sizes except the large stocks, which is in line with the literature (e.g. Baker and Wurgler, 2006; 2007; Kumar and Lee, 2006; Lemmon and Portniaguina, 2006). However, it consistently fails to predict the growth stock returns as shown by its insignificant slope coefficients across all forecast horizons. For the S^{PLS}, the results show that it has a strong predictive power on the cross-sectional stock returns since it predicts significantly returns of all portfolios sorted based on different characteristics across short-term forecast horizons of up to 12 months. This finding is consistent with the results presented in Table 3.5, which depicts that S^{PLS} is a strong predictor of aggregate stock market returns over the short-term forecast horizons. Besides that, all investor sentiment measures considered in this section do not predict well the time-series of the cross-sectional stock returns at 36-month forecast horizon.

In short, S^{TV} predicts equally well the time-series of the cross-sectional stock returns. The enhanced investor sentiment index, on average, shows that investor sentiment effect penetrates into almost every single portfolio, justifying the predictive power of S^{TV} on the aggregate stock market returns in Section 3.4.1. The results in this sub-section also reaffirm the hypothesis that sentiment today predicts negative future stock returns. Meanwhile, the differential sentiment effect on the cross-sectional stock returns as one would expect is well

Table 3.6: Predictive performance of investor sentiment indexes on the time series of cross-sectional stock returns

	S^{TV}			S^{BW}			S^{PLS}		
	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)
	Panel A: 1-month horizon								
I. Size portfolios									
Small	-0.35	-2.15	1.50	-0.75	-2.39	1.33	-0.95	-3.20	2.09
2	-0.34	-2.47	1.38	-0.62	-1.99	0.90	-0.83	-2.80	1.56
3	-0.32	-2.52	1.37	-0.53	-1.83	0.71	-0.86	-3.59	1.86
4	-0.30	-2.36	1.27	-0.55	-2.00	0.84	-0.85	-3.66	1.95
5	-0.26	-2.19	1.00	-0.49	-1.81	0.70	-0.84	-4.13	2.02
6	-0.25	-2.17	1.02	-0.45	-1.70	0.69	-0.81	-3.66	2.13
7	-0.24	-2.20	1.00	-0.41	-1.53	0.57	-0.78	-4.19	2.02
8	-0.21	-2.08	0.77	-0.33	-1.29	0.39	-0.66	-3.51	1.53
9	-0.18	-1.99	0.69	-0.25	-1.07	0.26	-0.69	-4.22	1.98
Large	-0.10	-1.34	0.26	-0.20	-0.78	0.20	-0.65	-3.78	2.08
II. Book-to-market portfolios									
Growth	-0.09	-0.90	0.14	-0.29	-0.94	0.31	-0.78	-3.28	2.10
2	-0.19	-2.15	0.76	-0.20	-0.79	0.18	-0.66	-4.31	1.80
3	-0.16	-1.79	0.54	-0.24	-1.04	0.25	-0.74	-5.07	2.28
4	-0.19	-1.80	0.75	-0.28	-1.06	0.32	-0.63	-3.08	1.61
5	-0.07	-0.85	0.12	-0.23	-1.08	0.25	-0.61	-3.12	1.66
6	-0.13	-1.45	0.39	-0.24	-1.10	0.28	-0.55	-2.99	1.41
7	-0.14	-1.35	0.43	-0.34	-1.51	0.50	-0.67	-2.97	1.89
8	-0.17	-2.10	0.64	-0.27	-1.32	0.31	-0.61	-2.61	1.57
9	-0.18	-1.99	0.62	-0.30	-1.21	0.36	-0.53	-2.52	1.05
Value	-0.26	-2.66	0.83	-0.41	-1.55	0.42	-0.65	-2.43	1.02
III. Momentum portfolios									
Loser	-0.29	-1.54	0.60	-0.78	-1.83	0.86	-1.11	-3.70	1.66
2	-0.17	-1.12	0.32	-0.29	-0.95	0.20	-0.68	-2.87	1.04
3	-0.19	-1.50	0.58	-0.24	-0.89	0.19	-0.67	-4.46	1.40
4	-0.15	-1.45	0.47	-0.23	-0.93	0.22	-0.59	-2.55	1.33
5	-0.14	-1.55	0.47	-0.18	-0.81	0.16	-0.60	-3.24	1.62
6	-0.14	-1.53	0.47	-0.32	-1.25	0.47	-0.74	-3.69	2.39
7	-0.13	-1.97	0.41	-0.22	-0.94	0.23	-0.61	-4.21	1.75
8	-0.10	-1.20	0.23	-0.23	-1.00	0.26	-0.70	-4.87	2.25
9	-0.11	-1.16	0.24	-0.40	-1.76	0.64	-0.76	-5.35	2.24
Winner	-0.25	-1.93	0.75	-0.52	-1.90	0.66	-0.92	-5.24	2.06

	S^{TV}			S^{BW}			S^{PLS}		
	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)
	Panel B: 3-month horizon								
I. Size portfolios									
Small	-0.32	-2.46	2.77	-0.70	-2.37	2.68	-0.94	-3.56	4.64
2	-0.29	-2.40	2.43	-0.57	-2.35	1.90	-0.81	-3.21	3.77
3	-0.28	-2.61	2.71	-0.48	-1.87	1.55	-0.83	-4.19	4.48
4	-0.27	-2.45	2.70	-0.50	-1.98	1.85	-0.82	-4.18	4.72
5	-0.22	-2.17	1.95	-0.44	-1.78	1.46	-0.79	-4.94	4.65
6	-0.23	-2.29	2.28	-0.41	-1.71	1.47	-0.78	-4.56	5.15
7	-0.23	-2.43	2.38	-0.36	-1.48	1.16	-0.74	-5.32	4.83
8	-0.19	-2.11	1.75	-0.29	-1.33	0.83	-0.63	-4.72	3.85
9	-0.19	-2.34	2.10	-0.22	-1.16	0.55	-0.65	-5.44	4.73
Large	-0.14	-2.02	1.50	-0.16	-0.68	0.39	-0.62	-4.72	5.57
II. Book-to-market portfolios									
Growth	-0.13	-1.41	0.78	-0.25	-0.88	0.61	-0.76	-4.25	5.36
2	-0.20	-2.48	2.42	-0.16	-0.67	0.31	-0.64	-4.70	4.58
3	-0.17	-2.05	1.74	-0.20	-0.94	0.49	-0.71	-6.30	5.82
4	-0.20	-2.15	2.30	-0.25	-1.01	0.71	-0.60	-3.24	4.07
5	-0.11	-1.62	0.85	-0.19	-0.99	0.49	-0.57	-3.40	4.06
6	-0.16	-2.05	1.78	-0.22	-1.07	0.66	-0.49	-2.87	3.31
7	-0.18	-2.03	1.95	-0.31	-1.50	1.06	-0.61	-3.40	4.08
8	-0.18	-2.36	1.91	-0.25	-1.32	0.70	-0.55	-2.87	3.41
9	-0.18	-2.24	1.81	-0.28	-1.24	0.83	-0.47	-2.66	2.32
Value	-0.28	-2.95	2.53	-0.39	-1.62	0.97	-0.62	-4.07	2.41
III. Momentum portfolios									
Loser	-0.37	-2.28	2.41	-0.72	-1.84	1.89	-1.02	-4.03	3.59
2	-0.22	-1.78	1.53	-0.27	-0.97	0.45	-0.62	-3.16	2.35
3	-0.21	-2.21	1.91	-0.20	-0.80	0.36	-0.60	-4.50	3.03
4	-0.18	-2.06	1.70	-0.21	-0.89	0.46	-0.52	-2.87	2.87
5	-0.18	-2.20	2.08	-0.15	-0.72	0.29	-0.52	-3.24	3.27
6	-0.18	-2.15	1.92	-0.26	-1.09	0.81	-0.66	-4.48	5.28
7	-0.15	-2.38	1.76	-0.16	-0.80	0.41	-0.56	-4.37	4.51
8	-0.11	-1.44	0.85	-0.19	-0.91	0.51	-0.66	-5.85	5.85
9	-0.16	-1.98	1.42	-0.36	-1.78	1.51	-0.73	-6.43	5.98
Winner	-0.22	-2.13	1.63	-0.45	-1.82	1.41	-0.90	-6.10	5.41

Table 3.6 (Continued)

	S^{TV}			S^{BW}			S^{PLS}			S^{TV}			S^{BW}			S^{PLS}		
	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)
	Panel C: 6-month horizon									*Panel D: 9-month horizon*								
I. Size portfolios																		
Small	-0.24	-2.07	3.05	-0.68	-2.28	4.89	-0.86	-3.83	7.55	-0.21	-2.33	3.61	-0.62	-2.34	6.28	-0.67	-2.65	7.15
2	-0.21	-1.91	2.68	-0.57	-2.06	3.97	-0.74	-2.90	6.53	-0.19	-1.96	3.44	-0.52	-2.14	5.28	-0.59	-2.29	6.45
3	-0.19	-2.04	2.65	-0.49	-1.93	3.36	-0.73	-3.83	7.40	-0.17	-2.21	3.43	-0.44	-2.00	4.54	-0.57	-2.83	7.25
4	-0.20	-2.10	3.03	-0.51	-2.02	3.91	-0.73	-3.67	7.91	-0.18	-2.30	4.10	-0.45	-2.03	5.04	-0.57	-2.78	7.76
5	-0.17	-1.94	2.18	-0.43	-1.82	2.98	-0.70	-4.00	7.46	-0.17	-2.23	3.59	-0.39	-1.80	3.82	-0.55	-3.11	7.48
6	-0.18	-2.12	2.84	-0.40	-1.72	2.94	-0.70	-3.96	8.41	-0.18	-2.48	4.56	-0.35	-1.70	3.62	-0.56	-3.13	8.56
7	-0.17	-1.93	2.47	-0.35	-1.75	2.13	-0.67	-4.90	7.61	-0.16	-3.02	3.52	-0.30	-3.69	2.49	-0.54	-3.40	7.77
8	-0.14	-1.85	1.95	-0.29	-1.41	1.64	-0.56	-3.79	6.05	-0.14	-2.23	3.11	-0.25	-1.34	1.87	-0.44	-3.20	5.86
9	-0.15	-2.06	2.43	-0.22	-1.08	1.12	-0.57	-4.28	6.93	-0.15	-2.70	3.61	-0.19	-0.99	1.20	-0.46	-3.78	6.98
Large	-0.14	-2.20	2.61	-0.17	-0.75	0.82	-0.56	-4.14	8.43	-0.15	-3.18	4.63	-0.15	-0.67	0.84	-0.49	-3.46	9.20
II. Book-to-market portfolios																		
Growth	-0.10	-1.25	0.88	-0.26	-0.94	1.20	-0.73	-4.54	9.33	-0.12	-1.82	1.84	-0.23	-0.91	1.41	-0.68	-4.15	11.76
2	-0.15	-2.01	2.57	-0.17	-0.72	0.70	-0.58	-4.06	7.66	-0.15	-2.55	3.84	-0.14	-0.62	0.68	-0.50	-3.42	8.33
3	-0.15	-2.16	2.88	-0.20	-0.96	0.98	-0.61	-5.08	8.56	-0.16	-2.96	4.52	-0.17	-0.87	1.03	-0.48	-3.73	8.07
4	-0.17	-2.00	3.19	-0.28	-1.18	1.71	-0.53	-3.19	5.95	-0.17	-2.66	4.89	-0.26	-1.26	2.35	-0.42	-2.40	5.89
5	-0.12	-1.96	1.98	-0.20	-1.17	1.08	-0.47	-3.28	5.56	-0.14	-2.77	3.59	-0.18	-1.12	1.23	-0.36	-2.44	4.86
6	-0.15	-2.27	3.08	-0.25	-1.27	1.58	-0.41	-2.71	4.32	-0.17	-2.82	5.43	-0.23	-1.31	2.07	-0.31	-1.85	3.64
7	-0.19	-2.46	3.49	-0.32	-1.71	1.98	-0.50	-2.90	4.82	-0.20	-3.25	5.56	-0.28	-1.70	2.28	-0.35	-2.37	3.52
8	-0.18	-2.70	3.44	-0.27	-1.57	1.61	-0.44	-2.91	4.14	-0.16	-2.96	4.60	-0.24	-1.55	2.03	-0.31	-1.86	3.26
9	-0.18	-2.36	3.24	-0.31	-1.59	2.01	-0.40	-2.32	3.22	-0.17	-2.79	4.85	-0.30	-1.62	3.03	-0.31	-1.91	3.03
Value	-0.24	-2.92	3.66	-0.38	-1.76	1.88	-0.50	-2.33	3.13	-0.22	-3.09	5.22	-0.33	-1.70	2.32	-0.34	-1.54	2.44
III. Momentum portfolios																		
Loser	-0.33	-2.54	3.64	-0.71	-1.84	3.37	-0.86	-2.70	4.83	-0.33	-3.01	5.60	-0.60	-1.74	3.72	-0.72	-2.23	5.22
2	-0.20	-2.04	2.37	-0.29	-1.05	1.00	-0.51	-2.40	3.04	-0.22	-2.82	4.40	-0.24	-0.92	1.04	-0.41	-1.93	3.05
3	-0.20	-2.92	3.57	-0.19	-0.75	0.61	-0.50	-3.10	4.20	-0.20	-3.59	5.53	-0.13	-0.55	0.45	-0.41	-2.41	4.41
4	-0.18	-2.51	3.24	-0.21	-1.04	0.94	-0.41	-2.19	3.32	-0.18	-3.00	5.31	-0.16	-1.05	0.87	-0.29	-1.62	2.69
5	-0.18	-2.61	3.95	-0.16	-0.80	0.67	-0.41	-2.68	4.04	-0.18	-3.45	6.59	-0.13	-0.71	0.67	-0.31	-2.15	3.67
6	-0.18	-2.57	3.74	-0.24	-1.10	1.42	-0.54	-3.23	6.70	-0.19	-3.61	6.32	-0.20	-1.01	1.40	-0.42	-2.74	6.26
7	-0.15	-2.74	3.72	-0.15	-0.90	0.71	-0.47	-3.60	6.58	-0.16	-3.31	5.58	-0.11	-1.05	0.58	-0.36	-2.84	5.79
8	-0.11	-1.61	1.57	-0.20	-1.02	1.10	-0.60	-5.68	9.35	-0.11	-1.83	2.30	-0.18	-1.00	1.29	-0.51	-4.31	9.64
9	-0.15	-2.10	2.43	-0.38	-1.92	3.07	-0.68	-5.51	9.54	-0.15	-3.84	3.50	-0.35	-1.97	3.92	-0.56	-8.33	9.89
Winner	-0.15	-1.56	1.45	-0.45	-1.93	2.78	-0.89	-5.91	10.45	-0.14	-1.72	1.93	-0.42	-1.97	3.58	-0.78	-4.61	12.20

Table 3.6 (Continued)

	S^{TV}			S^{BW}			S^{PLS}			S^{TV}			S^{BW}			S^{PLS}		
	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)
	Panel E: 12-month horizon									*Panel F: 24-month horizon*								
I. Size portfolios																		
Small	-0.21	-1.94	4.93	-0.54	-2.18	6.50	-0.53	-2.58	6.16	-0.05	-0.78	0.69	-0.31	-1.53	5.43	-0.22	-1.23	2.50
2	-0.20	-2.01	5.05	-0.46	-2.00	5.54	-0.48	-1.92	5.82	-0.04	-0.76	0.62	-0.26	-1.46	4.57	-0.20	-1.23	2.67
3	-0.19	-2.46	5.69	-0.39	-1.87	4.95	-0.46	-2.34	6.74	-0.04	-0.97	0.83	-0.23	-1.48	4.57	-0.23	-1.71	4.21
4	-0.20	-2.62	6.84	-0.39	-1.85	5.24	-0.46	-2.32	7.15	-0.05	-1.18	1.18	-0.21	-1.31	3.93	-0.20	-1.41	3.55
5	-0.20	-2.95	6.80	-0.34	-1.64	4.02	-0.46	-2.65	7.24	-0.05	-1.40	1.23	-0.18	-1.17	3.12	-0.23	-1.68	4.68
6	-0.20	-3.23	8.11	-0.30	-1.56	3.67	-0.47	-2.67	8.40	-0.06	-1.78	1.96	-0.14	-0.98	2.01	-0.24	-1.84	5.51
7	-0.18	-3.04	6.42	-0.25	-1.70	2.41	-0.46	-2.94	7.69	-0.06	-2.79	1.68	-0.09	-0.62	0.71	-0.22	-1.85	4.55
8	-0.16	-3.02	5.83	-0.20	-1.16	1.78	-0.37	-2.67	5.59	-0.05	-1.45	1.16	-0.06	-0.48	0.46	-0.17	-1.43	3.10
9	-0.17	-3.75	6.77	-0.15	-0.83	1.06	-0.40	-3.23	7.15	-0.07	-2.32	2.48	-0.02	-0.17	0.06	-0.21	-1.86	4.81
Large	-0.17	-4.42	7.52	-0.11	-0.52	0.60	-0.44	-2.98	9.67	-0.09	-3.21	3.98	0.05	0.33	0.28	-0.24	-1.59	5.50
II. Book-to-market portfolios																		
Growth	-0.15	-2.77	3.85	-0.18	-0.76	1.16	-0.63	-3.74	13.35	-0.07	-1.81	1.68	0.03	0.20	0.09	-0.33	-2.14	8.18
2	-0.16	-3.22	6.14	-0.10	-0.46	0.46	-0.44	-3.10	8.94	-0.06	-2.31	1.91	0.08	0.51	0.75	-0.22	-1.56	5.00
3	-0.17	-3.96	7.55	-0.12	-0.68	0.78	-0.39	-3.20	7.64	-0.06	-3.89	1.95	0.01	0.10	0.02	-0.21	-1.98	5.09
4	-0.19	-3.31	8.59	-0.23	-1.23	2.59	-0.35	-2.12	5.72	-0.08	-2.29	3.34	-0.12	-0.91	1.86	-0.20	-1.62	4.37
5	-0.16	-3.55	6.51	-0.14	-1.04	1.11	-0.28	-1.96	4.07	-0.06	-1.92	2.09	-0.07	-0.58	0.52	-0.14	-1.49	2.37
6	-0.20	-3.98	10.55	-0.21	-1.26	2.34	-0.25	-1.73	3.40	-0.08	-2.47	4.16	-0.12	-1.14	1.89	-0.15	-1.22	2.90
7	-0.22	-4.47	9.49	-0.24	-1.59	2.34	-0.27	-2.94	2.73	-0.09	-3.39	3.20	-0.15	-1.32	1.90	-0.12	-0.93	1.26
8	-0.17	-3.56	7.46	-0.21	-1.48	2.28	-0.24	-1.56	2.87	-0.05	-2.42	1.77	-0.15	-1.38	2.75	-0.14	-1.13	2.26
9	-0.19	-3.60	7.73	-0.28	-1.50	3.67	-0.28	-1.90	3.40	-0.07	-2.03	2.53	-0.17	-1.08	3.16	-0.22	-1.49	4.75
Value	-0.24	-3.74	9.24	-0.27	-1.78	2.35	-0.25	-1.19	1.90	-0.10	-2.25	3.97	-0.13	-0.99	1.35	-0.11	-0.63	0.91
III. Momentum portfolios																		
Loser	-0.34	-3.32	8.17	-0.48	-1.52	3.29	-0.65	-2.17	5.78	-0.16	-2.08	3.94	-0.10	-0.64	0.36	-0.27	-1.30	2.30
2	-0.25	-3.66	7.84	-0.18	-0.73	0.87	-0.37	-1.84	3.36	-0.08	-1.68	1.93	0.04	0.21	0.10	-0.15	-0.93	1.44
3	-0.22	-4.30	8.70	-0.07	-0.31	0.17	-0.35	-2.05	4.13	-0.07	-1.65	1.92	0.13	0.77	1.37	-0.10	-0.61	0.76
4	-0.20	-3.80	8.77	-0.11	-0.64	0.56	-0.24	-1.41	2.48	-0.07	-2.06	2.41	0.06	0.40	0.37	-0.08	-0.66	0.70
5	-0.21	-4.88	11.46	-0.09	-0.55	0.50	-0.26	-1.95	3.66	-0.08	-2.85	4.20	0.02	0.21	0.07	-0.14	-1.42	2.57
6	-0.21	-4.59	10.92	-0.15	-0.86	1.18	-0.36	-2.35	6.15	-0.08	-2.81	3.92	-0.01	-0.09	0.02	-0.17	-1.29	3.23
7	-0.18	-4.23	9.62	-0.07	-0.65	0.33	-0.30	-2.25	5.16	-0.08	-2.97	4.40	0.04	0.37	0.23	-0.12	-1.24	1.79
8	-0.13	-2.57	4.25	-0.16	-0.90	1.26	-0.44	-3.36	9.49	-0.04	-1.36	1.02	-0.07	-0.51	0.63	-0.27	-2.68	8.54
9	-0.16	-3.20	5.75	-0.31	-1.91	4.21	-0.48	-3.20	9.52	-0.07	-2.07	2.33	-0.18	-1.40	3.37	-0.23	-1.88	5.28
Winner	-0.15	-2.18	3.21	-0.37	-1.89	3.77	-0.69	-3.89	12.74	-0.07	-1.82	1.63	-0.20	-1.32	2.83	-0.40	-2.86	10.94

Table 3.6 (Continued)

	S^{TV}			S^{BW}			S^{PLS}			S^{TV}			S^{BW}			S^{PLS}		
	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)	β (%)	*t*-stat	R^2 (%)
	Panel G: 36-month horizon									*Panel H: 60-month horizon*								
I. Size portfolios																		
Small	-0.01	-0.22	0.06	-0.28	-1.46	7.31	-0.13	-0.84	1.55	-0.03	-0.56	0.64	-0.38	-2.54	22.10	-0.22	-1.29	6.75
2	-0.02	-0.42	0.23	-0.23	-1.66	6.51	-0.12	-0.94	1.62	-0.04	-0.83	1.49	-0.32	-2.84	20.81	-0.19	-1.24	6.71
3	-0.03	-0.75	0.71	-0.20	-1.67	6.13	-0.14	-1.44	2.69	-0.05	-1.25	3.21	-0.26	-3.64	20.76	-0.16	-1.25	7.23
4	-0.03	-0.72	0.61	-0.18	-1.52	5.39	-0.11	-1.15	1.82	-0.04	-1.18	2.69	-0.27	-3.52	23.12	-0.15	-1.19	6.45
5	-0.03	-0.87	0.89	-0.16	-1.35	4.09	-0.14	-1.50	3.06	-0.05	-1.32	3.28	-0.24	-3.16	19.06	-0.17	-1.45	8.92
6	-0.04	-1.10	1.23	-0.10	-1.09	1.92	-0.12	-1.57	2.75	-0.05	-1.54	4.17	-0.18	-2.72	11.99	-0.14	-1.34	7.17
7	-0.03	-1.20	0.90	-0.03	-0.34	0.18	-0.09	-1.13	1.38	-0.05	-1.77	5.14	-0.11	-1.40	4.68	-0.10	-0.94	3.87
8	-0.03	-1.39	0.93	-0.02	-0.23	0.08	-0.07	-0.89	1.03	-0.04	-1.76	4.52	-0.08	-1.17	2.74	-0.09	-0.98	3.69
9	-0.04	-1.52	2.00	0.03	0.37	0.21	-0.09	-1.03	1.45	-0.05	-2.08	5.58	-0.02	-0.19	0.13	-0.07	-0.73	2.08
Large	-0.05	-1.72	2.11	0.14	1.25	3.11	-0.07	-0.61	0.78	-0.05	-2.19	3.26	0.07	0.69	1.38	-0.07	-0.64	1.15
II. Book-to-market portfolios																		
Growth	-0.03	-0.85	0.56	0.13	1.05	2.19	-0.16	-1.31	3.08	-0.04	-1.52	1.56	0.06	0.60	0.95	-0.18	-2.27	7.50
2	-0.03	-1.04	0.87	0.14	1.29	3.75	-0.09	-0.88	1.32	-0.04	-1.69	2.78	0.03	0.26	0.24	-0.10	-0.96	3.06
3	-0.04	-1.36	1.55	0.05	0.60	0.56	-0.09	-1.18	1.66	-0.05	-2.40	6.54	-0.01	-0.18	0.11	-0.09	-1.08	3.77
4	-0.04	-1.42	2.13	-0.06	-0.78	0.89	-0.07	-0.67	0.99	-0.05	-2.02	6.39	-0.11	-1.29	5.52	-0.07	-0.59	1.95
5	-0.03	-0.89	0.86	-0.04	-0.62	0.35	-0.06	-0.78	0.86	-0.05	-1.93	5.44	-0.07	-0.81	2.34	-0.05	-0.52	1.26
6	-0.05	-1.81	3.15	-0.05	-0.66	0.67	-0.06	-0.65	0.90	-0.05	-2.00	5.06	-0.06	-0.66	1.49	-0.05	-0.51	1.09
7	-0.05	-1.51	1.75	-0.08	-0.84	0.92	0.00	-0.04	0.00	-0.05	-2.40	4.65	-0.07	-0.82	1.58	0.02	0.22	0.20
8	-0.03	-1.25	0.99	-0.10	-1.25	2.17	-0.04	-0.42	0.33	-0.04	-2.11	3.64	-0.10	-1.58	4.80	-0.01	-0.14	0.07
9	-0.05	-1.90	2.22	-0.09	-0.89	1.57	-0.10	-0.98	2.02	-0.05	-2.31	6.85	-0.10	-1.39	5.21	-0.05	-0.50	1.18
Value	-0.05	-1.60	2.17	-0.07	-0.74	0.74	-0.01	-0.07	0.01	-0.05	-1.96	3.77	-0.11	-1.51	4.22	0.02	0.18	0.13
III. Momentum portfolios																		
Loser	-0.10	-1.51	2.93	-0.01	-0.08	0.01	-0.05	-0.50	0.18	-0.08	-1.65	3.88	-0.13	-1.05	2.33	-0.14	-0.95	2.37
2	-0.05	-1.28	1.50	0.11	1.00	1.55	0.00	-0.01	0.00	-0.06	-1.82	5.00	0.01	0.05	0.01	-0.06	-0.44	0.87
3	-0.05	-1.11	1.54	0.16	1.55	3.60	0.02	0.25	0.08	-0.05	-2.15	4.10	0.06	0.58	0.93	-0.02	-0.19	0.11
4	-0.04	-1.32	1.57	0.10	1.26	2.31	0.02	0.25	0.08	-0.05	-2.05	4.94	0.03	0.35	0.48	0.00	0.03	0.00
5	-0.05	-1.96	2.99	0.09	0.91	1.71	-0.03	-0.37	0.18	-0.06	-3.16	7.20	0.05	0.53	1.23	-0.02	-0.26	0.20
6	-0.04	-1.49	1.53	0.05	0.49	0.42	-0.05	-0.51	0.49	-0.04	-2.11	3.71	-0.03	-0.47	0.43	-0.07	-0.80	1.80
7	-0.04	-1.32	1.42	0.08	0.98	1.47	-0.03	-0.34	0.14	-0.04	-1.85	3.24	0.00	0.03	0.00	-0.05	-0.54	0.91
8	-0.02	-0.75	0.49	-0.05	-0.46	0.48	-0.20	-2.49	7.53	-0.04	-1.50	3.03	-0.11	-1.27	4.28	-0.18	-1.99	10.62
9	-0.03	-1.04	0.86	-0.13	-1.25	3.06	-0.11	-1.18	2.07	-0.04	-1.49	2.37	-0.19	-2.33	12.81	-0.11	-1.13	3.95
Winner	-0.03	-0.99	0.65	-0.13	-1.00	2.09	-0.26	-2.43	8.04	-0.04	-1.35	1.65	-0.20	-2.58	9.90	-0.24	-2.81	14.12

Notes: This table reports the slope coefficients obtained from equation (3.4) for the time-varying weighted investor sentiment index (S^{TV}), the Baker and Wurgler investor sentiment index (S^{BW}), and the aligned investor sentiment index (S^{PLS}). Panel A to H report the estimation results for different investor sentiment indexes across different forecast horizons. The Newey-West (automatic bandwidth selection) *t*-statistics and R^2 values are reported in the table. The critical values of one-tailed *t*-test are: 1.282 (α = 0.10), 1.646 (α = 0.05) and 2.330 (α = 0.01). The sample period covers from December 1968 to December 2014.

exhibited. Concretely, S^{TV} generates greater absolute beta coefficients for small stocks (except those in longer forecast horizons) and past losers, suggesting that the sentiment effects on these stocks is more pronounced than on large stocks and past winners. With regards to the BM-sorted portfolios, S^{TV} and S^{BW} show that investor sentiment has greater influence on the value stocks as compared to growth stocks, which is consistent with Baker and Wurgler (2006) and Schmeling (2009).

3.5 Conclusion

This study addresses a puzzle that the investor sentiment index constructed by Baker and Wurgler (2006) does not have a strong time-series forecasting power for future aggregate market returns. It is puzzling since it utilises numerous variables which individually have been themselves widely employed in prior literature as effective sentiment proxies. This chapter propose an enhancement to the original Baker and Wurgler (2006) method which grants the resulting sentiment index the previously lacking forecasting power, a feature it should always have had. The approach is based on the consideration that the construction of the original index implicitly assumes a time-invariant ability of each of its component sentiment proxy to empirically capture the unobservable investor sentiment. However, this study conjectures that the ability may vary over time, which would lead to the contribution of each proxy to the aggregate investor sentiment index being time-varying. Hence, a new, time-varying investor sentiment index, S^{TV} is constructed. The approach employed in this study captures the dynamic contributions of investor sentiment proxies to the aggregate index while also avoiding any look-ahead bias.

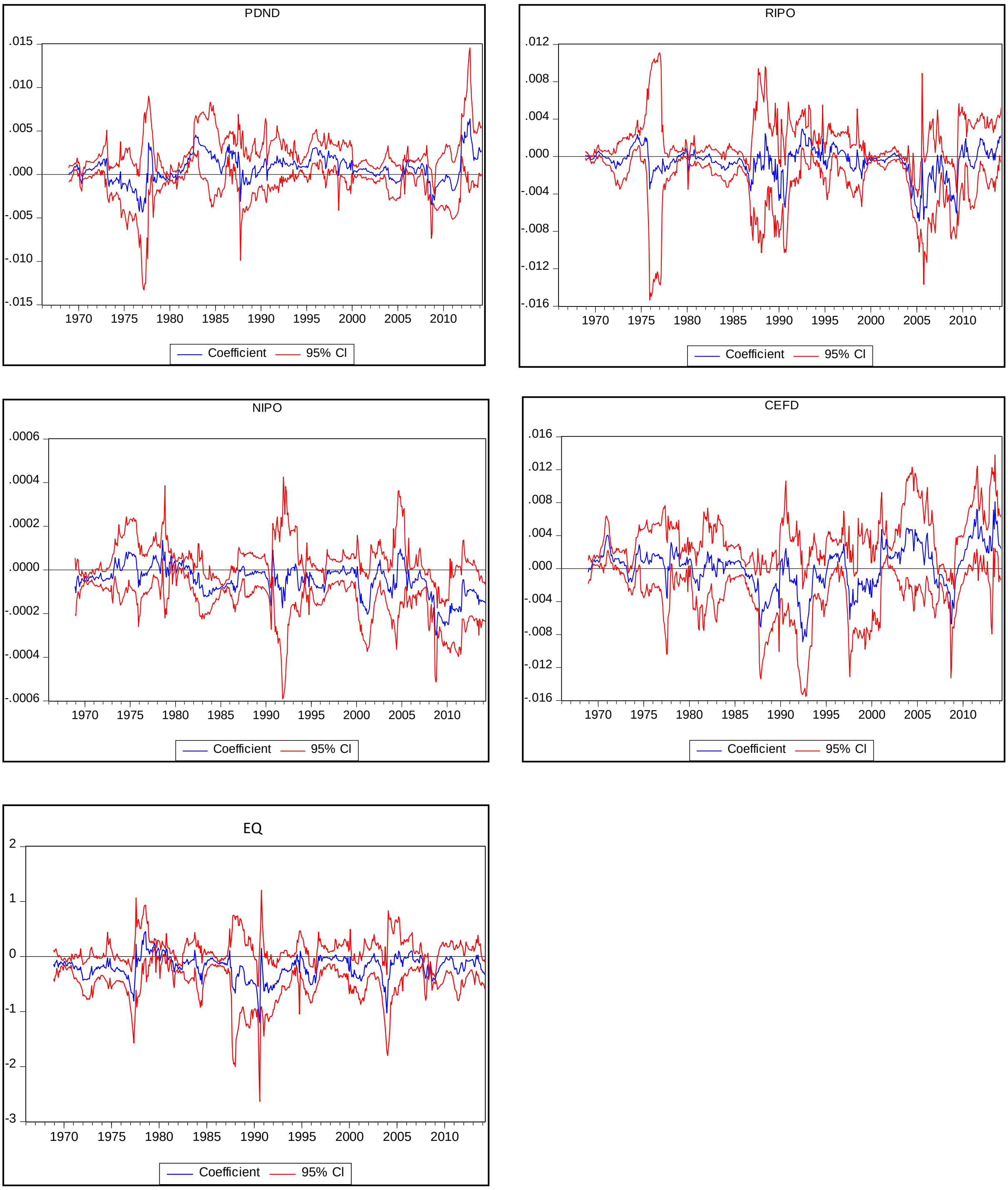
The basic property of a good investor sentiment measure (i.e. high sentiment today predicts future stock returns negatively) is evaluated by examining whether S^{TV} consistently generates negative slope coefficient even after removing as much fundamental effects as possible in the sentiment-return regression framework. Empirically, the findings show that S^{TV} is a superior measure of investor sentiment: it consistently generates a significant negative effect on future stock market returns even after controlling for a set of fundamental economic predictors, in line with the theoretical rationale behind a good sentiment proxy. Moreover, S^{TV} greatly enhances the predictive power of investor sentiment at the aggregate stock market level as compared to the original Baker and Wurgler (2006) construct, and outperforms other sentiment measures in predicting stock market returns across different forecast horizons. The strong predictive power of S^{TV} index at the aggregate level is further supported by its predictive power for the time-series of the cross-sectional stock returns. Specifically, the results reveal that that S^{TV} index generates significant influence on portfolios sorted based on firm size, book-to-market value and momentum across time.

Overall, the proposed enhancement to the original Baker and Wurgler (2006) index significantly improves its ability to empirically capture the latent investor sentiment. The new index should therefore be of value in future academic research where a good empirical proxy for sentiment is required, and to stock market investors, as demonstrated by the predictive ability of S^{TV}.

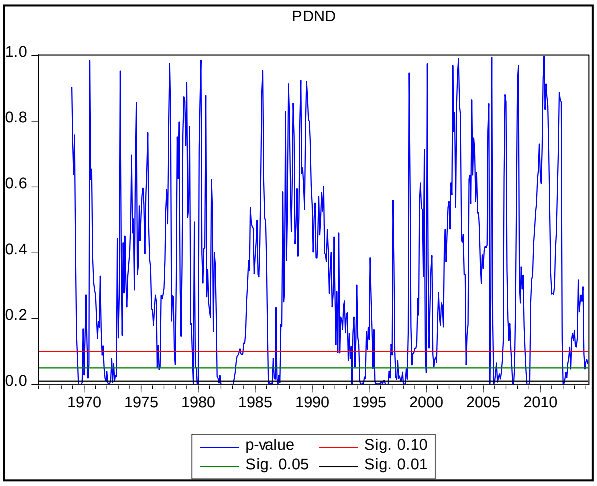
Appendix

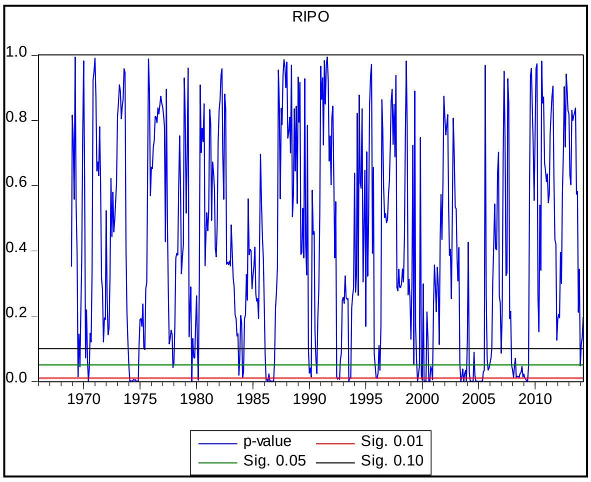
Figure A. 1: The rolling regression estimates of each individual investor sentiment proxy after controlling for macroeconomic factors.

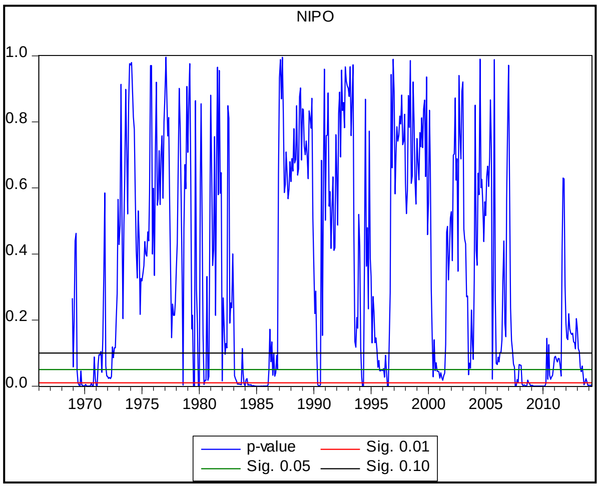
Panel A: Rolling coefficient estimates

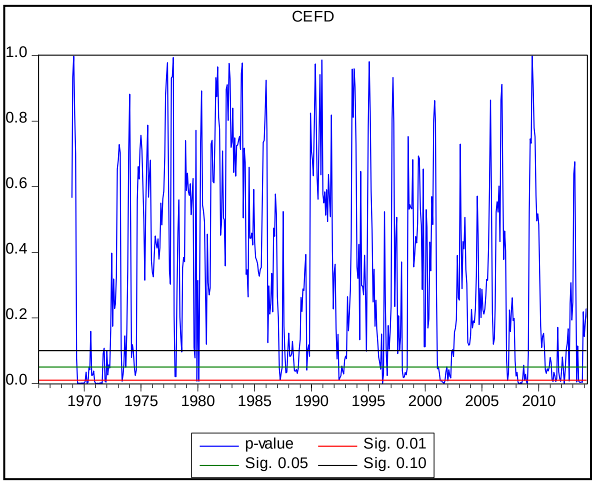


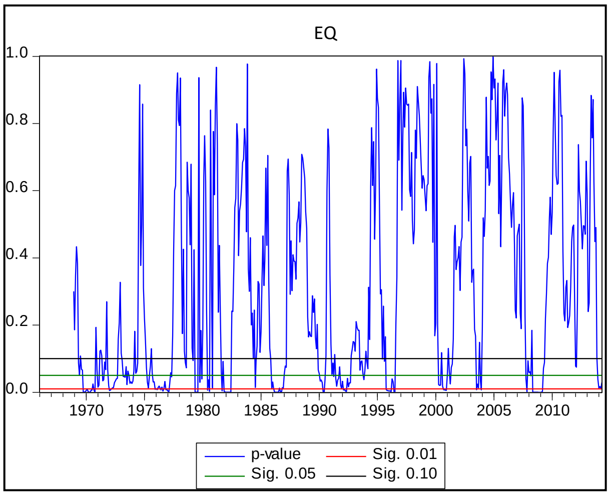
Panel B: Rolling *p*-values



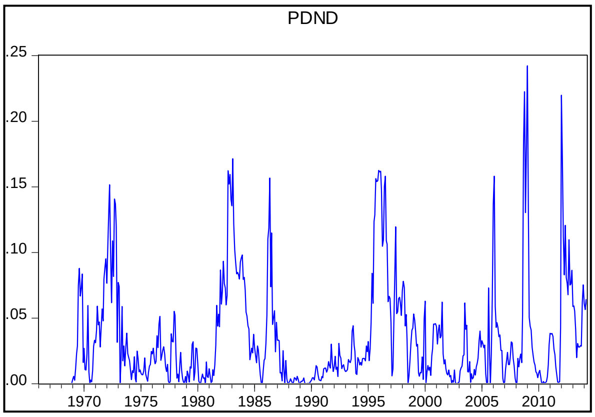


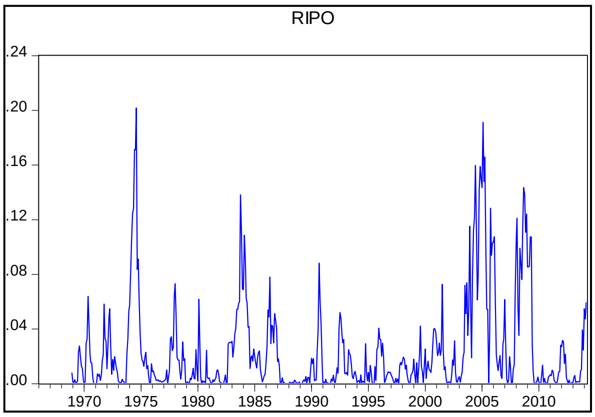


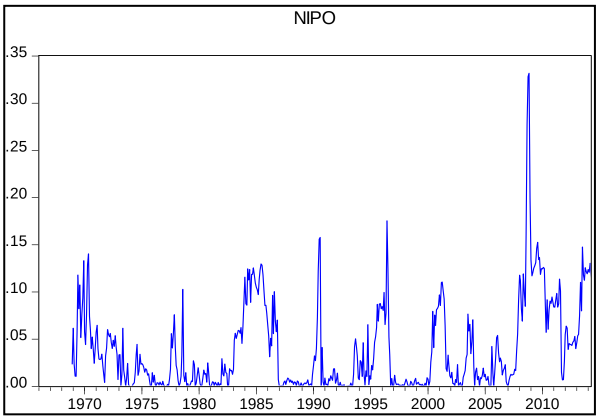


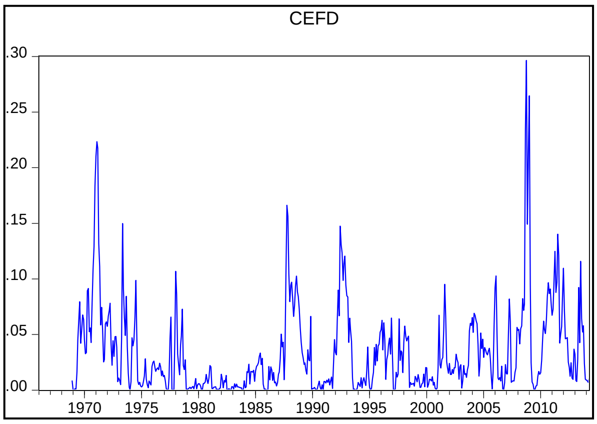


Panel C: Rolling R-squared









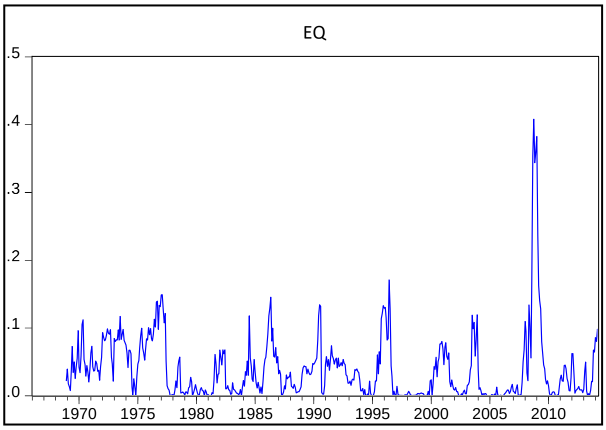


Table A. 1: Predictive performance of S^{TV} computed using different estimation window lengths

	Prediction horizons							
	h = 1	h = 3	h = 6	h = 9	h = 12	h = 24	h = 36	h = 60
1-year S^{TV}								
β (%)	-0.078	-0.093*	-0.011	-0.010	0.004	-0.021	-0.013	0.014
t-statistic	[-0.731]	[-1.341]	[-0.197]	[-0.198]	[0.109]	[-0.549]	[-0.429]	[0.623]
R^2	0.001	0.004	0.000	0.000	0.000	0.001	0.001	0.002
2-year S^{TV}								
β (%)	0.005	0.037	0.056	0.010	-0.043	-0.070**	-0.052**	-0.029*
t-statistic	[0.070]	[0.609]	[1.071]	[0.213]	[-1.142]	[-1.944]	[-1.887]	[-1.366]
R^2	0.000	0.001	0.004	0.000	0.004	0.022	0.021	0.012
3-year S^{TV}								
β (%)	-0.124*	-0.157**	-0.147**	-0.157***	-0.177***	-0.083***	-0.049**	-0.048**
t-statistic	[-1.447]	[-2.177]	[-2.429]	[-3.200]	[-4.254]	[-3.131]	[-1.728]	[-2.275]
R^2	0.004	0.018	0.029	0.049	0.081	0.038	0.022	0.039
4-year S^{TV}								
β (%)	-0.035	-0.024	0.001	-0.004	-0.003	0.015	0.006	0.024
t-statistic	[-0.504]	[-0.425]	[0.015]	[-0.081]	[-0.045]	[0.287]	[0.132]	[0.820]
R^2	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.011
5-year S^{TV}								
β (%)	0.013	0.023	0.011	-0.002	-0.001	0.030	0.010	0.039
t-statistic	[0.218]	[0.361]	[0.159]	[-0.029]	[-0.020]	[0.549]	[0.257]	[1.350]
R^2	0.000	0.001	0.000	0.000	0.000	0.006	0.001	0.035

Notes: This table reports the estimates obtained from equation (3.2) for the time-varying weighted investor sentiment index (S^{TV}) computed using different rolling window lengths across different prediction horizons. The Newey-West (automatic bandwidth selection) t-statistics are shown in brackets. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The sample period covered are 1966:12-2014:12 for 1-year S^{TV}, 1967:12 – 2014:12 for 2-year S^{TV}, 1968:12 – 2014:12 for 3-year S^{TV}, 1969:12 – 2014:12 for 4-year S^{TV}, 1970:12 – 2014:12 for 5-year S^{TV}.

Table A. 2: Predictive performance of S^{TV} after controlling for individual economic predictor

	Prediction horizons							
	h = 1	h = 3	h = 6	h = 9	h = 12	h = 24	h = 36	h = 60
S^{TV}	-0.001*	-0.002**	-0.001***	-0.002***	-0.002***	-0.001***	0.000***	0.000***
	[-1.538]	[-2.087]	[-3.257]	[-3.665]	[-4.049]	[-2.985]	[-1.756]	[-2.219]
DP	0.003***	0.004**	0.004**	0.004*	0.004*	0.005*	0.004*	0.004
	[0.745]	[0.795]	[1.605]	[1.692]	[1.127]	[1.254]	[1.420]	[3.265]
Adj-R^2	0.001	0.018	0.034	0.059	0.097	0.077	0.075	0.157
S^{TV}	-0.001*	-0.002**	-0.001***	-0.002***	-0.002***	-0.001**	0.000**	0.000**
	[-1.530]	[-2.084]	[-3.247]	[-3.383]	[-4.044]	[-2.972]	[-1.736]	[-2.203]
DY	0.004	0.004	0.004*	0.004*	0.004	0.004	0.004*	0.004***
	[0.841]	[0.809]	[1.641]	[1.499]	[1.135]	[1.224]	[1.402]	[3.235]
Adj-R^2	0.002	0.018	0.034	0.059	0.097	0.075	0.073	0.154
S^{TV}	-0.001*	-0.002**	-0.001***	-0.002***	-0.002***	-0.001***	0.000**	0.000**
	[-1.613]	[-2.282]	[-2.452]	[-3.219]	[-4.340]	[-3.178]	[-1.733]	[-2.250]
EP	0.002	0.002	0.002	0.002	0.002	0.001	0.001	0
	[0.370]	[0.336]	[0.319]	[0.464]	[0.566]	[0.360]	[0.376]	[0.089]
Adj-R^2	0.001	0.015	0.027	0.049	0.083	0.037	0.021	0.035
S^{TV}	-0.001*	-0.002**	-0.001**	-0.002***	-0.002***	-0.001***	0.000*	0.000**
	[-1.529]	[-2.060]	[-2.186]	[-4.292]	[-4.258]	[-2.974]	[-1.525]	[-1.710]
DE	0.001	0.003	0.004	0.003	0.003	0.005**	0.005**	0.007***
	[0.198]	[0.506]	[0.735]	[1.192]	[0.799]	[1.855]	[1.861]	[4.636]
Adj-R^2	0.000	0.016	0.030	0.050	0.083	0.071	0.068	0.224
S^{TV}	-0.001*	-0.002**	-0.001**	-0.002***	-0.002***	-0.001***	0.000**	0.000**
	[-1.643]	[-2.207]	[-2.313]	[-3.185]	[-4.488]	[-3.226]	[-1.670]	[-2.294]
SVAR	-1.047***	-0.263	0.109	0.214*	0.192**	0.205**	0.106	0.133*
	[-3.473]	[-0.535]	[0.528]	[1.542]	[1.903]	[2.296]	[1.088]	[1.485]
Adj-R^2	0.013	0.016	0.026	0.049	0.082	0.046	0.023	0.049
S^{TV}	-0.001*	-0.002***	-0.001**	-0.002***	-0.002***	-0.001***	0.000**	0.000**
	[-1.588]	[-3.163]	[-2.292]	[-3.126]	[-4.378]	[-3.130]	[-1.725]	[-2.224]
BM	0.000	0.000	0.001	0.002	0.002	0.000	0.000	0.001
	[-0.031]	[0.089]	[0.221]	[0.258]	[0.259]	[0.076]	[-0.081]	[0.310]
Adj-R^2	0.000	0.014	0.026	0.046	0.079	0.035	0.018	0.038

Table A. 2 (Continued):

	Prediction horizons							
	h = 1	*h* = 3	*h* = 6	*h* = 9	*h* = 12	*h* = 24	*h* = 36	*h* = 60
S^{TV}	-0.001*	-0.002**	-0.001***	-0.002***	-0.002***	-0.001***	0.000*	0.000***
	[-1.569]	[-2.199]	[-2.362]	[-3.289]	[-4.456]	[-3.145]	[-1.624]	[-2.438]
NTIS	-0.056	-0.027	-0.031	-0.036	-0.04	-0.032	-0.02	-0.049
	[-0.383]	[-0.181]	[-0.226]	[-0.296]	[-0.350]	[-0.625]	[-0.444]	[-1.063]
$Adj\text{-}R^2$	0.001	0.015	0.027	0.047	0.081	0.04	0.021	0.068
S^{TV}	-0.001*	-0.001**	-0.001**	-0.002***	-0.002***	-0.001***	0.000*	-0.001**
	[-1.505]	[-2.121]	[-2.284]	[-3.788]	[-4.330]	[-2.930]	[-1.577]	[-2.331]
TBL	-0.076	-0.059	-0.049	-0.042	-0.035	-0.02	-0.013	0.016
	[-1.262]	[-1.000]	[-1.104]	[-1.122]	[-0.909]	[-0.752]	[-0.513]	[0.527]
$Adj\text{-}R^2$	0.003	0.020	0.033	0.053	0.084	0.039	0.021	0.042
S^{TV}	-0.001*	-0.002**	-0.001***	-0.002***	-0.002***	-0.001***	0.000**	0.000***
	[-1.556]	[-2.214]	[-2.353]	[-3.181]	[-4.442]	[-3.104]	[-1.731]	[-2.456]
LTY	-0.052	-0.035	-0.022	-0.004	0.005	0.027	0.047	0.078
	[-0.686]	[-0.453]	[-0.360]	[-0.051]	[0.085]	[0.556]	[1.128]	[2.539]
$Adj\text{-}R^2$	0.001	0.015	0.027	0.045	0.078	0.040	0.042	0.145
S^{TV}	-0.001*	-0.002**	-0.001**	-0.002***	-0.002***	-0.001***	0.000*	0.000**
	[-1.443]	[-2.118]	[-2.229]	[-3.099]	[-4.366]	[-3.075]	[-1.640]	[-2.231]
LTR	0.136***	0.046	0.074***	0.053***	0.042***	0.021**	0.016**	0.013***
	[2.529]	[1.127]	[3.551]	[2.533]	[3.166]	[2.090]	[1.948]	[2.369]
$Adj\text{-}R^2$	0.009	0.017	0.040	0.056	0.086	0.039	0.022	0.041
S^{TV}	-0.001	-0.001**	-0.001**	-0.001***	-0.001***	0.000**	0.000	0.000
	[-1.049]	[-1.729]	[-1.853]	[-2.682]	[-3.943]	[-1.917]	[-0.431]	[-1.047]
TMS	0.221**	0.187*	0.175**	0.193**	0.185**	0.177***	0.186***	0.136**
	[1.709]	[1.541]	[1.748]	[1.896]	[2.267]	[2.688]	[4.137]	[2.197]
$Adj\text{-}R^2$	0.006	0.025	0.044	0.077	0.117	0.109	0.156	0.166
S^{TV}	-0.001*	-0.001**	-0.001**	-0.001***	-0.002***	-0.001***	0.000*	0.000**
	[-1.333]	[-1.965]	[-1.912]	[-2.728]	[-3.851]	[-2.793]	[-1.367]	[-1.690]
DFY	0.384	0.345	0.496*	0.386	0.31	0.214	0.187	0.358**
	[0.609]	[0.662]	[1.298]	[1.067]	[0.943]	[1.061]	[0.798]	[1.906]
$Adj\text{-}R^2$	0.002	0.018	0.039	0.057	0.087	0.045	0.031	0.122

Table A. 2 (Continued):

	Prediction horizons							
	h = 1	*h* = 3	*h* = 6	*h* = 9	*h* = 12	*h* = 24	*h* = 36	*h* = 60
S^{TV}	-0.001*	-0.002**	-0.001**	-0.002***	-0.002***	-0.001***	0.000**	0.000**
	[-1.548]	[-2.167]	[-2.309]	[-3.175]	[-4.426]	[-3.160]	[-1.691]	[-2.268]
DFR	0.208	0.115*	0.084	0.047	0.023	0.007	0.009	0.01
	[1.116]	[1.329]	[1.215]	[1.038]	[0.552]	[0.255]	[0.496]	[0.647]
Adj-R^2	0.005	0.019	0.03	0.047	0.078	0.035	0.018	0.036
S^{TV}	-0.001*	-0.001**	-0.001**	-0.001***	-0.002***	-0.001***	0.000*	0.000**
	[-1.531]	[-2.027]	[-2.053]	[-2.875]	[-4.165]	[-2.760]	[-1.398]	[-1.934]
INFL	-0.139	-0.418	-0.669*	-0.744**	-0.592**	-0.285*	-0.229*	-0.136
	[-0.181]	[-0.843]	[-1.610]	[-1.757]	[-1.727]	[-1.388]	[-1.480]	[-0.807]
Adj-R^2	0.000	0.016	0.038	0.067	0.095	0.043	0.027	0.04
S^{TV}	-0.001*	-0.002**	-0.001**	-0.002***	-0.002***	-0.001***	0.000**	0.000***
	[-1.616]	[-2.188]	[-2.273]	[-3.043]	[-4.493]	[-3.399]	[-1.996]	[-2.708]
CAY	0.017	0.102	0.149**	0.174**	0.190***	0.227***	0.216***	0.159***
	[0.206]	[1.225]	[1.888]	[2.338]	[2.644]	[4.024]	[5.354]	[6.049]
Adj-R^2	0.000	0.020	0.049	0.092	0.151	0.255	0.349	0.365
S^{TV}	-0.001	-0.001*	-0.001**	-0.001***	-0.001***	-0.001**	0.000	0.000
	[-0.994]	[-1.637]	[-1.700]	[-2.356]	[-3.526]	[-1.829]	[-0.616]	[-1.135]
OG	-0.090***	-0.087***	-0.084***	-0.080***	-0.073***	-0.063***	-0.060***	-0.055***
	[-2.964]	[-2.838]	[-2.786]	[-3.083]	[-2.709]	[-3.135]	[-4.618]	[-6.790]
Adj-R^2	0.017	0.058	0.102	0.147	0.189	0.213	0.285	0.429
S^{TV}	-0.001*	-0.002**	-0.001***	-0.001***	-0.002***	-0.001***	0.000*	0.000**
	[-1.510]	[-2.137]	[-2.372]	[-4.244]	[-4.178]	[-2.920]	[-1.361]	[-2.241]
SCR	-0.002	-0.002	-0.002*	-0.003***	-0.003***	-0.003***	-0.002***	-0.003***
	[-1.034]	[-1.176]	[-1.611]	[-3.331]	[-2.694]	[-3.056]	[-3.587]	[-5.318]
Adj-R^2	0.003	0.023	0.043	0.073	0.115	0.111	0.122	0.206

Notes: This table reports the parameter estimates for the time-varying weighted investor sentiment index (S^{TV}) and individual economic predictor as described in Section 4.3 across different prediction horizons. The Newey-West (automatic bandwidth selection) *t*-statistics are shown in brackets. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. *Adj*-R^2 denotes the adjusted R^2 statistic. The sample period ranges from December 1968 to December 2014, except for VIX which starts from January 1990.

Chapter 4. The Relative Importance of Investor Sentiment to the Stock Market Movements

4.1 Introduction

As early as 1980s, it was acknowledged that either the rational pricing model, which involves time-varying risk, or the noise trader model (Fama and French, 1988a; Poterba and Summer, 1988), can be used to explain the phenomenon of negative autocorrelation in stock returns for horizons of more than a year. Poterba and Summer (1988) distinguish these two competing explanations and conclude that the patterns of stock returns lean towards the noise traders view. Although noise traders model provides potential explanation, they further suggested that future work examine whether the mean-reverting behaviour of stock prices is better explained by either one of these models "require information other than stock returns, such as data on fundamental values, proxies for noise trading …"[47]. Contributing to this vein of research, this chapter evaluates the relative importance of the investor sentiment versus a set of fundamental factors to the stock market fluctuations through their forecasting performance on the stock market returns.

The time-series predictability of stock market returns has been of long-standing interest in the finance literature. Voluminous return predictors have been proposed to forecast the stock market returns over the last three decades[48]. Proponents of fundamental predictors argued that stock market returns, which are inversely related to the business cycle, are predictable by variables that capture the business cycle risk, for instance dividend yields, earnings yields, and term yield spread (e.g. Cochrane, 1991; Fama and French, 1989; Pesaran and Timmermann, 1995). Besides these, variables that reflect the time-varying risk aversion and the level of consumption, such as the consumption-wealth ratio (Lettau and Ludvigson, 2001a) and the surplus consumption ratio (Campbell and Cochrane, 1999) are suggested in the literature as good return predictors. Compared to in-sample analysis, the out-of-sample forecasting performance of economic predictors is arguably considerable poorer (see, for example, Rapach et al., 2016; Lettau and van Nieuwerburgh, 2008; Welch and Goyal, 2008). On the other hand, the behavioural view, as discussed in the previous chapter, advocates that

[47] The demands from noise traders are affected by investor sentiment (refer to Chapter 2 for a review) and the proxies for noise trading suggested by Poterba and Summer (1988) have been employed as the measures of investor sentiment in other studies.

[48] The detailed reviews of return predictors are given in Section 2.3 and 2.4.

the predictability of the stock market returns stems from investor sentiment (e.g. Brown and Cliff, 2005; Schmeling, 2009; Huang et al., 2015). Whilst most literature sits into these two distinct groups, the question of whether one dominates the other, or whether both fundamentals and sentiment complement each other in predicting the stock market returns of different horizons, is still largely unanswered.

Accordingly, this chapter considers the return predictors from both streams of research in forecasting stock market returns – fundamental and behavioural. As Chapter 3 clearly demonstrated, the newly constructed investor sentiment index, S^{TV}, predicts significantly the future stock market returns. This chapter aims to answer: (1) Is S^{TV} able to forecast future stock market returns in the out-of-sample context? (2) Are economic predictors able to forecast future stock market returns in the out-of-sample context? (3) Whether investor sentiment or economic predictors exert greater influence in the stock market? If investor sentiment plays a more important role in the stock market movement, S^{TV} is expected to outperform its fundamental counterparts in predicting stock market returns.

The empirical investigation starts by comparing the predictive performance of S^{TV} with other sentiment measures in the out-of-sample context to further ascertain whether S^{TV} is indeed an investor sentiment measure that predicts superior out-of-sample stock market returns better than its competitor sentiment indexes. The superior performance of S^{TV} confirms that it can be used as a benchmark sentiment proxy in our subsequent analysis. A battery of out-of-sample forecasting tests is performed to compare the forecasting performances of S^{TV} and 17 well-known economic predictors employed by Welch and Goyal (2008) and Huang et al. (2015)[49]. Finally, as a different way of assessing the relative importance of investor sentiment, the economic value of the return forecasts produced by S^{TV} and other return predictors are also evaluated.

To preview the main results, this chapter finds that the out-of-sample results support the in-sample findings of Chapter 3 that the S^{TV} is a good sentiment measure since the forecast encompassing test reveals that S^{TV} encompasses other disparate sentiment measures in forecasting the excess market returns. Albeit most of the economic predictors are unable to beat the historical mean model (HMM), S^{TV} forecasting performance against HMM is encouraging. Furthermore, forecast encompassing tests reveal that S^{TV} possesses unique

[49] As discussed in Section 2.4, the issues associated with the out-of-sample forecasting are well acknowledged in this study and necessary precautions are taken to guard against the potential bias.

information for forecasting future market returns over an assorted of economic predictors. The enhanced investor sentiment index is also found to deliver real economic benefits, in terms of certainty equivalent return (CER) gains and Sharpe ratios, to an investor who holds an optimal mean-variance portfolio, especially for higher level of investor risk aversion. At the same time, it delivers consistent and higher CER gain rankings relative to its competitors. All these results imply that investor sentiment, from both statistical and economic perspective, has a stronger influence on the stock market returns as compared to economic predictors.

This study complements existing literature on stock market returns predictability by presenting a more comprehensive comparison on the out-of-sample predictive performance of investor sentiment against fundamental predictors based on a consistent methodological approach. Such comparison permits a robust conclusion on the relative importance of a particular type of predictor being the main driving force of the stock market movements. Therefore, this study is of high relevance to the debate between behaviourists and rationalists.

The most closely related works are Huang et al. (2015) and Kadilli (2015). Kadilli considered the effects of both investor sentiment and economic predictors on annual stock returns of financial companies. However, their analysis is more limited compared to this study, as their results are derived from an in-sample analysis using only the consumer confidence indicators. As we show, for a more complete picture of the role of sentiment, an out-of-sample analysis should be considered in addition to any in-sample analysis. Furthermore, as we have shown in Chapter 3, the CCI is an inferior sentiment measure compared to our own sentiment index.

Moreover, to the best of our knowledge, most studies in behavioural finance have focused solely on the predictive power of investor sentiment on future stock market return over the entire sample as if market participants had perfect foresight, which is unrealistic. Studies that are an exception to this can be found in Chung et al. (2012) and Huang et al. (2015). Nevertheless, their forecasting exercises do not emphasize long-horizon forecasts. The correction from mispricing caused by sentiment takes a longer period of time to correct and a vast literature has documented an enhanced long-horizon return predictability by economic predictors (see, for example, Campbell and Shiller, 1998; Fama and French, 1988a, 1988b; Patelis, 1997; Poterba and Summers, 1988; Rapach and Wohar, 2005). Therefore, it is of relevance to compare and contrast the predictive performance of investor sentiment against economic predictors in the longer horizon prediction.

The rest of this chapter is organised as follows: Section 4.2 presents the methodology used in the out-of-sample forecasting, followed by data descriptions in Section 4.3. Section 4.4 presents the out-of-sample forecasting performances of S^{TV} against its competitors. Section 4.5 reports the robustness check and some extension analyses. Section 4.6 concludes.

4.2 Methodology

4.2.1 Generating out-of-sample return forecasts

The out-of-sample analysis reveals the genuine return predictability by different return predictors, providing a solid conclusion on the relative importance of a particular predictor to stock market fluctuations. To perform the rolling regression forecasts, a fixed window length of 15 years, following Henkel, Martin and Nardari (2011)[50], is used. The first estimation period used to generate the first return forecast for December 1983 is December 1968 to November 1983[51]. The estimation window is then rolled over by one month to obtain next forecast for January 1984, and so forth. The sample of forecasts from December 1983 to December 2014 is retained for forecast evaluations.

Although the standard regression model as stated in equation (3.2) can be estimated using OLS, it suffers from size distortions when predictors are persistent and endogenous as discussed in Section 2.4. Besides that, the heteroscedasticity of return innovations violates the best linear unbiased estimator (BLUE) property of OLS. To ensure that the out-of-sample results are reliable, this study employs the Feasible Generalised Least Square (FGLS) framework introduced by Westerlund and Narayan (2012), which is an extension to the estimator proposed by Lewellen (2004). First, the regression in equation (3.2) is modified to account for persistent and endogeneous predictors as follow:

$$R_{m,t+h} = \theta + \beta_{adj} x_t + \gamma(x_{t+h} - \rho_0 x_{t+h-1}) + \eta_{t+h} \tag{4.1}$$

[50] They found that 15 years of monthly observations (i.e. 180 months) is required to produce reliable estimation for the US stock market.

[51] The in-sample estimation of the first window starts from December 1968 since the observations of S^{TV} from January 1966 to December 1968 are constructed based on the constant loading assigned to each sentiment component.

where $\theta = \alpha - \gamma\mu(1-\rho)$, $\beta_{adj} = \beta - \gamma(\rho - \rho_0)$ is the bias-adjusted parameter estimate, x_t and x_{t+h} are the individual predictor at time *t* and *t+h*, respectively, and ρ_0 = 1[52]. All data are weighted by $1/\sigma_{\eta_t}$, where the estimator of the variance of errors, $\hat{\sigma}^2_{\eta_t}$, is defined as the fitted value of the regression that regresses estimated squared innovation, $\hat{\eta}_t^2$, on a constant and its lagged values, in order to account for the autoregressive conditional heteroskedasticity (ARCH) structure of return innovations. Using the parameter estimates, $\hat{\theta}$ and $\hat{\beta}_{adj}$, obtained from equation (4.1), the forecast of *h*-step-ahead excess market return is computed as follow:

$$R_{m,t+h} = \hat{\theta} + \hat{\beta}_{adj} x_t \tag{4.2}$$

The whole procedure is conducted on a moving window of 15 years with the step size of one month. The out-of-sample forecasts for all investor sentiment indexes and economic predictors are generated using the same approach. Note that for S^{BW}, this study re-estimates the index based on the information in the past 15 years when new forecast of excess market return is to be computed in each window, so avoiding look-ahead bias[53].

Given the relatively large number of economic predictors used in this study, we also consider the diffusion index of economic predictors[54]. Specifically, PCA is employed to extract the common factor of economic predictors in every estimation window, the first principle component of these economic factors is being labelled PC-ECON henceforth. The use of diffusion index does not only avoid the over-parameterization issue, but has been found to perform better empirically than individual components (e.g. Rapach et al., 2010; Neely et al., 2014). Comparing the forecasting performance of S^{TV} with PC-ECON in this way therefore gives us an extra layer of robustness to the results.

4.2.2 Out-of-sample evaluation tests

Three popular out-of-sample evaluation tests are used in this study, namely: Campbell and Thomson (2008) out-of-sample *R*-squared statistic (R^2_{OS}), Clark and West (2007) adjusted

[52] Refer to Westerlund and Narayan (2012, pp. 2633) for the rationale of setting $\rho_0 = 1$.

[53] The sentiment proxies of S^{BW} in each in-sample estimation window (i.e. 15 years) are assigned with constant loadings.

[54] This study does not consider the kitchen sink regression in the out-of-sample forecast as it has been shown to perform poorly in the out-of-sample analysis (see Welch and Goyal, 2008; Rapach, Strauss and Zhou, 2010).

mean squared forecast error (*MSFE-adjusted*) statistic, and Harvey, Leybourne and Newbold (1998) forecast encompassing test (ENC). To compute the R_{OS}^2 and the *MSFE-adjusted* statistics, the historical mean model (HMM)[55] has been used as a benchmark model. For the ENC, the forecasting performance of S^{TV} against other predictors is of interest. Therefore, the forecast performances evaluated based on R_{OS}^2 and *MSFE-adjusted* statistics present results for the nested models; the evaluation based on ENC shows the forecast performance of non-nested models[56]. The description of each test is provided below.

(I) Out-of-sample R² (R_{OS}^2)

The R_{OS}^2 measures the forecast accuracy of predictive regression model relative to that of HMM in the out-of-sample periods based on the following equation.

$$R_{OS}^2 = 1 - \frac{\sum_{t=p}^{T-h}\left(R_{m,t+h} - \hat{R}_{m,t+h}\right)^2}{\sum_{t=p}^{T-h}\left(R_{m,t+h} - \bar{R}_{m,t+h}\right)^2} \tag{4.3}$$

where R_{t+h}^m is the h-month-ahead realized excess market return, $\hat{R}_{m,t+h}$ and $\bar{R}_{m,t+h}$ denote the h-month-ahead forecast of excess market return produced by predictive regression model and HMM, respectively. A predictive regression model is said to beat the historical mean forecast if $R_{OS}^2 > 0$. However, an unrestricted model (i.e. predictive regression model) could produce a greater *MSFE* as compared to HMM simply due to its additional slope parameter, which generates a noisier forecast, leading to a negative R_{OS}^2. Therefore, another test – *MSFE-adjusted* – is used in conjunction with the R_{OS}^2 in comparing the forecasting performance between a predictive regression model and the HMM.

[55] HMM is the historical average return computed on a rolling window basis for every time point *t*.

[56] Nested models are two different forecasting models with the larger model can be easily reduced to the parsimonious model in the null hypothesis by constraining the additional parameter associated with the larger model to be zero. Hence, two models are said to be nested when the forecast of any predictor ($R_{m,t+h} = \alpha + \beta_{adj} x_t + \varepsilon_t$) considered in this study is compared to the forecast of historical mean ($R_{m,t+h} = \alpha + \varepsilon_t$). In contrast, non-nested models are two different competing models with neither of them can be transformed into one another, for example, S^{TV} forecast against S^{BW} forecast. The forecast encompassing test introduced by Harvey et al. (1998) is originated from the idea that each individual forecast should contribute optimally to the combined forecast when combining forecasts produced by different predictors. A particular forecast is said to encompass its competitor if that forecast received entire weight in the forecast combination.

(II) MSFE-adjusted statistic

The *MSFE-adjusted* statistic determines if the HMM has a significantly lower *MSFE* against the predictive regression model (i.e. unrestricted model) under the null hypothesis ($H_0 : MSFE_{HMM} \leq MSFE_{PR}$ against $H_1 : MSFE_{HMM} > MSFE_{PR}$). According to Clark and West (2007), forecasts produced by unrestricted model are contaminated by noise since the additional slope parameter in the model has a non-zero value, which is different from the zero population value under the null, and thus, inflating the forecast error of unrestricted model. To ensure the fairness in forecast comparison, Clark and West (2007) adjust the *MSFE* statistic to accommodate for this bias in unrestricted model under the null. Hence, one can reject the null hypothesis that HMM has a better forecast even though R^2_{OS} is negative (Huang et al., 2015; Neely et al., 2014). This test can be easily performed by regressing $\hat{f}_{t+h}$ on a constant term (*α*), where $\hat{f}_{t+h}$ is computed as follow.

$$\hat{f}_{t+h} = \left(R_{m,t+h} - \bar{R}_{m,t+h}\right)^2 - \left[\left(R_{m,t+h} - \hat{R}_{m,t+h}\right)^2 - \left(\bar{R}_{m,t+h} - \hat{R}_{m,t+h}\right)^2\right] \tag{4.4}$$

The null hypothesis is rejected when the constant term, *α*, is significantly greater than zero having accommodate for the autocorrelation of the standard error in the long-horizon forecasts using the Newey-West estimator.

(III) Forecast encompassing test (ENC)

Unlike previous tests, which compare the forecasting performance of each predictor to that of the benchmark model (HMM), the forecast encompassing test focuses on the difference in information content between individual predictors in the forecast combination, $\hat{R}_{c,t+h}$, which can be expressed as follow:

$$\hat{R}_{c,t+h} = (1-\lambda)\hat{R}_{1,t+h} + \lambda\hat{R}_{2,t+h} \ , \qquad 0 \leq \lambda \leq 1 \tag{4.5}$$

where $\hat{R}_{1,t+h}$ is a given forecast, $\hat{R}_{2,t+h}$ denotes the competing forecast and λ represents the optimal weight associated with the competing forecast. ENC tests the null hypothesis that the given forecast encompasses the competing forecast ($\lambda = 0$). Alternatively, the competing forecast does provide useful information to the combined forecast that is not already embodied in the given forecast if $\lambda > 0$. The usual *t*-statistic leads to over rejection of the null hypothesis due to autocorrelation and conditional heteroscedasticity features in the errors of combined forecast. Therefore, Harvey et al. (1998) propose the following modified Diebold-Mariano (*MDM*) test statistic for long-horizon forecast evaluation:

$$DM = \frac{\sqrt{n}\bar{d}}{n^{-1}\sum_{\tau=-(h-1)}^{h-1}\sum_{t=|\tau+1|}^{n}(d_t-\bar{d})(d_{t-|\tau|}-\bar{d})} \quad , \quad d_t = (e_{1t}-e_{2t})e_{1t}$$

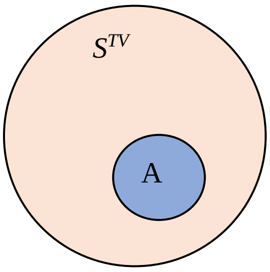
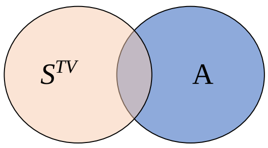
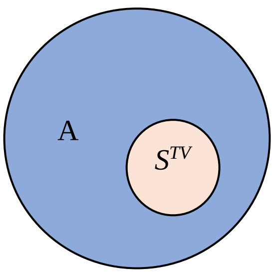
$$MDM = DM\left[\frac{n+1-2h+n^{-1}h(h-1)}{n}\right]^{1/2} \tag{4.6}$$

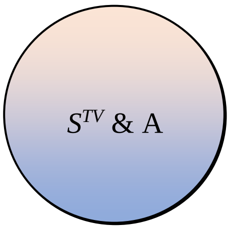
where e_{1t} and e_{2t} are forecast errors of given forecast and competing forecast, respectively, at time *t*, *h* denotes the forecast horizon, and *n* is the number of observations. The null hypothesis that a given forecast encompasses competing forecast is rejected if the *MDM* test statistic is greater than the critical value of the one-sided t_{n-1} distribution.

When applying encompassing tests in the context of this research, there is no a priori reason as to which forecast (from S^{TV} or the competing predictor) should be treated as a *given* forecast or a *competing* forecast. The possible outcomes based on the results from two different tests performed in both directions are illustrated in the Figure 4.1.

Figure 4.1 illustrates that there are four different possible outcomes which could be obtained by combining the results from test 1 and test 2. The forecast of S^{TV} is treated as the given forecast in test 1 and as the competing forecast in test 2. Outcome 1 indicates that S^{TV} forecast encompasses the forecast retrieved from alternative predictor (A). It is obtained when the weight of competing forecast, i.e. λ in equation (4.5), is not significantly different from zero ($\lambda = 0$) in test 1 and the weight of S^{TV} forecast in test 2 is significantly greater than zero ($\lambda > 0$). Outcome 3 is observed when the *MDM* statistic reveals the opposite findings in both tests. Meanwhile, outcome 2 implies that both predictors could provide complementary information to forecast combination when both tests produce lambda that is significantly greater than zero. That is, both given and competing forecasts have additional information that is useful in predicting stock market returns. On the other hand, when both tests generate insignificant lambda as shown by outcome 4, it means that two forecasts encompass each other (i.e. encompassing observed in both directions) and the information content of both forecasts are redundant. Therefore, outcome 1 and 2 are in line with the hypothesis that the forecast based on S^{TV} captures unique information that is not already incorporated in the forecast by alternative predictor (the S^{TV} forecast dominates: it encompasses, but is not encompassed by, the alternative predictor's forecast corresponding to outcome 1). Outcome 3 implies that forecasts by alternative predictor dominate those forecasts produced by S^{TV}, and outcome 4 suggests that the forecast based on S^{TV} is neither dominated by nor dominant over the alternative predictor's forecast.

Figure 4.1: Outcomes of forecast encompassing tests

No	Outcome	Explanation	Test 1 (S^{TV} is the given forecast)	Test 2 (S^{TV} is the competing forecast)
1		S^{TV} forecast encompasses alternative forecast (A) S^{TV} forecast outperforms alternative forecast and alternative forecast does not contain useful information in forecasting future stock market returns. All relevant information in alternative forecast is contained in S^{TV} forecast.	$\lambda = 0$	$\lambda > 0$
2		Neither forecast encompasses the other one. Both forecasts embody incremental information while sharing some common information. Hence, both forecasts provide (partially) complementary information in forecasting future stock market returns.	$\lambda > 0$	$\lambda > 0$
3		Alternative forecast (A) encompasses S^{TV} forecast. Alternative forecast dominates S^{TV} forecast and hence S^{TV} forecast does not contain useful incremental information in forecasting future stock market returns. All relevant information in S^{TV} forecast is contained in alternative forecast.	$\lambda > 0$	$\lambda = 0$

No	Outcome	Explanation	Test 1 (S^{TV} is the given forecast)	Test 2 (S^{TV} is the competing forecast)
4		Two forecasts encompass each other. Both predictors produce forecasts that are of equal accuracy. They have identical predictive ability, in which the information contained in both forecasts is identical. Therefore, neither forecast contains unique information for forecasting future stock market returns (Wang and Bessler, 2004).	λ = 0	λ = 0

Notes:

Alternative forecast (A) S^{TV}–based forecast

λ denotes the optimal weight associated with the competing forecast in the following forecast combination:

$$\hat{R}_{c,t+h} = (1-\lambda)\hat{R}_{1,t+h} + \lambda\hat{R}_{2,t+h}$$

S^{TV} forecast is treated as the given forecast, $\hat{R}_{1,t+h}$, in the first test and as competing forecast, $\hat{R}_{2,t+h}$, in the second test.

4.2.3 Certainty equivalent return (CER) and Sharpe ratio

Contrary to previous statistical evaluation methods, economic significance measure takes into account the risk faced by an investor, which makes it more relevant in the real world. In line with the literature, the certainty equivalent return (CER), which is the certain return an investor will receive on an investment that generates the same expected utility as a risky portfolio with uncertain returns (see Campbell and Thompson, 2008; Cenesizoglu and Timmermann, 2012; Huang et al., 2015; Marquering and Verbeek, 2004; Rapach et al., 2010; Rapach et al., 2016), is employed.

Assuming a mean-variance investor who holds a portfolio consisting of equities and risk-free assets, one can determine the optimal equity allocation (ω_t^*) based on the forecast of excess market return ($\hat{R}_{m,t+h}$)[57] produced by a given predictor at the end of month t:

[57] Compounding return is used for the asset allocation exercise. For this exercise, the out-of-sample spans from January 1985 to December 2014 in order to ensure that the total out-of-sample period is evenly divided by the portfolio rebalanced frequency across different forecast horizons. This out-of-sample period is also used in Huang et al. (2015).

$$\omega_t^* = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{R}_{m,t+h}}{\hat{\sigma}_{t+h}^2}\right) \tag{4.7}$$

where γ is the risk-aversion coefficient and $\hat{\sigma}_{t+h}^2$ is the forecasted variance of excess market return computed using ten-year moving window of past excess market return (see Rapach et al., 2016). Following the literature, a constraint on ω_t^* values to be between 0 and 1.5 is imposed based on the assumptions of no short sales and leverage of no more than 50%. The CER is defined as the average utility of the portfolio over the forecasting period:

$$CER = \bar{R}_p - \frac{\gamma}{2}\sigma_p^2 \tag{4.8}$$

where $\bar{R}_p$ is the average portfolio return and σ_p^2 is the portfolio variance. The CER gain is the difference in CER between a predictive regression using a specific predictor variable and HMM forecasts, and is expressed as an annualized term, representing the annual portfolio management fees an investor would be willing to pay to receive the information contained in the predictive regression forecast (rather than relying on HMM forecasts). The portfolio rebalancing frequency is similar to the forecast horizon. The Sharpe ratio, which is computed as excess market returns over the risk, is employed as a second measure of economic performance.

4.3 Data and descriptive statistics

Since the data description of investor sentiment indexes have been given in Section 3.2.1, this section provides the descriptions of 17 economic predictors, which can be categorised into financial indicators, business-cycle indicators and macroeconomic indicators. The data for financial and business-cycle indicators are retrieved from the website of Amit Goyal. The brief description for each economic predictor, as stated in Welch and Goyal (2008), are given below. The detailed description of each predictor is provided on their website.

4.3.1 Financial indicators

a) Dividend-price ratio (DP): computed as log of dividends minus log of prices.
b) Dividend yield (DY): computed as log of dividends minus log of lagged prices.
c) Earnings-price ratio (EP): calculated by subtracting log of prices from log of earnings.

d) Dividend-payout ratio (DE): computed as the log of the ratio of dividends to earnings.

e) Stock return variance (SVAR): calculated as the total of squared daily returns on the S&P 500 index in a month.

f) Book-to-market ratio (BM): calculated as the ratio of book value to market value for the Dow Jones Industrial Average.

g) Net equity expansion (NTIS): defined as the ratio of 12-month moving sums of net issues by NYSE-listed stocks to total market capitalization of NYSE stocks.

4.3.2 Business-cycle indicators

a) Treasury bill rate (TBL): three-month Treasury bill rate in the secondary market.

b) Long-term yield (LTY): yields on long-term government bond.

c) Long-term return (LTR): returns on long-term government bonds.

d) Term yield spread (TMS): defined as the deviation between LTY and TBL.

e) Default yield spread (DFY): computed by deducting the yields of AAA-rated corporate bond from BAA-rated corporate bond.

f) Default return spread (DFR): defined as the deviation between long-term corporate bond returns and long-term government bond returns.

g) Inflation (INFL): lagged two months inflation is used to take into consideration of the delay in Consumer Price Index (CPI) releases.

4.3.3 Macroeconomic indicators

a) Consumption-wealth ratio (CAY): The quarterly data is retrieved from Martin Lettau's webpage[58]. To obtain the monthly data, 'missing values' between two quarters are filled with the data from the most recent quarter until the next quarter's data becomes available.

b) Output gap (OG): residuals (ε_t) from regression that regress the log of industrial production[59] (y_t) on a linear time trend (t) and a quadratic trend (t^2)[60]. (Cooper and Priestley, 2009). Since the data reported is delayed by a month, this study employs lagged two months OG in the return predictive regression following Cooper and Priestley (2009).

[58] http://faculty.haas.berkeley.edu/lettau/data_cay.html

[59] The data of total seasonally adjusted Industrial Production index is obtained from the Federal Reserve.

[60] The OG measure computed in this study is the primary measure used in Cooper and Priestley (2009). They demonstrated that the results are not affected with the use of other measures.

$$y_t = \alpha + \beta.t + \phi.t^2 + \varepsilon_t \tag{4.9}$$

c) Log surplus consumption ratio (SCR): estimated with nondurable and service consumption data following Campbell and Cochrane (1999). The consumption data employed here is the monthly seasonally adjusted real per capita consumption expenditures on nondurable goods and services[61]. s_t is used to represent log surplus consumption ratio[62] in the following equations:

$$s_{t+1} = (1-\varphi)\bar{s} + \varphi s_t + \lambda(s_t)(\Delta c_{t+1} - g)\ , \quad 0<\varphi<1 \tag{4.10}$$

where φ is the habit persistence parameter being set at 0.92 following Tallarini and Zhang (2005)[63], $\bar{s}$ is the steady-state of log $\bar{S}$, $\lambda(s_t)$ is the sensitivity function, and Δc_t is the consumption growth governed by the following process:

$$\Delta c_{t+1} = g + v_{t+1} \tag{4.11}$$

where g denotes the average consumption growth rate. The sensitivity function, $\lambda(s_t)$, is defined as:

$$\begin{aligned} \lambda(s_t) &= \begin{cases} \dfrac{1}{\bar{S}}\sqrt{1-2(s_t-\bar{s})} - 1\ , & s_t \le s_{\max} \\ 0 \qquad\qquad\qquad\qquad\ , & s_t \ge s_{\max}\ , \end{cases} \\ \text{where } \bar{s} &= \log \bar{S} = \log\left(\sigma\sqrt{\frac{\gamma}{1-\varphi}}\right), \\ s_{\max} &= \log(S_{\max}) = \left(\bar{s} + \frac{1}{2}(1-\bar{S}^2)\right) \end{aligned} \tag{4.12}$$

σ is the standard deviation of the consumption growth and the curvature of utility function, γ, is being set at 2 (see Campbell and Cochrane, 1999; Li, 2001).

[61] The nominal consumption expenditures and price indexes for consumption are retrieved from the National Income and Product Accounts published by the U.S. Bureau of Economic Analysis (BEA). The US resident population data is available on Federal Reserve Economic Data (FRED).

[62] Lowercase letters represent variables that expressed in logarithms and uppercase letters are used for variables at original scale thereafter.

[63] The habit persistence parameter measures the adjustment speed of habit to previous consumption and it is found to approach unity. Other acceptable persistence parameters are 0.80, 0.90, 0.95, 0.99 (see Li, 2001; 2005; Li and Zhong, 2005), and previous studies generally found that their results are robust to different ρ.

4.3.4 Descriptive statistics of data

Table 4.1 presents the descriptive statistics for economic predictors described in previous sub-sections. Most of the economic predictors have positive mean value, except a few financial indicators, SCR and CAY. Besides that, most economic predictors have a first-order autocorrelation of close to unity, indicating that economic predictors are highly persistence. The persistent feature of return predictors justifies the use of FGLS framework in generating the return forecasts.

Table 4.1: Descriptive statistics of economic predictors

	Mean	*SD*	Skewness	Kurtosis	*Min*	*Max*	*ρ(1)*
DP	-3.592	0.418	-0.197	2.109	-4.524	-2.753	0.994
DY	-3.586	0.418	-0.202	2.135	-4.531	-2.751	0.994
EP	-2.819	0.456	-0.794	5.629	-4.837	-1.899	0.989
DE	-0.773	0.327	2.921	18.066	-1.244	1.380	0.985
SVAR	0.002	0.005	9.821	125.703	0.000	0.071	0.467
BM	0.506	0.274	0.688	2.411	0.121	1.207	0.994
NTIS	0.011	0.020	-0.747	3.686	-0.058	0.051	0.979
TBL	0.051	0.032	0.527	3.726	0.000	0.163	0.988
LTY	0.070	0.026	0.664	3.207	0.021	0.148	0.989
LTR	0.007	0.031	0.384	5.317	-0.112	0.152	0.034
TMS	0.019	0.015	-0.456	2.757	-0.037	0.046	0.953
DFY	0.011	0.005	1.778	7.125	0.003	0.034	0.962
DFR	0.000	0.015	-0.409	9.318	-0.098	0.074	-0.077
INFL	0.003	0.003	0.136	7.504	-0.018	0.018	0.618
OG	0.000	0.062	0.131	2.073	-0.139	0.139	0.993
SCR	-4.373	1.033	-2.160	7.621	-9.119	-3.511	0.981
CAY	-0.002	0.020	-0.208	2.204	-0.047	0.044	0.968

Notes: *SD* denotes standard deviation, *Min* is the minimum value, *Max* is the maximum value and *ρ(1)* is the first-order autocorrelation. The description of each economic predictor variable is given in the text. The sample period spans for 588 months, from January 1966 until December 2014.

4.4 Empirical results

This section is split into three sub-sections. The first sub-section evaluates the out-of-sample (OOS) forecast performance of S^{TV} in order to answer the first research question. The forecasting performance of S^{TV} is compared to that of other sentiment measures, providing further support to the claim that S^{TV} is indeed a superior sentiment measure that forecasts future stock market returns better than other sentiment measures. To answer the main research question of this chapter – whether investor sentiment or economic predictors play(s) a greater role in the stock market fluctuation, the second sub-section provides statistical proof on the out-of-sample forecasting performance of S^{TV} against other economic predictors. Later on, the economic value generated by different predictors is assessed to provide further support to the main findings of this chapter.

4.4.1 The OOS predictive performance of S^{TV} versus other sentiment indexes

Given that S^{TV} outperforms competing variables in capturing the latent investor sentiment, and assuming that sentiment systematically affects stock prices, we would expect S^{TV} to have significant forecasting power for future stock returns, and to outperform other sentiment proxies in this respect. Table 4.2 presents the out-of-sample forecasting performance of investor sentiment measures based on R^2_{OS} and *MSFE-adjusted* statistics as described in Section 4.2.2. The former statistic tells us of the extent that *MSFE* of a predictive regression model is reduced as compared to HMM, and the latter statistic helps to gauge the statistical significance of results, informing us if the predictive regression model has a forecast error that is statistically lower than that generated by the HMM after adjusting for the noise in predictive model. The null hypothesis of *MSFE-adjusted* statistic (i.e. *MSFE* generated by HMM is less than or equal to that of predictive regression model) can still be rejected even though R^2_{OS} is negative due to the negative bias associated with the predictive regression model (see Huang et al., 2015; Neely et al., 2014; Rapach and Zhou, 2013). Thus, the inference is based largely on the results of *MSFE-adjusted* test.

The results reported in Table 4.2 show that the *MSFE-adjusted* statistic for S^{TV}-generated forecasts is statistically significant at 5% level for 3-month forecasts, suggesting that S^{TV} has statistically superior out-of-sample forecasting power as compared to HMM at the 3-month forecast horizon. In addition, S^{TV} consistently beats the benchmark model from 9-months until 24-months forecast horizon as the R^2_{OS} is significantly greater than zero. These results indicate that S^{TV} has strong predictive power for the future stock market returns even in the out-of-sample context.

On the other hand, Table 4.2 also shows that S^{BW} generates negative R^2_{OS} values and insignificant negative *MSFE-adjusted* statistics, across most forecast horizons, except for positive R^2_{OS} values for next month forecasts. Nevertheless, its forecast error is not significantly lower than that of HMM at 1-month horizon. These results suggest that S^{BW} fails to outperform HMM since it produces greater forecast error across most forecast horizons. Overall, for both in-sample and out-of-sample result, the original S^{BW} index has been shown to have poor predictive power for excess market returns, whereas the time-varying modification of the original BW approach proposed in Chapter 3 improves its forecasting power considerably.

Consistent with Huang et al. (2015), S^{PLS} has a strong predictive power over short horizons. The null hypothesis of the *MSFE-adjusted* test is strongly rejected at 1% significance level for 1- and 3-month forecast horizons. It also generates the highest R^2_{OS} values for 1- and 3-month predictions (i.e., 2% and 5.77%, respectively) among all predictive regression models. This superior performance, however, does not last beyond 6-month forecast horizon. Indeed, the inferior forecast performance exacerbates for longer forecast horizons, with R^2_{OS} value of more than -30% and has the worst 5-year forecast performance, with R^2_{OS} of about -44%, among all investor sentiment indexes. Thus, unlike the S^{TV} index, S^{PLS} does not seem to produce consistent out-of-sample statistical benefits across both shorter and longer forecast horizons.

The results show that MS does not outperform HMM in any forecast horizon, likewise for the CCI, except for 36-month and 60-month horizons, at which the R^2_{OS} values are more than 10%. Campbell and Thompson (2008), however, claim that high R^2_{OS} value does not make much sense economically since everyone would become rich by just exploiting the information contained in that model. Overall, the results of R^2_{OS} and MSFE-adjusted statistic suggest that S^{TV} not only outperforms HMM for most forecast horizons, it also has a superior forecasting performance as compared to other investor sentiment indexes.

Table 4.3 presents the results of forecast encompassing test, which provides an insight into the information content of forecasts produced by different investor sentiment measures, each pitched against S^{TV}. The forecasting performance of S^{TV} against other sentiment measures is presented with each entry in the column λ(1) and λ(2), with the null hypothesis that the given forecast encompasses the competing forecast (i.e. λ = 0) determined based on the *MDM* statistic in test 1 and test 2, as described in Section 4.2.2. The λ value and its associated *MDM* statistic (in square brackets) are reported for both tests. Significance of λ indicates that the weight of the competing forecast is greater than zero, and that the competing forecast contains information that is not already included in a given forecast but is useful for the optimal combination forecast. The outcomes for each pairing following the decision rules as summarised in Figure 4.1 are presented next to the λ(2) column for each forecast horizon. An

Table 4.2: Out-of-sample forecasting results: S^{TV} vs. other investor sentiment measures

	h = 1		*h* = 3		*h* = 6		*h* = 9		*h* = 12		*h* = 24		*h* = 36		*h* = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
S^{TV}	-0.52	0.02	-0.32	1.81**	-0.41	0.64	1.04	1.40*	2.43	1.65*	0.59	1.31*	-0.41	0.49	-4.58	-0.57
S^{BW}	0.39	1.04	-2.00	-1.18	-4.42	-0.29	-6.31	-0.04	-4.63	0.67	-23.36	-0.73	-20.70	-1.71	-33.78	-2.26
S^{PLS}	2.00	2.40***	5.77	3.58***	0.45	1.41*	-8.70	-0.07	-13.79	-0.44	-30.96	-1.73	-36.53	-1.93	-43.62	-4.35
MS	-1.66	-0.4	-3.94	-0.54	-9.5	-1.38	-15.15	-1.62	-16.52	-1.24	-19.38	-0.51	-22.08	-0.02	-16.65	1.08
CCI	-1.50	-0.15	-4.10	-0.39	-5.74	-0.36	-5.74	0.03	-4.71	0.49	-2.82	1.01	11.00	1.54*	19.10	1.75**

Notes: This table presents the Campbell and Thompson (2008) R^2_{OS} (in percentage) and the Clark and West (2007) *MSFE-adjusted* statistic of various investor sentiment measures: time-varying weighted investor sentiment index (S^{TV}), the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the University of Michigan Consumer Sentiment Index (MS) and the Conference Board Consumer Confidence Index (CCI). *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively, based on Newey-West *t*-statistic for *MSFE-adjusted* test. The in-sample period ranges from December 1968 to November 1983 and out-of-sample period from December 1983 to December 2014.

Table 4.3: Forecast encompassing tests: S^{TV} vs. other investor sentiment measures

	h = 1			*h = 3*			*h = 6*			*h = 9*			*h = 12*			*h =24*			*h = 36*			*h = 60*		
	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome
S^{BW}	0.75*	0.25	***3***	0.29	0.71***	***1***	0.04	0.96**	***1***	0.05	0.95***	***1***	0.12	0.88***	***1***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00	***4***
	[1.64]	[0.57]		[0.88]	[2.67]		[0.18]	[2.27]		[0.13]	[3.33]		[0.26]	[2.92]		[-0.46]	[1.49]		[-0.92]	[1.67]		[0.00]	[0.00]	
S^{PLS}	1.00***	0.00	***3***	0.87***	0.13	***3***	0.54*	0.46*	***2***	0.15	0.85**	***1***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.00	1.00	***4***
	[2.74]	[-0.45]		[3.07]	[0.64]		[1.39]	[1.29]		[0.38]	[1.65]		[-0.14]	[1.67]		[-1.02]	[1.74]		[-1.30]	[1.62]		[-9.45]	[0.00]	
MS	0.20	0.80*	***1***	0.25	0.75**	***1***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.02	0.98**	***1***	0.40	0.60	***4***
	[0.21]	[1.48]		[0.61]	[1.87]		[-0.34]	[1.61]		[-0.55]	[2.22]		[-0.80]	[2.16]		[-0.26]	[1.62]		[0.12]	[1.83]		[0.96]	[0.93]	
CCI	0.26	0.74**	***1***	0.22	0.78***	***1***	0.09	0.91**	***1***	0.12	0.88**	***1***	0.17	0.83**	***1***	0.42	0.58*	***1***	0.74	0.26	***4***	0.81*	0.19	***3***
	[0.51]	[1.83]		[0.79]	[2.95]		[0.24]	[1.93]		[0.33]	[2.19]		[0.34]	[1.87]		[0.77]	[1.48]		[1.09]	[1.04]		[1.42]	[0.42]	

Notes: This table presents the forecast encompassing tests results of the time-varying weighted investor sentiment index (S^{TV}) against other investor sentiment measures: the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the University of Michigan Consumer Sentiment Index (MS) and the Conference Board Consumer Confidence Index (CCI). λ represents the optimal weight associated with the competing forecast. The forecast based on S^{TV} is treated as the given forecast in the test 1 and as the competing forecast in test 2. The values in the brackets are *MDM* test statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The in-sample period ranges from December 1968 to November 1983 and out-of-sample period from December 1983 to December 2014.

outcome 1, which represents S^{TV} outperforming other sentiment measures, is obtained when the weight (λ) of competing forecast in test 1 is insignificant and the weight (λ) of S^{TV} forecast is significant in test 2.

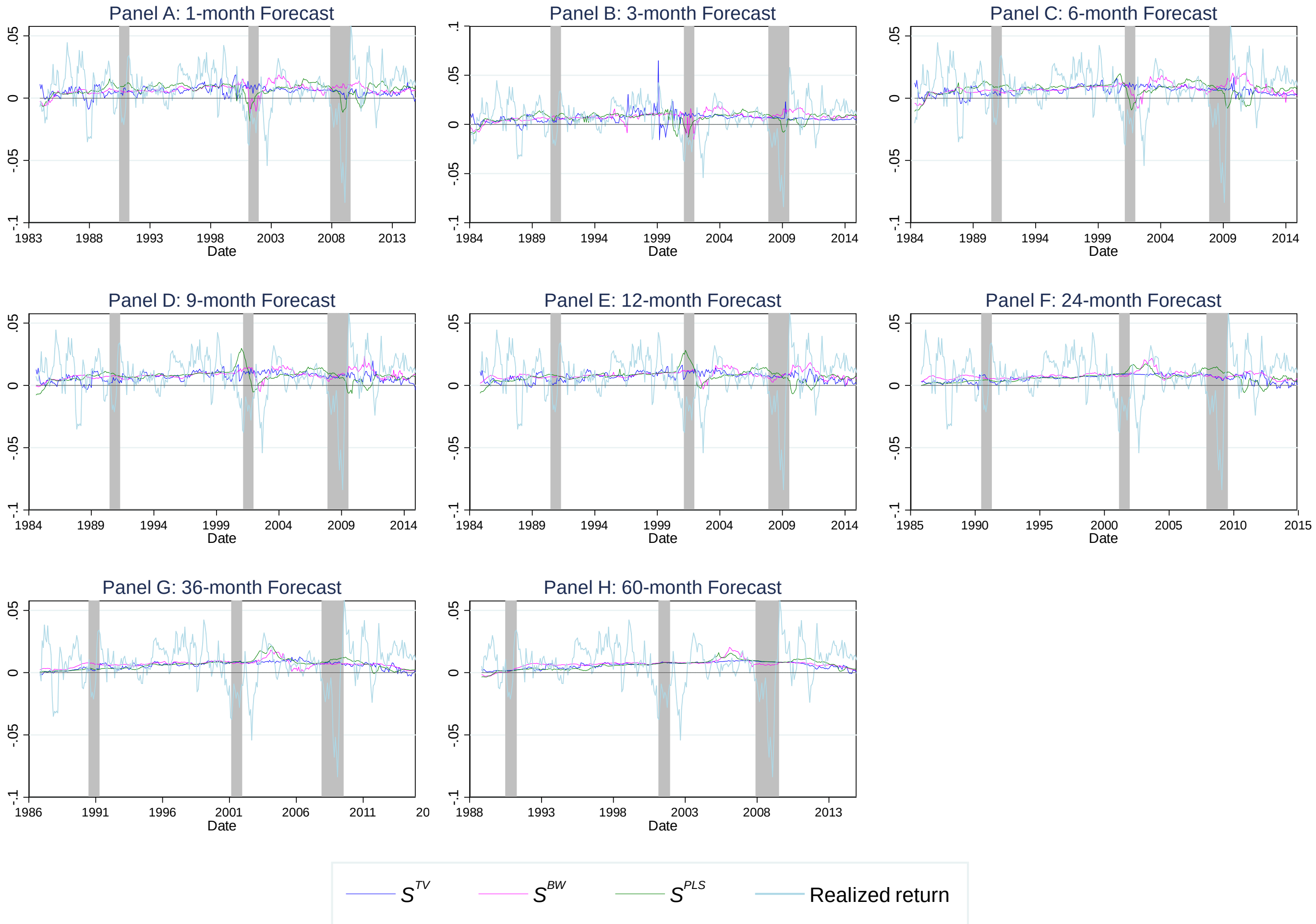
The findings in Table 4.3 provide support for the hypothesis that S^{TV} contains useful information which is not already included in the competing sentiment proxies. Outcome 1 is consistently observed beyond the next month forecast and up to the 36-month forecast horizon when the forecasting performance of S^{TV} is compared to that of S^{BW}, suggesting that S^{TV} forecasts dominate S^{BW} forecasts across all forecast horizons, except for 1-month and 60-month horizons. At the 1-month forecast horizon, the comparison between S^{TV} and S^{BW} yields an outcome of 3 which implies that S^{BW} is a better return predictor at the next-month forecast horizon. However, at the 60-month forecast horizon, forecasts produced by both sentiment measures do not contain unique information and their forecasts are redundant since an outcome 4 is obtained.

In addition, S^{TV}–based forecasts also dominate those based on S^{PLS} beyond forecast horizon of six months, while S^{PLS} dominates S^{TV} only for 1-month and 3-month forecast horizons. At h = 6, an outcome 2 is observed for the pairing between S^{TV} and S^{PLS}, implying that the forecasts of both predictors provide complementary information to the optimal forecast combination at the 6-month forecast horizon. These results are consistent with the in-sample analysis in that, whilst S^{PLS} produces more accurate return forecasts over the short run, S^{TV} forecasts stock market returns well over longer forecast horizons. As for the MS and CCI, the results depict that S^{TV}–based forecasts dominate the forecasts based on those variables for most forecast horizons except the long-term horizons.

Counting the occurrence of outcome 1 leads us to a conclusion that all other sentiment measures can be excluded from the optimal combination forecast in 72% of the all cases considered, since S^{TV}–based forecasts encompasses forecasts of other sentiment measures significantly at 10% level (i.e., S^{TV}-based forecasts deliver all the useful information); this high probability associated with outcome 1 is too high to be purely driven by chance at 10% significance level. In contrast, only four out of 32 cases show forecasts based on other sentiment measures to encompass S^{TV} forecast, as shown by outcome 3. This is well depicted in the Figure 4.2, where S^{TV} index captures well the dynamics of stock market returns and moves along with the direction of realized excess return even at the longer forecast horizons.

Figure 4.2: The forecasts of excess market returns across different forecast horizons

This figure illustrates the out-of-sample forecasts produced by the time-varying weighted investor sentiment index (S^{TV}), the Baker and Wurgler investor sentiment index (S^{BW}), and the aligned investor sentiment index (S^{PLS}). The forecasts are produced on a rolling window basis with a fixed window length of 15 years, and are compared against the realized return (6-month moving average of excess market return). Shaded areas represent NBER-dated recessions.



Overall, the enhanced investor sentiment index not only improves on the original BW approach in terms of time-series forecasting power, it also outperforms other competing measures of investor sentiment. These findings reinforce the findings documented in the previous chapter: S^{TV} is a superior measure of latent investor sentiment that forecasts well future stock market returns.

As a robustness check, a comparison of the forecasting performances of nth-year S^{TV} indexes and other sentiment measures is conducted to further investigate the relative forecasting power of S^{TV} index constructed on a 3-year rolling window size, which is termed as the benchmark S^{TV} for further analysis in this sub-section. To recall, Table A. 1 shows that the benchmark S^{TV} outperforms other nth-year S^{TV} indexes constructed based on differing windows (i.e. 1-year, 2-year, 4-year, and 5-year S^{TV}) in the in-sample evaluation. These results indicate that the benchmark S^{TV} index can optimally capture the time-varying contribution of each sentiment proxy and hence better predicts stock market returns. This sub-section presents the out-of-sample forecasting performance of nth-year S^{TV} indexes as compared to the benchmark S^{TV} and other investor sentiment measures given that in-sample forecasting performance might not represent out-of-sample forecasting power.

The analysis is split into two parts: (1) the forecasting performance of nth-year S^{TV} indexes against other investor sentiment measures, and (2) the forecasting performance of nth-year S^{TV} indexes as compared to the benchmark (i.e. 3-years-moving-windows-based, as used across in this thesis) S^{TV} index. The first analysis aims to provide further support to the importance of allowing the loadings of each proxy to vary over time, should we have nth-year S^{TV} indexes outperform other investor sentiment measures in the out-of-sample forecasting. If forecasts produced by nth-year S^{TV} indexes are indeed more accurate than those generated by other sentiment measures, comparing the performance of nth-year S^{TV} indexes to the benchmark S^{TV} in the second step of the analysis aims at validating whether the 3-years window length is optimal in capturing the time-varying contribution of each sentiment proxy to the index, and whether the benchmark S^{TV} therefore generates superior out-of-sample forecasts (as it did in the in-sample analysis).

Table 4.4 shows the results of the forecast encompassing test for 1-year S^{TV} (panel A), 2-year S^{TV} (panel B), 4-year S^{TV} (panel C), and 5-year S^{TV} (panel D). In each panel, the forecasting performance of nth-year S^{TV} index is compared with that of the benchmark S^{TV} (i.e.

Table 4.4: The forecast encompassing test performances of n^th-year S^{TV} indexes

	h = 1			*h = 3*			*h = 6*			*h = 9*			*h = 12*			*h =24*			*h = 36*			*h = 60*		
	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome
Panel A: 1-year S^{TV} vs. Investor sentiment indexes																								
Benchmark S^{TV}	0.91**	0.09	***3***	0.49**	0.51**	***2***	0.63	0.37	***4***	0.41	0.59*	***1***	0.62*	0.38	***3***	0.86**	0.14	***3***	0.58	0.42	***4***	0.00	1.00***	***1***
	[2.05]	[0.19]		[1.98]	[1.93]		[1.01]	[0.56]		[0.99]	[1.39]		[1.49]	[0.95]		[1.66]	[0.23]		[0.92]	[0.72]		[0.00]	[3.92]	
S^{BW}	0.91***	0.09	***3***	0.19	0.81***	***1***	-0.07	1.07**	***1***	0.00	1.00***	***1***	0.10	0.90**	***1***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1	***4***
	[2.45]	[0.25]		[0.67]	[2.65]		[0.04]	[1.82]		[-0.65]	[2.81]		[0.19]	[1.74]		[-0.37]	[1.38]		[-1.35]	[1.74]		[0.00]	[0.00]	
S^{PLS}	1.00***	0.00	***3***	0.98***	0.02	***3***	0.62*	0.38	***3***	0.00	1.00*	***1***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1	***4***
	[3.42]	[-0.76]		[3.21]	[0.08]		[1.38]	[0.93]		[-0.29]	[1.42]		[-0.57]	[1.37]		[-1.17]	[1.68]		[-1.52]	[1.71]		[-7.26]	[0.00]	
MS	0.55	0.45	***4***	0.11	0.89*	***1***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.03	0.97**	***1***	0.37	0.63	***4***
	[1.12]	[1.15]		[0.15]	[1.57]		[-0.96]	[1.58]		[-1.55]	[2.00]		[-1.34]	[1.93]		[-0.29]	[1.58]		[0.11]	[1.70]		[0.86]	[0.93]	
CCI	0.55*	0.45*	***2***	0.11	0.89***	***1***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.09	0.91**	***1***	0.48	0.52*	***1***	0.73	0.27	***4***	0.78*	0.22	***3***
	[1.48]	[1.41]		[0.35]	[2.43]		[-0.15]	[1.92]		[-0.53]	[2.12]		[0.15]	[1.67]		[0.83]	[1.40]		[1.01]	[0.99]		[1.39]	[0.47]	
Panel B: 2-year S^{TV} vs. Investor sentiment indexes																								
Benchmark S^{TV}	0.37	0.63	***4***	0.53**	0.47	***3***	0.66*	0.34	***3***	0.49*	0.51*	***2***	0.60*	0.4	***3***	0.59	0.41	***4***	0.90*	0.10	***3***	0.93*	0.07	***3***
	[0.64]	[0.88]		[1.95]	[1.18]		[1.62]	[0.78]		[1.42]	[1.43]		[1.61]	[1.07]		[1.12]	[0.84]		[1.44]	[0.17]		[1.61]	[0.06]	
S^{BW}	0.75*	0.25	***3***	0.03	0.97**	***1***	0.17	0.83**	***1***	0.00	1.00***	***1***	0.11	0.89**	***1***	0.00	1.00*	***1***	0.00	1.00*	***1***	0.00	1.00	***4***
	[1.53]	[0.48]		[0.10]	[1.84]		[0.50]	[1.74]		[-0.29]	[2.34]		[0.18]	[1.94]		[-0.39]	[1.42]		[-0.83]	[1.40]		[0.00]	[0.00]	
S^{PLS}	1.00***	0.00	***3***	1.00***	0.00	***3***	0.65*	0.35	***3***	0.04	0.96*	***1***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.00	1.00	***4***
	[2.76]	[-0.59]		[2.83]	[-0.64]		[1.58]	[0.91]		[0.08]	[1.50]		[-0.30]	[1.42]		[-1.01]	[1.72]		[-1.20]	[1.52]		[0.00]	[0.00]	
MS	0.11	0.89*	***1***	0.00	1.00	***4***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.02	0.98**	***1***	0.42	0.58	***4***
	[0.04]	[1.45]		[-0.11]	[1.20]		[-0.54]	[1.46]		[-1.11]	[1.98]		[-1.16]	[1.93]		[-0.32]	[1.60]		[0.10]	[1.79]		[0.94]	[0.91]	
CCI	0.18	0.82**	***1***	0.00	1.00**	***1***	0.11	0.89**	***1***	0.00	1.00**	***1***	0.09	0.91*	***1***	0.43	0.57*	***1***	0.77	0.23	***4***	0.84*	0.16	***3***
	[0.28]	[1.77]		[-0.06]	[1.95]		[0.28]	[1.80]		[-0.21]	[2.25]		[0.13]	[1.56]		[0.72]	[1.54]		[1.01]	[1.05]		[1.41]	[0.37]	
Panel C: 4-year S^{TV} vs. Investor sentiment indexes																								
Benchmark S^{TV}	0.39	0.61	***4***	0.39*	0.61*	***2***	0.63	0.37	***4***	0.70**	0.30	***3***	0.85***	0.15	***3***	0.83	0.17	***4***	0.72	0.28	***4***	0.51	0.49**	***1***
	[0.61]	[0.88]		[1.32]	[1.58]		[1.19]	[0.61]		[1.89]	[0.81]		[2.51]	[0.51]		[1.15]	[0.25]		[0.87]	[0.32]		[0.00]	[1.71]	
S^{BW}	0.71**	0.29	***3***	0.00	1.00***	***1***	0.11	0.89**	***1***	0.17	0.83**	***1***	0.47	0.53*	***1***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00***	***1***
	[1.77]	[0.72]		[-0.22]	[3.20]		[0.64]	[1.93]		[0.59]	[2.31]		[0.96]	[1.36]		[-0.38]	[1.55]		[-0.90]	[1.78]		[-4.38]	[9.80]	
S^{PLS}	1.00***	0.00	***3***	1.00***	0.00	***3***	0.62*	0.38	***3***	0.11	0.89*	***1***	0.00	1.00	***4***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1.00***	***1***
	[2.87]	[-0.58]		[3.28]	[-0.06]		[1.65]	[1.05]		[0.27]	[1.34]		[-0.14]	[1.27]		[-1.44]	[1.84]		[-1.60]	[1.81]		[-4.89]	[9.56]	
MS	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.01	0.99*	***1***	0.40	0.60	***4***
	[-0.21]	[1.81]		[-0.42]	[1.98]		[-0.68]	[1.63]		[-0.73]	[1.92]		[-0.65]	[1.72]		[-0.46]	[1.57]		[0.09]	[1.61]		[0.96]	[0.88]	
CCI	0.25	0.75**	***1***	0.00	1.00***	***1***	0.07	0.93**	***1***	0.17	0.83**	***1***	0.35	0.65*	***1***	0.48	0.52*	***1***	0.79	0.21	***4***	0.81*	0.19	***3***
	[0.53]	[2.03]		[-0.34]	[2.49]		[0.33]	[1.88]		[0.44]	[1.87]		[0.66]	[1.38]		[0.92]	[1.31]		[1.28]	[0.76]		[1.61]	[0.42]	
Panel D: 5-year S^{TV} vs. Investor sentiment indexes																								
Benchmark S^{TV}	0.57	0.43	***4***	0.58**	0.42	***3***	0.97**	0.03	***3***	1.00**	0.00	***3***	1.00***	0.00	***3***	0.83*	0.17	***3***	0.59***	0.41	***3***	0.75	0.25	***4***
	[1.00]	[0.53]		[2.33]	[1.26]		[2.06]	[0.00]		[2.25]	[-0.03]		[2.35]	[-0.06]		[1.55]	[0.30]		[3.23]	[0.73]		[1.24]	[0.33]	
S^{BW}	0.81**	0.19	***3***	0.32	0.68**	***1***	0.64**	0.36	***3***	0.69**	0.31	***3***	0.76**	0.24	***3***	0.05	0.95*	***1***	0.00	1.00**	***1***	0.00	1.00***	***1***
	[2.02]	[0.37]		[1.04]	[2.06]		[1.73]	[0.95]		[1.65]	[1.03]		[1.71]	[0.90]		[0.38]	[1.59]		[-1.12]	[1.78]		[-0.74]	[2.37]	
S^{PLS}	1.00***	0.00	***3***	1.00***	0.00	***3***	0.82**	0.18	***3***	0.45	0.55	***4***	0.21	0.79	***4***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1.00***	***1***
	[3.24]	[-0.82]		[3.86]	[-0.27]		[2.23]	[0.61]		[1.01]	[0.96]		[0.47]	[1.02]		[-1.02]	[1.90]		[-1.49]	[1.88]		[-1.90]	[2.57]	
MS	0.09	0.91*	***1***	0.24	0.76*	***1***	0.26	0.74	***4***	0.12	0.88*	***1***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.43	0.57	***4***
	[-0.01]	[1.34]		[0.45]	[1.52]		[0.48]	[1.07]		[0.25]	[1.31]		[-0.02]	[1.30]		[-0.13]	[1.77]		[0.19]	[1.48]		[1.09]	[0.80]	
CCI	0.26	0.74**	***1***	0.20	0.80**	***1***	0.50	0.50	***4***	0.63	0.37	***4***	0.66	0.34	***4***	0.57	0.43*	***1***	0.77*	0.23	***3***	0.83**	0.17	***3***
	[0.51]	[1.65]		[0.55]	[2.21]		[1.11]	[1.11]		[1.07]	[0.82]		[0.99]	[0.81]		[1.18]	[1.44]		[1.39]	[0.91]		[1.81]	[0.36]	

Notes: This table reports the forecast encompassing test results of n^th-year S^{TV} indexes against other sentiment measures. λ represents the optimal weight associated with the competing forecast. The forecast based on n^th-year S^{TV} is treated as the given forecast in the test 1 and as the competing forecast in test 2. The values in the brackets are *MDM* test statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The in-sample period ranges from December 1968 to November 1983 and out-of-sample period from December 1983 to December 2014.

3-year S^{TV}) index, the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the University of Michigan Consumer Sentiment Index (MS), and the Conference Board Consumer Confidence Index (CCI), all across different forecast horizons, *h*. Within every forecast horizon, each entry in the column λ(1) and λ(2) corresponds to the null hypothesis that the competing forecast does not contain useful information for the optimal combination forecast (i.e. λ = 0) when the modified Diebold-Mariano (*MDM*) test statistic is less than the critical value of one-sided t_{n-1} distribution. Based on the decision rule in Figure 4.1 , the outcome of each pairing is presented next to the column of λ(2). Outcome 1 derived from the comparison between nth-year S^{TV} index and other investor sentiment measures (i.e. excluding the first row in each panel) indicates that nth-year S^{TV} index outperforms another sentiment measure; whereas outcome 3 reveals the opposite result. Outcome 2 indicates that nth-year S^{TV} index contains unique information for return forecasting (but so does its competitor), whereas outcome 4 suggests that both predictors are equivalent to one another (i.e., none possesses any unique information which would not be contained in the other one).

Each panel in Table 4.4 shows that nth-year S^{TV} yields outcome 1 at 10% significance level for a large majority of cases, especially from 3-month forecast horizon onwards, when comparing with other sentiment measures, i.e. S^{BW}, S^{PLS}, MS, and CCI. Conversely, fewer pairings are seen to have outcome 3. In general, the forecasting performance of nth-year S^{TV} indexes is similar to that of the benchmark S^{TV} as presented in Table 4.3 in that: 1) forecasts of nth-year S^{TV} indexes tend to encompass (represented by outcome 1) those of S^{BW} from 3-month up to 36-month forecast horizons except 5-year S^{TV} index, 2) nth-year S^{TV} indexes dominate S^{PLS} across different forecast horizons, except short-run forecasts, and 3) outcome 1 is generated for most of the comparisons between nth-year S^{TV} indexes and MS as well as for the CCI.

Table 4.5 summarises the results of forecast encompassing tests by presenting the frequency of each outcome for each nth-year S^{TV} index. Among the nth-year S^{TV} indexes, 4-year S^{TV} outperforms other investor sentiment measures in forecasting stock market returns in three quarters of all pairings considered in panel C of Table 4.4. Even though the 5-year S^{TV} index has the lowest number of cases for outcome 1 as compared to other nth-year S^{TV} indexes, it still performs better than other sentiment measures in half of all cases (and in additional 21.9% of cases, it is not worse than the alternative predictor). The last column of Table 4.5 shows that nth-year S^{TV} indexes, on average, outperform other investor sentiment measures given that the probability of outcome 1 exceeds 60%. On the other hand, each of the nth-year

S^{TV} indexes shows outcome 3 (i.e., is dominated by its competitors) for about 15% of all pairings, except 5-year S^{TV}. Therefore, the average probability of outcome 3 across different nth-year S^{TV} indexes is at 18.8%. These results imply that nth-year S^{TV} indexes contain useful information that is not already embedded in other investor sentiment measures, and hence tend to dominate competitor sentiment indexes in forecasting stock market returns.

Table 4.5: The probability associated with each outcome of ENC test for nth-year S^{TV} indexes

	1-year S^{TV}	2-year S^{TV}	4-year S^{TV}	5-year S^{TV}	Average
Outcome 1	0.656	0.688	0.750	0.500	0.648
Outcome 2	0.031	0.000	0.000	0.000	0.008
Outcome 3	0.156	0.156	0.156	0.281	0.188
Outcome 4	0.156	0.156	0.094	0.219	0.156

Notes: This table presents the probability of each outcome for the forecasting encompassing test estimated by comparing the forecasts produced by nth-year S^{TV} indexes to the forecasts of other investor sentiment indexes which include the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the University of Michigan Consumer Sentiment Index (MS), and the Conference Board Consumer Confidence Index (CCI). The description of each outcome is presented in Figure 4.1. The average probability of each outcome across different nth-year S^{TV} indexes is shown in the last column.

Given that S^{TV} indexes constructed based on differing window lengths are good sentiment measures, as they produce more accurate forecasts as compared to other sentiment measures, the next task is to examine whether the benchmark (3-years moving window) S^{TV} index continues to outperform other nth-year S^{TV} indexes in the out-of-sample forecasts, as it did in the in-sample evaluation. The results relevant to this question are shown in the first row of each panel of Table 4.4. Whilst outcome 1 is favourable to nth-year S^{TV} indexes (as it implies that the benchmark S^{TV} index is dominated by the nth-year S^{TV} index), outcome 3 – a result opposite to outcome 1 – implies a superior forecasting performance of the benchmark S^{TV}. Aggregating the results from first rows across four panels, which totals 32 cases, we conclude that outcome 3 has a probability/frequency of 50%. However, outcome 1 only occurs in fewer than 10% of 32 cases. The high probability associated with outcome 3 confirms that benchmark 3-years S^{TV} generally outperforms other S^{TV} indexes constructed on different window lengths in out-of-sample forecasts (in addition to its superior in-sample predictive power as documented in Table A. 1).

In summary, the comparison between nth-year S^{TV} indexes and other investor sentiment measures lends further support to our approach of allowing the loading of each sentiment proxy to vary over time when constructing the investor sentiment index, as S^{TV} indices based on time-varying nature of their composite proxies generally outperform their competitors in the out-of-sample context. Furthermore, the forecasting performance of S^{TV} is robust to the choice of various window lengths, in that S^{TV} indices computed over widows of one to five years all seem to outperform alternative sentiment proxies in out-of-sample forecasting tests. Last but not least, the outperformance of our benchmark S^{TV} index over n^{th}-year S^{TV} indexes indicates that the 3-year window length is optimal in its ability to reflect the time-varying ability of each index component to empirically capture unobservable investor sentiment.

4.4.2 The OOS predictive power of S^{TV} vs. economic predictors

Having empirically established that S^{TV} is the superior sentiment measure, this sub-section turns the attention to the key question of this chapter – is sentiment or fundamentals the main driver of the stock market movements? This question can be answered through examining whether information contained in sentiment, as captured by S^{TV}, is unique and can be utilised to improve forecasts of future stock returns, above and beyond of information contained by popular economic predictors. To the extent that the US stock market is expected to be driven mostly by news about fundamentals, S^{TV}, the proxy of irrational sentiment, is not necessarily expected to have higher forecasting power than every single economic variable considered; it might contain useful additional information about future stock returns only in comparison to a few economic predictors and still be considered a useful addition to the forecaster's toolbox. The results of forecasting performance of S^{TV} index against economic predictors based on R^2_{OS} and *MSFE-adjusted* statistics are presented in Table 4.6. For the ease of comparison, the results of S^{TV} are presented in the first row, followed by the performances for different economic predictors from second row onwards.

The results in Table 4.6 demonstrate that most economic predictors underperform HMM, given that they produce negative R^2_{OS} with large magnitudes and insignificant *MSFE-adjusted* statistics. This result is consistent with previous literature which finds that economic predictors have limited predictive power out-of-sample (Welch and Goyal, 2008; Rapach, Strauss and Zhou, 2010; Rapach et al., 2016). Generally, S^{TV} outperforms most economic predictors when the forecast accuracy is compared between the forecasts of individual predictors and HMM. However, some exceptional results can be seen for DP, OG and CAY. While DP is a good predictor over the short-term period with positive R^2_{OS} values and significant *MSFE-adjusted* statistics can be observed from 1-month up to 6-month forecast, CAY forecasts well the excess market returns over longer horizons. The last row demonstrates that the diffusion index of economic predictors (PC-ECON) outperforms HMM

Table 4.6: Out-of-sample forecasting results: S^{TV} index vs. economic predictors

	h = 1		*h* = 3		*h* = 6		*h* = 9		*h* = 12		*h* = 24		*h* = 36		*h* = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
S^{TV}	-0.52	0.02	-0.32	1.81**	-0.41	0.64	1.04	1.40*	2.43	1.65*	0.59	1.31*	-0.41	0.49	-4.58	-0.57
DP	1.05	1.89**	3.95	2.02**	3.22	1.36*	-4.07	1.01	-13.14	0.59	-41.15	-0.19	-63.54	-0.4	-89.8	-0.1
DY	-0.94	0.17	2.19	1.41*	0.55	1.16	-4.36	0.91	-12.92	0.68	-44.64	-0.31	-68.58	-0.55	-113.97	-0.39
EP	-5.9	-0.77	-7.3	-0.33	-16.36	-0.65	-26.9	-0.6	-29.43	-0.77	-50.14	-1.44	-75.7	-1.37	-107.94	-2.02
DE	-0.02	0.71	0.44	1.12	-7.91	-0.13	-4.91	0.27	-3.66	0.46	-35.16	0.12	-44.21	0.06	8.57	1.79**
SVAR	-6.32	-0.2	-30.03	-0.93	-82.68	-0.06	-95.89	0.06	-46.11	0.9	-15.26	0.88	-15.61	-0.06	-28.01	-1.09
BM	-0.52	-0.7	-0.4	0.95	-2.18	0.96	-10.4	0.3	-19.52	0.05	-36.97	-0.74	-46.85	-1.38	-83.9	-1.21
NTIS	-0.48	1.15	-2.44	1.05	-4.61	1.25	-11.86	1.12	-15.07	1.27	-18.43	1.28	-20.26	1.22	-57.59	0.63
TBL	-1.08	0.04	-1.77	0.34	-5.16	-0.33	-4.93	-0.08	0.16	0.73	5.87	0.96	7.4	0.97	-41.8	-1.49
LTY	-1.65	-0.17	-1.24	1.09	-3.77	0.47	-1.18	0.88	-0.3	0.95	-9.66	0.57	-25.29	-0.25	-59.05	0.35
LTR	-8.81	0.19	-1.77	-0.19	0.05	0.7	1.06	0.98	3.31	1.62*	1.74	0.84	2.44	1.09	-2.29	-0.76
TMS	-1.07	-0.01	-3.59	-0.14	-5.93	-1.2	-1.73	0.59	-1.47	0.56	0.19	0.69	21.81	2.21**	6.96	1.51*
DFY	-2.49	0.37	-14.4	0.23	-39.17	-0.35	-73.41	-0.71	-44.18	-0.71	-29.47	-1.24	-14.85	-1.54	-19.37	-1.19
DFR	-16.41	0.48	-9.55	-1.1	-3.76	-0.59	-0.46	0.52	-0.65	0.36	-1.22	0.33	0.53	0.45	-1.69	-0.39
INFL	-0.13	0.23	-1.55	-0.39	-1.06	-0.36	2.65	1.52*	2.26	1.15	-0.37	0.11	-2.61	-0.29	-8.31	-1.31
OG	-0.38	1.34*	-1.30	1.80**	-1.64	1.94**	-3.28	2.12**	-9.45	1.79**	-83.60	0.85	-105.82	0.69	46.89	2.41***
SCR	-3.19	0.27	-15.93	-0.36	-55.72	-0.83	-81.49	-1.08	-83.11	-1.34	-62.45	1.06	-248.32	1.22	-96.65	1.13
CAY	-0.26	1.22	-4.8	-0.2	2.07	1.84**	4.08	2.51***	8.43	3.33***	17.91	2.13**	16.82	2.03**	-10.92	1.43*
PC-ECON	-1.84	-1.14	-1.55	0.05	1.82	1.81**	5.48	1.79**	4.65	1.59*	-43.59	1.14	-61.53	0.88	-73.77	0.41

Notes: This table presents the Campbell and Thompson (2008) R^2_{OS} (in percentage) and the Clark and West (2007) *MSFE-adjusted* statistic of the time-varying weighted investor sentiment index (S^{TV}), and economic predictors as listed in Section 4.3. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively, based on Newey-West *t*-statistic for *MSFE-adjusted* test. The in-sample period stretches from December 1968 to November 1983 and out-of-sample period from December 1983 to December 2014.

Table 4.7: Forecast encompassing tests: S^{TV} vs. economic predictors

	h = 1			*h = 3*			*h = 6*			*h = 9*			*h = 12*			*h =24*			*h = 36*			*h = 60*		
	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome
DP	1.00**	0.00	***3***	0.78***	0.22	***3***	0.79*	0.21	***3***	0.39	0.61**	***1***	0.18	0.82***	***1***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.02	0.98**	***1***
	[2.10]	[-0.28]		[2.50]	[0.92]		[1.59]	[0.65]		[1.17]	[1.86]		[0.65]	[2.49]		[-0.14]	[2.28]		[-0.17]	[1.89]		[0.07]	[1.74]	
DY	0.46	0.54*	***1***	0.76**	0.24	***3***	0.56*	0.44	***3***	0.36	0.64**	***1***	0.20	0.80***	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.00	1.00*	***1***
	[0.82]	[1.35]		[2.03]	[0.98]		[1.41]	[1.22]		[1.08]	[2.11]		[0.72]	[2.82]		[-0.22]	[1.89]		[-0.28]	[1.53]		[-0.22]	[1.41]	
EP	0.00	1.00**	***1***	0.17	0.83*	***1***	0.00	1.00	***4***	0.00	1.00	***4***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00*	***1***	0.00	1.00*	***1***
	[-0.55]	[1.73]		[0.39]	[1.32]		[-0.19]	[1.03]		[-0.17]	[1.21]		[-0.29]	[1.58]		[-1.06]	[2.05]		[-0.98]	[1.38]		[-1.43]	[1.41]	
DE	0.61	0.39	***4***	0.56*	0.44*	***2***	0.12	0.88	***4***	0.22	0.78*	***1***	0.24	0.76*	***1***	0.03	0.97*	***1***	0.06	0.94*	***1***	0.57	0.43	***4***
	[1.14]	[0.70]		[1.52]	[1.29]		[0.26]	[1.19]		[0.45]	[1.36]		[0.38]	[1.39]		[0.19]	[1.59]		[0.23]	[1.60]		[1.21]	[0.78]	
SVAR	0.01	0.99**	***1***	0.04	0.96	***4***	0.04	0.96	***4***	0.04	0.96	***4***	0.07	0.93	***4***	0.15	0.85	***4***	0.10	0.90*	***1***	0.00	1.00	***4***
	[0.01]	[1.97]		[0.45]	[1.19]		[0.90]	[1.06]		[0.88]	[1.07]		[1.17]	[1.07]		[0.91]	[1.17]		[0.92]	[1.41]		[-0.45]	[1.06]	
BM	0.62	0.38	***4***	0.50*	0.50**	***2***	0.41	0.59*	***1***	0.17	0.83**	***1***	0.04	0.96**	***1***	0.00	1.00**	***1***	0.00	1.00**	***1***	0.00	1.00	***4***
	[0.75]	[0.75]		[1.57]	[1.88]		[1.17]	[1.58]		[0.60]	[1.75]		[0.17]	[1.91]		[-0.47]	[1.75]		[-0.84]	[1.90]		[-0.81]	[0.00]	
NTIS	0.51**	0.49*	***2***	0.42*	0.58**	***2***	0.42	0.58*	***1***	0.33	0.67**	***1***	0.33	0.67**	***1***	0.32*	0.68	***3***	0.30*	0.70*	***2***	0.14	0.86	***4***
	[1.65]	[1.62]		[1.40]	[1.84]		[1.23]	[1.38]		[1.16]	[1.67]		[1.28]	[1.80]		[1.55]	[1.23]		[1.29]	[1.33]		[0.68]	[1.28]	
TBL	0.31	0.69*	***1***	0.40	0.60*	***1***	0.20	0.80	***4***	0.20	0.80*	***1***	0.38	0.62*	***1***	0.73	0.27	***4***	0.99	0.01	***4***	0.00	1.00	***4***
	[0.74]	[1.51]		[1.05]	[1.59]		[0.33]	[1.15]		[0.51]	[1.47]		[0.87]	[1.46]		[0.77]	[0.64]		[0.80]	[0.17]		[-0.89]	[1.25]	
LTY	0.18	0.82**	***1***	0.45*	0.55**	***2***	0.33	0.67*	***1***	0.43	0.57*	***1***	0.42	0.58**	***1***	0.34	0.66**	***1***	0.07	0.93**	***1***	0.12	0.88***	***1***
	[0.61]	[2.23]		[1.62]	[2.19]		[0.81]	[1.39]		[1.09]	[1.52]		[1.00]	[1.97]		[0.60]	[2.07]		[0.02]	[2.06]		[0.65]	[2.39]	
LTR	0.08	0.92***	***1***	0.36	0.64**	***1***	0.60	0.40	***4***	0.50*	0.50*	***2***	0.60**	0.40	***3***	0.66	0.34	***4***	0.92*	0.08	***3***	1.00*	0.00	***3***
	[0.42]	[4.55]		[1.09]	[2.01]		[1.21]	[0.78]		[1.41]	[1.46]		[1.73]	[1.09]		[0.92]	[0.53]		[1.43]	[0.15]		[1.39]	[-0.02]	
TMS	0.30	0.70*	***1***	0.26	0.74***	***1***	0.00	1.00**	***1***	0.31	0.69**	***1***	0.20	0.80**	***1***	0.42	0.58*	***1***	1.00*	0.00	***3***	0.82***	0.18	***3***
	[0.64]	[1.31]		[0.78]	[2.42]		[-0.18]	[1.84]		[0.75]	[1.68]		[0.40]	[1.79]		[0.62]	[1.38]		[1.53]	[-0.99]		[3.18]	[0.29]	
DFY	0.36	0.64*	***1***	0.21	0.79	***4***	0.01	0.99	***4***	0.00	1.00	***4***	0.00	1.00	***4***	0.00	1.00*	***1***	0.00	1.00**	***1***	0.00	1.00	***4***
	[0.67]	[1.61]		[0.59]	[1.25]		[0.00]	[0.97]		[-0.39]	[1.01]		[-0.45]	[1.06]		[-0.77]	[1.29]		[-0.47]	[1.92]		[-0.41]	[1.10]	
DFR	0.12	0.88***	***1***	0.00	1.00***	***1***	0.10	0.90**	***1***	0.34	0.66	***1***	0.19	0.81*	***1***	0.31	0.69	***4***	0.61	0.39	***4***	1.00**	0.00	***3***
	[0.60]	[2.99]		[-0.05]	[2.61]		[0.28]	[1.73]		[1.05]	[1.93]		[0.44]	[1.65]		[0.46]	[0.72]		[1.27]	[0.75]		[2.06]	[-0.26]	
INFL	0.73	0.27	***4***	0.35	0.65**	***1***	0.37	0.63	***4***	0.68**	0.32	***3***	0.48	0.52*	***1***	0.35	0.65	***4***	0.19	0.81*	***1***	0.15	0.85	***4***
	[1.10]	[0.38]		[0.91]	[2.15]		[0.71]	[1.16]		[2.30]	[1.07]		[1.26]	[1.29]		[0.46]	[0.98]		[0.42]	[1.60]		[0.26]	[1.06]	
OG	0.57**	0.43*	***2***	0.53**	0.47**	***2***	0.57**	0.42**	***2***	0.54**	0.46**	***2***	0.44*	0.56**	***2***	0.17	0.83*	***1***	0.21	0.79*	***1***	0.93*	0.07	***3***
	[1.71]	[1.55]		[1.98]	[2.51]		[2.07]	[1.87]		[2.07]	[1.76]		[1.50]	[1.82]		[0.66]	[1.44]		[0.57]	[1.34]		[1.58]	[0.27]	
SCR	0.24	0.76*	***1***	0.04	0.96*	***1***	0.00	1.00	***4***	0.00	1.00	***4***	0.00	1.00	***4***	0.17	0.83	***4***	0.15	0.85	***4***	0.30	0.7	***4***
	[0.52]	[1.51]		[0.13]	[1.41]		[-0.50]	[1.03]		[-0.83]	[1.05]		[-1.02]	[1.14]		[1.16]	[1.01]		[0.97]	[0.98]		[0.90]	[0.84]	
CAY	0.57*	0.43	***3***	0.27*	0.73**	***2***	0.71**	0.29	***3***	0.66***	0.34	***3***	0.69***	0.31	***3***	0.81**	0.19	***3***	0.71**	0.29	***3***	0.46*	0.54	***3***
	[1.54]	[1.19]		[1.30]	[2.13]		[2.11]	[0.84]		[2.44]	[1.13]		[2.52]	[0.96]		[2.11]	[0.82]		[1.79]	[0.90]		[1.51]	[0.92]	
PC-ECON	0.00	1.00*	***1***	0.39	0.61*	***1***	0.66**	0.34	***3***	0.68**	0.32	***3***	0.55*	0.45*	***2***	0.25	0.75*	***1***	0.24	0.76*	***1***	0.18	0.82***	***1***
	[-0.21]	[1.56]		[0.98]	[1.53]		[1.79]	[0.85]		[1.95]	[0.99]		[1.60]	[1.67]		[0.93]	[1.31]		[0.68]	[1.55]		[0.38]	[2.81]	

Notes: This table presents the forecast encompassing tests results of the time-varying weighted investor sentiment index (S^{TV}) against economic predictors (as listed in Section 4.3). λ represents the optimal weight associated with the competing forecast. The forecast based on S^{TV} is treated as the given forecast in the test 1 and as the competing forecast in test 2. The values in the brackets are MDM test statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The in-sample period ranges from December 1968 to November 1983 and out-of-sample period from December 1983 to December 2014.

substantially beyond 3-month forecast horizon, but its predictive performance worsens after the 12-month forecast horizon.

Having examined the forecast accuracy of each predictor against HMM, the predictive performance of the new investor sentiment index, S^{TV}, against those economic predictors is presented next. The corresponding forecast encompassing results are presented in Table 4.7. As in Section 4.4.1, S^{TV} forecast is treated as the given forecast in test 1 and as the competing forecast in test 2. Based on tests 1 and 2, the possible outcome is reported in Table 4.7 in the column denoted "Outcome" for each forecast horizon. The outcome 1, which shows that S^{TV} dominates an economic predictor, for each pairing is particularly of interest.

As can be seen in Table 4.7, most pairings yield outcome 1 for different economic predictors across different forecast horizons, suggesting that most economic predictors are dominated by S^{TV} in terms of their ability to forecast future stock market returns. Specifically, this result occurs in 70 cases out of 144 pairings (i.e. about 50%) at 10% significance level. Furthermore, the comparison between S^{TV} and PC-ECON yields outcome 1 in more than half of the forecast horizons. On the other hand, PC-ECON forecast encompasses S^{TV} forecast, represented by outcome 3, only at horizons $h = 6$ and $h = 9$. As PC-ECON has been found in previous literature to predict stock returns better than individual economic predictors do, the outperformance of S^{TV} against PC-ECON is especially supportive of the expectation that S^{TV} has incremental forecasting power beyond those economic predictors (fundamental information).

Overall, these results show that the S^{TV} index is a strong predictor of excess market returns and that it contains unique, non-fundamental systematic component, given its outstanding performance against economic predictors. The findings demonstrate that stock market returns are significantly driven by investor irrationality, and this irrational sentiment is well captured by the S^{TV} index proposed here.

4.4.3 The economic value of S^{TV}

Given that S^{TV} performs well statistically, the next question is whether it adds economic value to investors. Campbell and Thompson (2008) show that even as small R^2_{OS} of 0.43% generates economic value to investors, and hence return forecasts are worthwhile. Therefore, this section explores the economic value of the S^{TV}-based forecasts in a realistic, out-of-sample framework, presenting a different way to evaluate the relative importance of investor sentiment in driving the stock market movements. If investor sentiment plays a greater role on the stock market fluctuations, S^{TV}-based forecasts should be of valuable to the investors.

Results for economic value of forecasts are presented in Table 4.8, the CER gain and Sharpe ratio are presented side by side and we rank the economic performance of each predictor based on their CER gain, which is called CER ranking, at each forecast horizon. The average of CER rankings for each predictor across different forecast horizons is denoted as mean rank. Two mean ranks are computed: mean rank (all) is the average of CER rankings across all forecast horizons and mean rank ($h \leq 24$) is the average of CER rankings from 1- to 24-month forecast horizons. Finally, a final rank is assigned to each predictor according to the mean rank value.

Panels A and B report the portfolio performance for an investor with the risk-aversion coefficient (γ) of 1 and 3,[64] respectively. Panel A demonstrates that S^{TV} consistently generates sizeable CER gains, ranging from 0.15% to 1.14%, to investors from 1-month up to 24-month forecast horizon, except for the 9-month forecast horizon. This indicates that investors are willing to pay a portfolio management fee of up to 1.14% to exploit the information contained in the S^{TV} forecast. Meanwhile, S^{BW} also produces greater CER than HMM model in five out of eight forecast horizons as shown by the positive CER gain. Taking a closer look at the magnitudes of CER gains, however, reveals that S^{BW} has lower CER gains than S^{TV} for most prediction horizons. Hence, once again the findings show that constructing the sentiment index in a way which allows for time-varying contributions of its components, as in S^{TV}, helps to improve the way the original approach by Baker and Wurgler (2006) captures the underlying sentiment.

At 1- and 3-month forecast horizons, S^{PLS} delivers the highest CER gains, which are 2.96% and 3.52%, respectively. Further analysis, however, shows that the CER gains of S^{PLS} is affected greatly beyond 6-month forecast horizon and S^{PLS} underperforms S^{TV} in term of

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[64] Previous studies have chosen a risk-aversion coefficient in the range of 1 to 3 (*e.g.* Campbell and Thompson, 2008; Dangl and Halling 2012; Dasgupta, 2008; Mehra and Sah, 2002; Rapach et al., 2016). Mehra and Prescott (1985) and Weil (1989) argue that even though a higher risk aversion coefficient produces a higher equity premium, a very high risk aversion coefficient generates another puzzle, the so called 'risk-free rate puzzle', since the observed low risk-free rate does not justify the model's high risk-free rate when investors are highly risk averse. Mehra and Prescott (1985) also mention that most studies documented an estimate of 1.0 – 2.0 for γ. Hence, the risk aversion coefficients, γ, of 1 and 3 are opted to represent a less risk averse investor and a more risk-averse investor, respectively.

Table 4.8: Out-of-sample CER gains and Sharpe ratios for a mean-variance investor

	$h = 1$			$h = 3$			$h = 6$			$h = 9$			$h = 12$			$h = 24$			$h = 36$			$h = 60$			Mean rank (all)	Final ranking (all)	Mean rank ($h \le 24$)	Final ranking ($h \le 24$)
	CER gain	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*				
														Panel A: $\gamma = 1$														
HMM	-	1.33		-	1.00		-	0.88		-	0.78		-	0.71		-	0.57		-	0.50		-	0.36					
S^{TV}	0.28	1.40	8	1.14	1.07	2	0.84	0.92	1	-0.08	0.76	9	0.87	0.73	2	0.15	0.56	3	-2.51	0.45	17	-1.64	0.36	12	6.75	2	4.17	1
S^{BW}	0.78	1.43	6	-1.00	0.99	15	-0.67	0.85	8	0.20	0.78	7	0.28	0.72	4	0.03	0.58	4	0.11	0.47	6	-4.30	0.31	21	8.88	6	7.33	4
S^{PLS}	2.96	1.55	1	3.52	1.18	1	0.13	0.89	4	-1.40	0.75	14	-1.07	0.69	12	-2.99	0.53	18	-5.28	0.43	22	1.53	0.38	7	9.88	9	8.33	6
MS	-2.02	1.26	20	-2.30	0.92	21	-3.29	0.78	21	-3.33	0.69	23	-1.51	0.67	15	-2.40	0.53	14	-1.81	0.48	16	-2.03	0.34	13	17.88	21	19.00	21
CCI	-2.22	1.25	22	-1.69	0.96	18	-2.99	0.80	20	-2.56	0.72	20	-2.43	0.64	19	-0.96	0.56	9	-0.70	0.49	11	-2.03	0.34	14	16.63	20	18.00	20
DP	2.39	1.51	2	1.10	1.11	3	-1.39	0.87	12	-2.11	0.73	17	-2.27	0.65	18	-2.70	0.53	16	-0.88	0.49	13	0.97	0.38	9	11.25	12	11.33	11
DY	-1.53	1.32	19	-0.37	1.04	13	-1.55	0.86	14	-1.82	0.74	16	-1.39	0.68	14	-2.88	0.53	17	-0.93	0.49	14	0.93	0.38	10	14.63	18	15.50	18
EP	-0.25	1.35	10	1.07	1.08	4	-2.20	0.84	17	-1.20	0.79	12	-2.65	0.66	20	-4.67	0.47	23	-6.38	0.41	23	1.88	0.39	5	14.25	16	14.33	16
DE	0.79	1.41	5	-0.06	1.01	9	-1.78	0.83	15	-1.21	0.74	13	-0.12	0.71	8	-1.32	0.54	12	0.37	0.46	5	2.89	0.38	2	8.63	4	10.33	10
SVAR	-1.05	1.34	14	-2.17	0.92	19	-0.93	0.86	9	-2.18	0.73	18	0.10	0.71	6	-0.47	0.56	7	-3.91	0.43	20	-2.67	0.33	19	14.00	15	12.17	14
BM	-1.15	1.29	15	-2.92	0.88	23	-2.43	0.82	19	-2.56	0.72	19	-2.70	0.64	21	-3.45	0.51	20	-3.74	0.45	19	-4.36	0.32	22	19.75	23	19.50	23
NTIS	-0.03	1.38	9	-2.57	0.92	22	0.74	0.89	2	0.83	0.78	1	0.06	0.67	7	-0.17	0.56	5	-1.26	0.45	15	1.74	0.38	6	8.38	3	7.67	5
TBL	-1.23	1.31	17	-1.18	0.99	16	-3.89	0.76	23	-2.86	0.71	21	-1.76	0.67	16	-0.76	0.57	8	-0.68	0.49	10	2.31	0.39	4	14.38	17	16.83	19
LTY	-0.70	1.34	13	-2.21	0.93	20	-3.79	0.75	22	-3.17	0.70	22	-2.18	0.66	17	-4.63	0.50	22	-0.12	0.46	7	-5.13	0.33	23	18.25	22	19.33	22
LTR	-3.08	1.19	23	-0.99	0.97	14	-0.50	0.85	7	0.28	0.78	5	0.12	0.71	5	-0.24	0.57	6	-0.25	0.49	8	-2.54	0.33	16	10.50	11	10.00	9
TMS	-1.22	1.28	16	-0.37	0.99	12	-0.30	0.87	6	0.53	0.79	2	0.69	0.73	3	-1.67	0.53	13	-0.72	0.49	12	-0.85	0.35	11	9.38	7	8.67	7
DFY	-1.52	1.36	18	0.56	1.07	7	-1.44	0.88	13	-0.40	0.78	10	-2.71	0.65	22	-4.40	0.50	21	-4.71	0.44	21	1.51	0.37	8	15.00	19	15.17	17
DFR	0.75	1.47	7	0.92	1.06	6	-1.22	0.84	10	0.27	0.78	6	-0.57	0.70	10	-3.18	0.52	19	0.53	0.50	4	-2.56	0.33	17	9.88	9	9.67	8
INFL	0.97	1.40	4	-0.27	0.99	11	0.09	0.88	5	0.46	0.78	4	-0.26	0.70	9	-1.05	0.56	10	-0.61	0.48	9	-2.62	0.33	18	8.75	5	7.17	3
OG	-0.66	1.30	12	0.93	1.04	5	0.67	0.90	3	0.50	0.79	3	0.96	0.73	1	-1.17	0.56	11	0.67	0.52	3	4.42	0.39	1	4.88	1	5.83	2
SCR	1.28	1.44	3	0.40	1.06	8	-1.27	0.89	11	-1.53	0.75	15	-3.19	0.63	23	-2.65	0.53	15	-2.83	0.46	18	-2.33	0.34	15	13.50	14	12.50	15
CAY	-0.26	1.32	11	-1.63	0.94	17	-1.85	0.80	16	-0.54	0.76	11	-1.31	0.62	13	1.21	0.57	1	5.67	0.61	1	-4.01	0.34	20	11.25	12	11.50	12
PC-ECON	-2.03	1.23	21	-0.07	1.00	10	-2.23	0.83	18	0.11	0.79	8	-1.05	0.68	11	0.27	0.59	2	0.91	0.52	2	2.41	0.39	3	9.38	7	11.67	13

Table 4.8 (Continued):

	h = 1			h = 3			h = 6			h = 9			h = 12			h = 24			h = 36			h = 60			Mean rank (all)	Final ranking (all)	Mean rank ($h \leq 24$)	Final ranking ($h \leq 24$)
	CER gain	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*	*CER gain*	*SR*	*CER Ranking*				
															Panel B: γ = 3													
HMM	-	1.16		-	0.81		-	0.72		-	0.65		-	0.58		-	0.49		-	0.44		-	0.33					
S^{TV}	1.76	1.32	5	1.92	0.95	8	1.37	0.81	3	0.41	0.68	4	1.61	0.67	3	1.23	0.51	3	-0.75	0.42	10	-4.54	0.32	19	6.88	2	4.33	1
S^{BW}	2.14	1.36	4	1.36	0.90	14	0.35	0.75	9	0.72	0.70	3	0.92	0.64	5	-1.62	0.50	8	0.53	0.46	6	-5.61	0.29	21	8.75	6	7.17	5
S^{PLS}	5.07	1.57	1	5.37	1.13	1	1.55	0.88	2	-0.76	0.71	11	-1.40	0.63	11	-5.03	0.42	21	-6.63	0.36	22	-1.13	0.33	10	9.88	7	7.83	6
MS	-0.05	1.15	20	0.51	0.85	17	-2.01	0.70	17	-2.95	0.62	18	-4.08	0.58	17	-3.54	0.49	17	-2.75	0.43	12	-0.73	0.34	6	15.50	19	17.67	21
CCI	-0.35	1.12	22	0.31	0.86	18	-2.73	0.72	21	-2.36	0.66	17	-3.38	0.63	16	-2.13	0.53	9	-5.10	0.49	18	0.35	0.34	4	15.63	20	17.17	19
DP	2.78	1.51	2	3.65	1.04	2	-3.66	0.78	22	-5.98	0.64	22	-6.66	0.55	23	-3.66	0.51	18	-4.85	0.48	16	-0.77	0.38	7	14.00	17	14.83	18
DY	0.40	1.20	14	2.06	0.94	6	-3.92	0.77	23	-5.99	0.63	23	-5.84	0.58	22	-3.54	0.53	16	-4.27	0.48	14	-1.51	0.38	11	16.13	21	17.33	20
EP	0.28	1.19	16	2.21	0.95	5	0.82	0.81	7	-0.74	0.69	10	-1.38	0.57	10	-5.60	0.38	22	-3.24	0.40	13	1.21	0.37	3	10.75	8	11.67	12
DE	0.96	1.26	12	1.94	0.96	7	1.25	0.80	4	0.29	0.68	5	1.09	0.64	4	-0.49	0.48	6	2.37	0.43	2	3.49	0.35	2	5.25	1	6.33	3
SVAR	1.19	1.27	10	-1.69	0.72	23	-0.17	0.74	10	-2.24	0.61	16	-0.59	0.61	9	-0.67	0.48	7	-1.64	0.40	11	-2.43	0.31	15	12.63	14	12.50	14
BM	-0.37	1.11	23	0.13	0.85	20	-2.39	0.81	19	-4.25	0.69	21	-4.85	0.60	19	-3.71	0.49	19	-5.64	0.45	19	-4.85	0.31	20	20.00	23	20.17	23
NTIS	0.98	1.26	11	0.29	0.87	19	3.72	0.84	1	2.59	0.71	1	3.74	0.66	1	1.97	0.53	2	-0.08	0.41	9	-3.88	0.36	18	7.75	3	5.83	2
TBL	1.20	1.28	9	1.61	0.91	11	-1.40	0.80	15	-2.02	0.70	15	-4.54	0.59	18	-4.64	0.51	20	-6.79	0.47	23	-0.94	0.34	9	15.00	18	14.67	17
LTY	1.24	1.28	8	0.78	0.86	16	-2.70	0.76	20	-3.96	0.68	20	-4.94	0.60	20	-7.57	0.48	23	0.34	0.38	8	-11.78	0.33	23	17.25	22	17.83	22
LTR	-0.01	1.16	19	-0.46	0.81	21	0.48	0.73	8	-0.29	0.66	9	-0.35	0.61	8	-0.27	0.50	4	0.37	0.44	7	-2.60	0.31	16	11.50	12	11.50	11
TMS	0.60	1.23	13	1.42	0.93	13	-1.19	0.74	13	-0.27	0.70	8	-0.02	0.64	6	-0.47	0.48	5	1.76	0.46	3	0.21	0.34	5	8.25	5	9.67	7
DFY	0.05	1.16	18	1.59	0.91	12	0.85	0.77	6	0.24	0.72	6	-0.26	0.63	7	-3.05	0.44	14	-4.46	0.38	15	-1.60	0.32	12	11.25	11	10.50	8
DFR	2.35	1.37	3	1.74	0.93	10	-1.59	0.68	16	-0.83	0.66	12	-1.59	0.61	12	-2.81	0.45	13	0.81	0.43	5	-3.29	0.31	17	11.00	9	11.00	9
INFL	0.38	1.21	15	-0.52	0.80	22	-0.97	0.74	12	0.15	0.70	7	-2.25	0.61	15	-2.15	0.49	10	1.17	0.44	4	-1.61	0.32	13	12.25	13	13.50	15
OG	1.72	1.32	6	2.31	0.99	4	-1.34	0.87	14	-1.40	0.78	14	-1.90	0.70	13	-3.22	0.55	15	-6.34	0.48	21	5.53	0.37	1	11.00	9	11.00	9
SCR	1.42	1.29	7	2.51	0.97	3	-0.86	0.83	11	-3.57	0.66	19	-5.65	0.55	21	-2.72	0.51	12	-6.32	0.47	20	-1.82	0.34	14	13.38	15	12.17	13
CAY	0.23	1.19	17	0.84	0.89	15	1.10	0.78	5	1.88	0.74	2	2.36	0.64	2	4.15	0.56	1	10.75	0.64	1	-9.81	0.34	22	8.13	4	7.00	4
PC-ECON	-0.20	1.14	21	1.79	0.93	9	-2.11	0.86	18	-0.91	0.79	13	-2.03	0.68	14	-2.15	0.57	11	-4.98	0.50	17	-0.86	0.38	8	13.88	16	14.33	16

Notes: This table reports the annualized certainty equivalent return (CER) gain (%) and the Sharpe ratio (SR) of portfolios formed based on excess market return forecasts constructed using different investor sentiment measures and economic predictors on a rolling window basis. Panel A and B report results for an investor with a mean-variance utility function with a coefficient of risk aversion of 1 and 3, respectively. Mean rank (all) represents the average ranking of the economic performance of each predictor across eight forecast horizons; whereas mean rank ($h \leq 24$) is the average ranking of each predictor from 1-month up to 24-month forecast horizons. The final ranking of each predictor is determined based on their mean rank across different forecast horizons. Investor is assumed to rebalance the portfolio at a frequency similar to the forecast horizon. The proportion of wealth invested equities is restricted to be between 0 and 1.50. The out-of-sample period stretches from January 1985 until December 2014.

CER gains beyond 3-month forecast horizon, except for h = 60. MS and CCI perform the worst among all sentiment measures since the portfolio return does not improves by using their forecasts in lieu of HMM forecasts. Overall, the comparison among investor sentiment measures shows that S^{TV} performs better than most sentiment measures in delivering the real benefits to a mean-variance investor with a risk-aversion coefficient of one.

As for the economic predictors, there is only weak evidence of CER gains for most of them. OG appears to be the best return predictor as it consistently generates positive CER gains beyond 1-month forecast horizon, other than 24-month forecast horizon.

When a higher risk aversion coefficient of 3 (panel B) is assumed, the S^{TV} stands out as the superior sentiment measure which consistently delivers positive CER gains up to 24-month forecast horizon. It is worth noting that the annual portfolio management fees an investor is willing to pay to gain access to the forecast based on S^{TV} is higher in panel B (i.e. ranging from 0.41% to 1.92%) as compared to that in panel A, where risk aversion was lower (i.e. ranging from 0.15% to 1.14%). Also, comparing with the results in panel A reveals that S^{TV} experiences a great improvement in CER gains for an investor with a risk aversion coefficient of 3 across most forecast horizons. These findings imply that the more risk-averse an investor is, the more she or he is willing to pay for access to forecasts generated by the new investor sentiment index, S^{TV}.

When risk aversion is higher (panel B), S^{PLS} generates positive CER gains over short-term forecasts of only up to 6-month horizon with the highest CER gains at 1- and 3-month forecast horizons (5.07% and 5.37%, respectively). These findings again confirm that S^{PLS} predicts stock market returns well only over the short-run period. In line with the results shown in panel A, S^{BW}, although producing positive CER gains for most forecast horizons, generally has lower CER gains than S^{TV}. MS and CCI are shown to provide positive CER gains to investors only occasionally and hence are ranked as the worst predictors among all investor sentiment measures.

Out of 17 individual economic predictors, only three of them, namely DE, NTIS and CAY, deliver positive CER gains over half of the forecast horizons. Surprisingly, the diffusion index of all economic predictors (PC-ECON) does not provide positive CER gains for most forecast horizons when $\gamma = 3$.

Since most predictors have their economic performance affected for long-term forecasts, two different final rankings are computed: (1) "final ranking (all)" accounts for

CER ranking across all forecast horizons, whereas (2) "final ranking ($h \leq 24$)" excludes the CER ranking in 36- and 60-month forecast horizons. Both final rankings demonstrate that S^{TV} delivers consistent results across horizons in panels A and B. Specifically, S^{TV} ranks first in both panels when 36- and 60-month forecasts have been excluded. Meanwhile, it ranks second in both panels when CER gains across all forecast horizons are taken into account. Other investor sentiment measures and economic predictors, however, do not produce consistent rankings across horizons in both panels. These results suggest that S^{TV} can consistently deliver economic gains to mean-variance investors across different forecast horizons and magnitudes of risk aversion.

Regarding the Sharpe ratio, S^{TV} consistently produces higher values relatively to HMM across most forecast horizons, regardless of the degree of risk aversion. This finding is in line with the results for CER gains. MS and CCI generate poorer risk-adjusted returns to investors with the risk aversion coefficient of 1 as compared to HMM, but CCI has a higher Sharpe ratio than HMM where this coefficient is equal to 3. The result of economic predictors is analogous to that of CCI: economic predictors rarely generate Sharpe ratios higher than that of HMM when $\gamma = 1$, but perform better when $\gamma = 3$.

Overall, the analysis of the economic value of forecasts strongly indicates that S^{TV} index outperforms competitor indices and economic predictors. Its superior performance does not only suggest that accounting for the dynamic structure in the contributions of sentiment components enhances the original Baker and Wurgler (2006) approach and captures the latent investor sentiment better than alternative proxies, but also confirms that investor sentiment has a relatively more important role for the stock market fluctuations.

4.5 Robustness check and extension

This section provides a robustness check to determine the relative importance of the investor sentiment or economic predictors to the fluctuations of stock market through examining the predictive performance of S^{TV} against economic predictors under the forecast restriction framework. The forecasting performance of S^{TV} against its sentiment counterparts is also conducted here to further affirm that S^{TV} is superior in capturing the unobservable investor sentiment even a different forecasting strategy is employed. Finally, an analysis of the predictive ability of various predictors over different states of business cycle is conducted.

4.5.1 *Forecasting performance of S^{TV} indexes under restrictive regression*

For robustness analysis, this study considers the restrictive regression model as another forecasting strategy. In particular, the slope coefficient of a given predictor is restricted to a zero value when the model delivers a coefficient with unexpected sign (i.e. inconsistent with the sign suggested by theory). This sign restriction strategy has been employed in previous studies (see Campbell and Thompson, 2008; Rapach et al., 2010; Rapach and Zhou, 2013; Welch and Goyal, 2008) since the dynamic nature of stock market fluctuations might potentially lead to the parameter instability issue in the return predictive framework. Among these papers, however, only Campbell and Thompson (2008) present strong support to their hypothesis that restrictive regression improves forecasting performances of economic predictors. Other studies generally found mixed results for individual economic predictors.

Given that investor sentiment tends to generate negative effects on future stock market returns, the coefficient of all investor sentiment indexes is restricted to be a non-positive value, otherwise, the coefficient value will be truncated to a zero value (i.e. the prediction reduces to HMM-based forecasts). As for economic predictors, the 'correct' sign of each predictor is determined following the work of Rapach et al. (2016)[65]. In particular, coefficient values of NTIS, TBL, LTY, INFL, OG and SCR are restricted to be less than zero; other predictors must have a non-negative coefficient. The PC-ECON is excluded from the restrictive regression analysis since PC-ECON is computed by extracting the common information from all economic predictors and its sign cannot be determined on a theoretical basis. The following sub-sections provide detailed discussion on the predictive performance of investor sentiment indexes and economic predictors under the sign restriction strategy.

(I) S^{TV} vs. other investor sentiment indexes

The predictive performance of S^{TV} against other sentiment indexes based on R^2_{OS} and *MSFE-adjusted* statistic is shown in Table 4.9. As explained, these two statistics evaluate the difference in *MSFE* between a predictive regression model and HMM. A positive R^2_{OS} and a significant *MSFE-adjusted* statistic indicate that forecasts produced by a given predictor is more accurate than HMM in terms of *MSFE.* As in Section 4.4, the results based mainly on

[65] The literature review in Section 2.4 also gives an indication of the 'correct' coefficient sign for each predictor.

Table 4.9: Out-of-sample forecasting results under the restrictive regression framework: S^{TV} vs. other sentiment measures

	h = 1		h = 3		h = 6		h = 9		h = 12		h = 24		h = 36		h = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
S^{TV}	-0.50	-0.05	-1.38	1.19	-0.73	0.55	1.04	1.40*	2.43	1.65*	-0.15	1.29	0.63	0.70	-4.64	-0.60
S^{BW}	0.50	1.12	-2.28	-0.48	-4.65	-1.60	-4.63	-0.80	-4.40	-0.17	-16.89	-1.13	-11.30	-1.57	-19.77	-1.48
S^{PLS}	2.02	2.42***	6.07	3.70***	1.76	1.66**	0.67	1.25	0.83	1.07	-14.78	-0.92	-14.32	-1.28	-19.42	-1.83
MS	-0.66	-1.15	-2.19	-0.48	-3.83	-0.87	-5.59	-0.68	-11.08	-0.85	-13.12	-0.12	-19.81	0.06	-16.15	1.10
CCI	-1.11	0.02	-2.04	0.29	-2.23	0.45	-2.02	0.49	-0.02	0.91	3.87	1.41*	10.32	1.51*	19.10	1.75**

Notes: This table presents the Campbell and Thompson (2008) R^2_{OS} (in percentage) and the Clark and West (2007) *MSFE-adjusted* statistic of various investor sentiment measures: the time-varying weighted investor sentiment index (S^{TV}), the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the University of Michigan Consumer Sentiment Index (MS) and the Conference Board Consumer Confidence Index (CCI) under the restrictive regression framework. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively, based on Newey-West *t*-statistic for *MSFE-adjusted* test. The in-sample period covers from December 1968 to November 1983 and out-of-sample period covers from December 1983 to December 2014.

Table 4.10: Forecast encompassing tests under the restrictive regression framework: S^{TV} vs. other sentiment measures

	h = 1			*h = 3*			*h = 6*			*h = 9*			*h = 12*			*h =24*			*h = 36*			*h = 60*		
	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome
S^{BW}	0.81*	0.19	*3*	0.40	0.60**	*1*	0.00	1.00**	*1*	0.00	1.00***	*1*	0.00	1.00***	*1*	-0.75	1.75	*4*	0.00	1.00***	*1*	0.00	1.00	*4*
	[1.63]	[0.39]		[1.10]	[2.08]		[-0.24]	[2.29]		[-0.03]	[2.80]		[-0.20]	[2.36]		[-0.68]	[1.20]		[-1.43]	[2.59]		[-0.67]	[1.21]	
S^{PLS}	1.00***	0.00	*3*	0.96***	0.04	*3*	0.63*	0.37	*3*	0.48	0.52*	*1*	0.43	0.57*	*1*	0.00	1.00	*4*	0.00	1.00*	*1*	0.00	1.00*	*1*
	[2.71]	[-0.40]		[3.33]	[0.17]		[1.56]	[1.03]		[1.24]	[1.38]		[0.94]	[1.29]		[-0.32]	[1.20]		[-0.87]	[1.44]		-0.95	[1.44]	
MS	0.46	0.54	*4*	0.46*	0.54**	*2*	0.20	0.80*	*1*	0.14	0.86*	*1*	0.00	1.00**	*1*	0.01	0.99	*4*	0.03	0.97*	*1*	0.41	0.59	*4*
	[0.60]	[0.96]		[1.29]	[2.04]		[0.34]	[1.64]		[0.38]	[1.62]		[-0.40]	[1.74]		[0.06]	[1.25]		[0.10]	[1.64]		[0.98]	[0.91]	
CCI	0.35	0.65**	*1*	0.46*	0.54**	*2*	0.36	0.64*	*1*	0.29	0.71*	*1*	0.36	0.64*	*1*	0.61	0.39	*4*	0.70	0.30	*4*	0.81*	0.19	*3*
	[0.73]	[1.65]		[1.64]	[2.33]		[0.96]	[1.55]		[0.74]	[1.63]		[0.74]	[1.42]		[1.13]	[1.05]		[1.03]	[1.16]		[1.42]	[0.42]	

Notes: This table presents the forecast encompassing tests results of the time-varying weighted investor sentiment index (S^{TV}) against other investor sentiment measures: the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the University of Michigan Consumer Sentiment Index (MS) and the Conference Board Consumer Confidence Index (CCI) under the restrictive regression framework. λ represents the optimal weight associated with the competing forecast. The forecast based on S^{TV} is treated as the given forecast in the test 1 and as competing forecast in test 2. The values in the brackets are *MDM* test statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The in-sample period covers from December 1968 to November 1983 and out-of-sample period covers from December 1983 to December 2014.

the *MSFE-adjusted* statistic since it adjusts for the noise forecasts produced by unrestricted models.

Comparing the statistics in Table 4.9 and Table 4.2, the results show that the sign restriction, in general, does not seem to have great impact on the performance of investor sentiment measures in terms of the statistical significance of *MSFE-adjusted* statistics. For instance, the *MSFE-adjusted* statistic of S^{TV} remains significant at h = 12 after imposing the sign restriction. The similar observation is also seen from S^{PLS}. In spite of that, S^{BW}, S^{PLS}, MS and CCI experience some improvements in the R^2_{OS} , albeit these improvements do not result in a significantly lower *MSFE*. Therefore, the forecast accuracy of other investor sentiment indexes relative to HMM does increase to a limited extent with the sign restriction strategy.

In contrast, the R^2_{OS} values for S^{TV} reduce slightly after imposing the coefficient sign restriction at certain forecast horizons, especially for the short-horizon of less than 9 months. The *MSFE-adjusted* statistic of S^{TV} also loses its significance at h = 3 and h = 24. These findings suggest that the sign restriction strategy leads to a mild reduction in the forecast performance of S^{TV} relative to HMM. As discussed in the literature, even though negative relationship between investor sentiment and future stock returns is commonly found in the literature, investor sentiment could have positive effect on future stock returns as well[66]. Therefore, S^{TV} could possibly capture well different effects of investor sentiment at different points in time and limiting the coefficient sign of S^{TV} to be a negative value over the entire estimation period does more harm than good to the forecasting performance of S^{TV}. The observed negative relationship between investor sentiment and future stock market returns in Section 3.4 could be due to that, on average, the negative effect of investor sentiment outweighs the positive effect of investor sentiment over the entire sample period.

Next, Table 4.10 presents the forecast encompassing test result of investor sentiment measures corresponds to the restricted forecast. Similarly, the outcomes are retrieved from the encompassing test in both directions. Outcome 1 means that S^{TV} forecasts dominate the forecasts based on alternative sentiment measure and the opposite finding is represented by

[66] Negative sentiment-return relationship is observed as current high (low) sentiment drives contemporaneous stock prices above (below) its fundamental value, and stock returns will subsequently experience a reversal when the mispricing is corrected by arbitrageurs. In contrast, a positive sentiment-return relationship is perceived when the high contemporaneous stock prices resulted from a current favourable sentiment lift up further the investor sentiment level, resulting in further increase in expected returns, and the reverse holds.

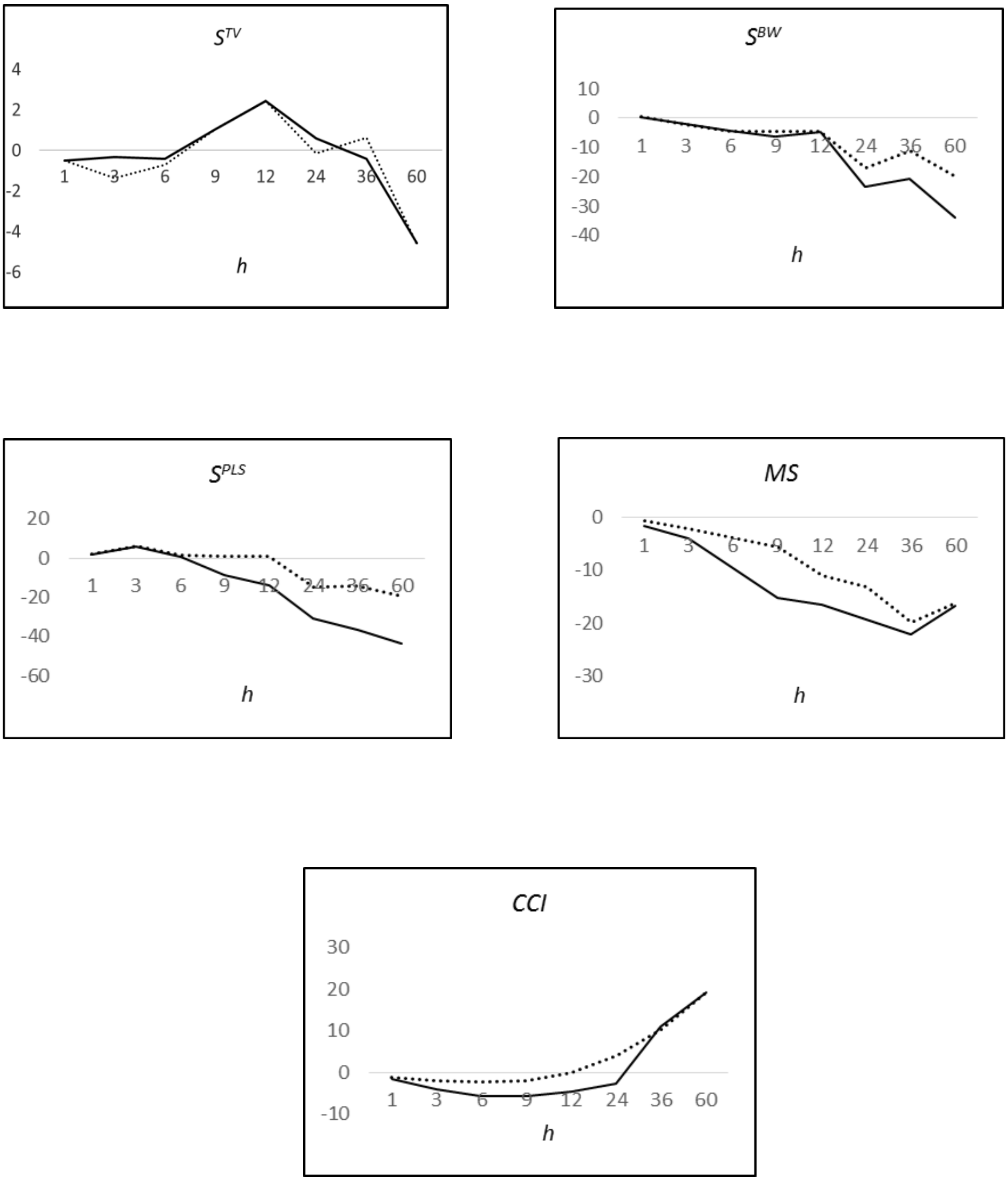
outcome 3. Apart from these two extreme results, the forecasts of S^{TV} and another sentiment measure could provide complementary information to the combination forecast and this is shown by outcome 2. Hence, combining both forecasts in predicting excess market returns would be an ideal option. Finally, both sentiment measures capture similar and redundant information when outcome 4 is obtained.

Table 4.10 shows that S^{TV} still stands out to be the best return predictors among all sentiment measures, in which the forecasts of S^{TV} encompass the forecasts of all other sentiment measures (i.e. outcome 1) for 53% of the total pairings, despite a slight drop in the predictive power of S^{TV} is observed. Contrarily, the reverse (outcome 3) happened for only about 16% of the total cases (5 out of 32 pairings). Particularly, the S^{TV} forecast encompasses S^{BW} forecast from 3-month forecast horizon up to 36-month forecast horizon, except for h = 24. However, the opposite finding is only seen at the monthly forecast. Combining forecasts of S^{TV} and S^{BW} provides redundant information at forecast horizons of 24-month and 60-month. Similarly, forecasts based on S^{TV} dominate forecasts of S^{PLS} in half of the forecast horizons, which are h = 9, 12, 36, and 60. On the other hand, S^{PLS} forecasts encompass S^{TV} forecasts only over the short-term horizons. Since the forecast performances of MS and CCI have been improved after restricting their coefficient signs, mixed results have been observed across different forecast horizons. Nevertheless, the fact that S^{TV}-based forecasts encompass forecasts produced by MS and CCI still dominates the comparison.

As a whole, the results show that S^{TV} continues to generate lower forecast errors relative to other sentiment measures under the restrictive regression framework based on forecast encompassing test results. Furthermore, panel A of Figure 4.3 clearly illustrates that the predictive performance of S^{TV} index is affected relatively less by the sign restriction strategy as compared to other sentiment measures since R^2_{OS} values do not vary a lot after imposing the sign restriction on the coefficient across all forecast horizons, implying that S^{TV} consistently produces appropriate coefficient sign. Hence, S^{TV} remains to be the superior investor sentiment measure even after imposing the sign restriction.

Figure 4.3: The R^2_{OS} statistics for each investor sentiment index across different forecast horizons

This figure exhibits the R^2_{OS} statistics for each investor sentiment index over the entire out-of-sample period. The solid (dotted) line denotes the R^2_{OS} statistics for each investor sentiment index prior to (after) the implementation of sign restriction.



(II) S^{TV} *vs. economic predictors*

The predictive performance of economic predictors against HMM as measured by R^2_{OS} and *MSFE-adjusted* statistic is presented in Table 4.11. The results of S^{TV} across different forecast horizons are presented in the first row for the ease of comparison.

The table shows that most economic predictors have their R^2_{OS} improved after imposing the sign restriction as compared to the statistics shown in Table 4.6. At the same time, the number of significant *MSFE-adjusted* statistic has seen an increase also across different economic predictors, with the most noticeable improvement can be seen from NTIS, TBL, LTY, TMS and OG. These findings suggest that restricting the coefficient sign leads to an improvement in the forecasting performance of economic predictors, which is consistent with the findings of Campbell and Thompson (2008) and Rapach and Zhou (2013). As discussed, the forecast accuracy of S^{TV} relative to HMM is, however, reduced slightly based on the R^2_{OS} and *MSFE-adjusted* statistics.

Therefore, the forecasting strategy that is useful to economic predictors may not be that useful to S^{TV} since both types of predictors convey different signals on future stock market returns. In view of this, other forecasting strategies that better suit to the sentiment measures could be explored in the future.

Next, Table 4.12 examines the predictive performance of S^{TV} against economic predictors under the restrictive regression model based on the forecast encompassing test. As expected, the results show that the forecasting performance of S^{TV} relative to that of economic predictors are affected under the restrictive regression since forecasting performances of economic predictors have greatly improved after the application of sign restriction. Looking at the occurrence of outcome 1, the results show that forecasts of S^{TV} encompass forecasts of economic predictors in 26 cases out of total 136 pairings (or 19%), but the opposite has a probability of 32%. Nevertheless, S^{TV} is shown to have a better performance against DP, DY, EP and BM, with more outcome 1 as compared to outcome 3 are observed across different forecast horizons. Counting on outcome 1 and outcome 2 jointly gives us a total probability of 0.31, approximates to that of the outcome 3 (i.e. 0.32). This shows that the inclusion of S^{TV} forecasts to optimal combination forecasts is still worthwhile as S^{TV} does provide complimentary information to economic predictors.

Table 4.11: Out-of-sample forecasting results under the restrictive regression framework: S^{TV} vs. economic predictors

	h = 1		*h* = 3		*h* = 6		*h* = 9		*h* = 12		*h* = 24		*h* = 36		*h* = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
S^{TV}	-0.50	-0.05	-1.38	1.19	-0.73	0.55	1.04	1.40*	2.43	1.65*	-0.15	1.29	0.63	0.70	-4.64	-0.60
DP	1.81	2.71***	3.95	2.02**	3.02	1.31*	-3.60	1.03	-9.32	0.86	-14.42	0.89	-13.45	0.88	4.36	1.54*
DY	-0.74	0.29	2.42	1.47*	1.12	1.18	-2.26	1.07	-7.50	1.06	-9.48	0.99	-7.88	0.89	7.22	1.48*
EP	-5.69	-0.80	-6.90	-0.26	-16.43	-0.66	-26.90	-0.60	-30.25	-0.84	-46.18	-1.24	-75.51	-1.39	-91.23	-1.51
DE	-0.44	0.21	0.49	0.97	-2.27	0.22	0.18	0.78	5.46	1.29*	-15.16	0.85	-21.67	1.05	13.13	1.87**
SVAR	-3.21	-1.01	-28.33	-0.63	-80.32	-0.07	-89.74	1.43*	-45.69	1.01	-12.79	1.67**	-12.11	0.02	-2.67	0.06
BM	-0.15	-0.41	-0.66	0.77	-2.05	0.98	-8.85	0.47	-15.42	0.38	-18.58	0.09	-20.79	-0.55	-40.77	-0.12
NTIS	-0.49	1.39*	-1.42	1.52*	-1.86	1.81**	-2.59	1.50*	-3.73	1.34*	1.16	1.16	0.11	1.01	-1.40	1.03
TBL	-0.18	0.87	1.62	2.51***	0.45	1.05	2.93	1.65*	5.80	1.63*	12.26	1.48*	12.36	1.35*	-38.52	-1.49
LTY	-0.63	0.65	0.01	1.77**	3.09	1.96**	4.72	1.56*	5.44	1.32*	0.96	0.78	-9.96	-1.02	-27.31	-1.29
LTR	-7.41	0.35	-1.80	-0.22	-0.06	0.59	1.59	1.19	3.46	1.74**	0.71	0.52	-0.60	-0.28	-0.33	-0.38
TMS	-0.65	0.17	-1.24	0.37	-1.51	0.00	1.57	1.55*	4.25	2.06**	3.76	1.33*	23.29	2.38***	9.49	1.72**
DFY	-0.54	-0.02	-1.06	0.01	0.20	0.87	1.12	1.04	3.30	1.53*	0.32	0.30	-1.68	-0.45	-9.58	-0.68
DFR	-16.24	0.50	-0.01	0.43	-0.91	-1.08	1.53	1.40*	1.83	1.64*	2.03	0.98	3.54	1.40*	-1.15	-0.41
INFL	-0.41	-0.38	-0.92	-0.15	0.45	0.84	2.18	1.48*	2.15	1.10	1.93	0.87	3.99	1.84**	0.85	1.03
OG	0.56	1.86**	0.79	1.99**	3.65	2.01**	5.04	2.13**	5.98	2.34**	-35.36	1.80**	-47.05	1.48*	46.99	2.41***
SCR	-0.13	0.02	-0.80	0.75	0.64	1.04	-1.42	0.26	-12.65	-0.68	-61.83	1.06	-249.46	1.21	-96.65	1.13
CAY	-0.08	-0.20	-1.15	0.53	1.17	1.55*	3.99	2.49***	8.43	3.33***	17.91	2.13**	16.82	2.03**	-6.76	1.61*

Notes: This table presents the Campbell and Thompson (2008) R^2_{OS} (in percentage) and *MSFE-adjusted* (Clark and West, 2007) statistic of the time-varying weighted investor sentiment index (S^{TV}) and economic predictors (as listed in Section 4.3) under the restrictive regression framework. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively, based on Newey-West *t*-statistic for *MSFE-adjusted* test. The in-sample period covers from December 1968 to November 1983 and out-of-sample period covers from December 1983 to December 2014.

Table 4.12: Forecast encompassing tests under the restrictive regression framework: S^{TV} indexes vs. economic predictors

	h = 1			*h = 3*			*h = 6*			*h = 9*			*h = 12*			*h =24*			*h = 36*			*h = 60*		
	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome	λ (1)	λ (2)	Outcome
DP	1.00***	0.00	*3*	0.82***	0.18	*3*	0.82*	0.18	*3*	0.41	0.59**	*1*	0.27	0.73**	*1*	0.30	0.70**	*1*	0.33	0.67***	*1*	0.67	0.33*	*1*
	[2.73]	[-1.13]		[2.75]	[0.82]		[1.57]	[0.62]		[1.19]	[1.80]		[0.92]	[2.18]		[0.78]	[2.14]		[0.67]	[4.27]		[1.07]	[1.47]	
DY	0.53	0.47	*4*	0.84***	0.16	*3*	0.63*	0.37	*3*	0.42	0.58**	*1*	0.31	0.69***	*1*	0.35	0.65**	*1*	0.37	0.63***	*1*	0.72	0.28	*4*
	[0.94]	[1.24]		[2.35]	[0.72]		[1.43]	[1.02]		[1.23]	[1.87]		[1.11]	[2.37]		[0.88]	[2.07]		[0.70]	[5.59]		[1.00]	[1.10]	
EP	0.00	1.00**	*1*	0.23	0.77	*4*	0.00	1.00	*4*	0.00	1.00	*4*	0.00	1.00*	*1*	0.00	1.00**	*1*	0.00	1.00*	*1*	0.00	1.00	*4*
	[-0.49]	[1.66]		[0.50]	[1.20]		[-0.18]	[1.03]		[-0.17]	[1.21]		[-0.34]	[1.61*]		[-0.79]	[1.89]		[-1.05]	[1.40]		[-1.04]	[1.13]	
DE	0.50	0.50	*4*	0.65**	0.35	*3*	0.36	0.64	*4*	0.44	0.56	*4*	0.67*	0.33	*3*	0.27	0.73	*4*	0.26	0.74	*4*	0.60	0.40	*4*
	[0.79]	[0.70]		[1.68]	[0.99]		[0.76]	[0.96]		[1.24]	[1.14]		[1.41]	[1.03]		[1.01]	[1.15]		[1.11]	[1.15]		[1.25]	[0.71]	
SVAR	0.00	1.00	*4*	0.07	0.93	*4*	0.04	0.96	*4*	0.06*	0.94	*3*	0.07	0.93	*4*	0.23*	0.77	*3*	0.10	0.90	*4*	0.71*	0.29	*3*
	[-0.45]	[0.96]		[0.91]	[1.13]		[1.00]	[1.03]		[1.38]	[1.03]		[1.22]	[1.07]		[1.52]	[1.06]		[0.51]	[1.12]		[1.37]	[0.45]	
BM	0.83	0.17	*4*	0.56**	0.44*	*2*	0.44	0.56*	*1*	0.22	0.78*	*1*	0.13	0.87**	*1*	0.11	0.89	*4*	0.00	1.00*	*1*	0.05	0.95*	*1*
	[1.06]	[0.25]		[1.77]	[1.64]		[1.24]	[1.52]		[0.76]	[1.64*]		[0.48]	[1.70]		[0.18]	[1.28]		[-0.33]	[1.49]		[0.16]	[1.50]	
NTIS	0.49**	0.51**	*2*	0.50**	0.50**	*2*	0.46**	0.54**	*2*	0.43*	0.57**	*2*	0.41	0.59**	*1*	0.53	0.47**	*4*	0.48	0.52**	*1*	0.72	0.28	*4*
	[1.76]	[1.71]		[2.17]	[2.14]		[1.85]	[1.97]		[1.51]	[2.25]		[1.22]	[2.09]		[1.20]	[1.94]		[0.89]	[1.92]		[1.01]	[0.89]	
TBL	0.65*	0.35	*3*	0.83**	0.17	*3*	0.65	0.35	*4*	0.65*	0.35	*3*	0.74*	0.26	*3*	1.00	0.00	*4*	1.00	0.00	*4*	0.00	1.00	*4*
	[1.34]	[0.80]		[2.23]	[0.61]		[1.25]	[0.65]		[1.50]	[0.88]		[1.38]	[0.68]		[1.18]	[-0.58]		[0.94]	[-0.40]		[-0.78]	[1.02]	
LTY	0.49*	0.51*	*2*	0.60***	0.40**	*2*	0.79**	0.21	*3*	0.69*	0.31*	*2*	0.62	0.38**	*1*	0.52	0.48**	*1*	0.00	1.00	*4*	0.00	1.00	*4*
	[1.33]	[1.57]		[2.36]	[1.88]		[1.89]	[0.71]		[1.58]	[1.32]		[1.19]	[2.15**]		[0.73]	[1.79]		[-0.37]	[0.81]		[-0.55]	[0.95]	
LTR	0.11	0.89***	*1*	0.45*	0.55**	*2*	0.64*	0.36	*3*	0.57*	0.43	*3*	0.61*	0.39	*3*	0.62	0.38	*4*	0.29	0.71	*4*	1.00*	0.00	*3*
	[0.57]	[4.18]		[1.29]	[1.76]		[1.35]	[0.76]		[1.38]	[1.18]		[1.41]	[0.91]		[0.86]	[0.59]		[0.31]	[0.79]		[1.40]	[-0.65]	
TMS	0.41	0.59	*4*	0.52*	0.48*	*2*	0.38	0.62	*4*	0.56*	0.44	*3*	0.67**	0.33	*3*	0.82	0.18	*4*	1.00*	0.00	*3*	0.90***	0.10	*3*
	[0.74]	[0.94]		[1.44]	[1.47]		[0.79]	[1.01]		[1.64]	[1.14]		[1.88]	[0.85]		[1.23]	[0.82]		[1.55]	[-1.05]		[6.01]	[0.17]	
DFY	0.65	0.35	*4*	0.61*	0.39*	*2*	0.81	0.19	*4*	0.60	0.40	*4*	0.63	0.37	*4*	0.62	0.38	*4*	0.15	0.85	*4*	0.00	1.00	*4*
	[0.94]	[1.05]		[1.52]	[1.57]		[1.20]	[0.65]		[1.03]	[0.94]		[1.13]	[0.79]		[0.71]	[0.73]		[0.07]	[0.73]		[-0.02]	[0.72]	
DFR	0.12	0.88***	*1*	0.68*	0.32	*3*	0.51	0.49	*4*	0.55**	0.45	*3*	0.47	0.53	*4*	0.88**	0.12	*3*	1.00*	0.00	*3*	1.00*	0	*3*
	[0.63]	[2.95]		[1.47]	[1.11]		[0.69]	[0.77]		[1.66]	[1.22]		[0.96]	[1.17]		[1.38]	[0.35]		[1.45]	[-0.08]		[1.42]	[-0.41]	
INFL	0.53	0.47	*4*	0.56*	0.44*	*2*	0.74	0.26	*4*	0.62**	0.38	*3*	0.47*	0.53*	*2*	0.79	0.21	*4*	0.96**	0.04	*3*	1.55**	-0.55	*3*
	[0.78]	[0.59]		[1.45]	[1.51]		[1.19]	[0.42]		[2.12]	[1.23]		[1.31]	[1.37]		[1.13]	[0.31]		[1.66]	[0.04]		[1.69]	[-0.85]	
OG	0.76**	0.24	*3*	0.66**	0.34**	*2*	0.72**	0.28	*3*	0.65**	0.35	*3*	0.61**	0.39	*3*	0.34**	0.66	*3*	0.37	0.63	*4*	0.82***	0.07	*3*
	[2.16]	[0.85]		[2.44]	[1.80]		[2.12]	[1.00]		[2.29]	[1.05]		[2.15]	[1.05]		[1.37]	[1.00]		[1.06]	[0.98]		[2.81]	[0.27]	
SCR	0.81	0.19	*4*	0.55**	0.45**	*2*	0.68*	0.32	*3*	0.28	0.72*	*1*	-0.54	1.54*	*1*	0.18	0.82	*4*	0.15	0.85	*4*	0.30	0.70	*4*
	[1.07]	[0.21]		[1.73]	[1.83]		[1.37]	[0.67]		[0.61]	[1.60]		[-0.54]	[1.33]		[1.17]	[1.01]		[0.94]	[0.99]		[0.90]	[0.84]	
CAY	0.91	0.09	*4*	0.54**	0.46**	*2*	0.69**	0.31	*3*	0.66***	0.34	*3*	0.69***	0.31	*3*	0.82**	0.18	*3*	0.71**	0.29	*3*	0.50**	0.50	*3*
	[1.03]	[0.10]		[1.76]	[1.78]		[1.98]	[0.93]		[2.42]	[1.14]		[2.52]	[0.96]		[2.09]	[0.82]		[1.76]	[0.91]		[1.87]	[0.83]	

Notes: This table presents the forecast encompassing tests results of the time-varying weighted investor sentiment index (S^{TV}) against economic predictors (as listed in Section 4.3) under the restrictive regression framework. λ represents the optimal weight associated with the competing forecast. The forecast based on S^{TV} is treated as the given forecast in the test 1 and as the competing forecast in test 2. The values in the brackets are *MDM* test statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. The in-sample period covers from December 1968 to November 1983 and out-of-sample period covers from December 1983 to December 2014.

To conclude, even though economic predictors have a stronger predictive power as compared to S^{TV} index under the restrictive regression, this demonstrates that most economic predictors do not generate theoretically aligned coefficient signs at all time, and hence having the need to tweak the forecasts. The pure predictive ability of economic predictors is opaque under the restrictive regression framework. The improved predictive performances of economic predictors are 'muddied' with the predictive performance of HMM since the forecast value is truncated to HMM-based forecast (i.e. slope coefficient of the predictor reduced to zero) when the coefficient sign of economic predictors is inconsistent with the theory. This implies that economic predictors predict well only at certain times since their predictive performances based on conventional regression[67] are poorer than that based on restrictive regression. Therefore, it is apparent that stock market movements are not driven mainly by economic predictors at all times.

On the other hand, the slight drop in the forecasting performance of S^{TV} due to the truncation of forecasts to HMM-based forecasts when S^{TV} produces 'inconsistent' sign indicating that investor sentiment indeed predicts well stock market returns for most of the time. Therefore, the outperformance (underperformance) of S^{TV} against economic predictors in forecasting stock market returns under the conventional (restrictive) regression framework reflects that investor sentiment has a dominant role in stock market fluctuations.

4.5.2 *Forecasting performances over the business cycle period*

Following most literature (*e.g.* Chung et al, 2012; Henkel et al., 2011; Huang et al., 2015), this section also considers the forecasting performance of various return predictors in the expansion and recession periods. Such analysis provides an understanding as to when (i.e. expansion or recession period) the investor sentiment captured by S^{TV} is having a more dominant role in stock market movements.

Chung et al. (2012) find that the predictive power of investor sentiment can only be seen in expansion periods but disappears in recession periods. The underlying causes of the asymmetry effect of investor sentiment could come from two channels – the growing optimism during expansion periods and the limit to arbitrage. The increased optimism, which has been found during expansion periods (Chung et al., 2012), attracts uninformed traders to actively involved in stock buying, leading to a substantial stock overvaluation (Antoniou et al.,

[67] Conventional regression is the regression performed in Section 4.4.

2016). Contrarily, the growing pessimism causes underpricing. Ideally, arbitrageurs would correct any mispricing occurred in the market immediately. However, the potential of investors becoming even more optimistic (De Long et al., 1990) coupled with the short sale constraints (see Shleifer and Vishny, 1997; Mitchell, Pulvino and Stafford, 2002) hinder the arbitrage activities, especially when short sale is required to rectify the overpricing phenomenon in the expansion period. Taking altogether, the sentiment effect could be more pronounced in expansion periods; whereas the sentiment-driven underpricing can be easily arbitraged away by buying underpriced stocks and thus the sentiment effect is not apparent during recession periods.

To shed further light on the asymmetric predictive power of investor sentiment, this sub-section evaluates and compares the out-of-sample forecasting performance of S^{TV} against other predictors across different business cycles. The expansion and recession periods are defined according to the National Bureau of Economic Research (NBER)-dated recession. The analyses are segregated into predictive performances of (1) investor sentiment measures and (2) economic predictors in different market states. The results are reported in terms of R^2_{OS} and *MSFE-adjusted* statistics. Similarly, both unrestricted and restricted forecasts are considered in each sub-section.

(I) Predictive power of investor sentiment measures in different business cycles

Table 4.13 depicts the conventional predictive regression performance of different investor sentiment measures in the expansion (panel A) and recession periods (panel B), respectively. Comparing results from panel A and B reveals that S^{TV} has a much stronger predictive power in the expansion period than in the recession period and so for other sentiment measures. All sentiment measures deliver greater R^2_{OS} value and tend to have more rejection on the null hypothesis of *MSFE-adjusted* statistic ($H_0: MSFE_{HMM} \leq MSFE_{PR}$), suggesting that forecast errors of investor sentiment indexes measured by *MSFE* is significantly lower than that of HMM during the expansion period.

The predictive performance of S^{TV} in the expansion period is even better than their whole sample performance as shown in Table 4.2. For instance, the R^2_{OS} value of S^{TV} at 9-month forecast horizon improves substantially from 1.04% to 5.49% in the expansion period. Besides that, S^{TV} also performs better than other investor sentiment measures during the expansion period. S^{PLS} is shown to predict well at 1-month and 3-month forecast horizons,

Table 4.13: Out-of-sample forecasting results for conventional regression in different business cycles: S^{TV} vs. other sentiment measures

	h = 1		h = 3		h = 6		h = 9		h = 12		h = 24		h = 36		h = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
	Panel A: Expansion period															
S^{TV}	-0.6	0.05	-0.3	1.89**	2.25	1.40*	5.49	2.27**	5.92	2.18**	-0.01	1.16	2.04	0.98	-4.73	-0.53
S^{BW}	-1.07	-0.09	-4.22	-0.65	-4.38	0.09	-1.12	1.17	0.78	1.37*	-11.05	0.04	-14.37	-1.37	-34.86	-2.51
S^{PLS}	1.53	2.10**	4.06	3.44***	-2.7	0.96	-9.49	0.23	-2.7	0.81	-27.11	-1.36	-33.72	-1.72	-47.99	-3.96
MS	-2.41	-2.49	-4.39	-0.89	-14.31	-1.48	-21.22	-1.42	-14.3	-0.45	-18.97	-0.23	-21.84	0.14	-19.4	1.06
CCI	-2.28	-0.61	-3.42	0.24	-6.2	0.02	-1.33	1.05	4.47	1.45*	-2.52	1.07	10.82	1.48*	23.21	1.83**
	Panel B: Recession period															
S^{TV}	-0.22	-0.14	-0.38	0.14	-5.99	-1.85	-6.88	-1.54	-3.68	-0.61	2.88	2.21**	-19.21	-	-3.41	-
S^{BW}	5.98	1.39*	0.96	0.48	-2.83	-2.44	-11.31	-5.59	-10.45	-2.27	-53.63	-1.41	-41.01	-	6.95	-
S^{PLS}	3.84	1.13	9.7	2.25**	7.06	1.33*	-7.28	-1.11	-33.26	-2.45	-45.69	-1.86	-58.04	-	-8.67	-
MS	1.25	0.51	-2.9	-0.09	0.59	0.51	-4.33	-1.38	-20.42	-3.38	-20.96	-5.41	-23.86	-	5.29	-
CCI	1.54	0.6	-5.67	-1.46	-4.76	-1.43	-13.62	-2.57	-20.81	-2.75	-3.96	-0.47	12.39	-	-13.8	-

Notes: This table presents the Campbell and Thompson (2008) R^2_{OS} (in percentage) and the Clark and West (2007) *MSFE-adjusted* statistic of various investor sentiment measures: the time-varying weighted investor sentiment index (S^{TV}), the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the University of Michigan Consumer Sentiment Index (MS) and the Conference Board Consumer Confidence Index (CCI). Panel A reports the forecasting performance of each sentiment measure in expansion periods; Panel B reports the forecasting performance of each sentiment measure in recession periods. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively, based on Newey-West t-statistic for *MSFE-adjusted* test. The in-sample period covers from December 1968 to November 1983 and out-of-sample period covers from December 1983 to December 2014.

Table 4.14: Out-of-sample forecasting results for restrictive regression in different business cycles: S^{TV} vs. other sentiment measures

	h = 1		*h* = 3		*h* = 6		*h* = 9		*h* = 12		*h* = 24		*h* = 36		*h* = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
	Panel A: Expansion period															
S^{TV}	-0.73	-0.17	-1.44	1.43*	1.77	1.35*	5.49	2.27**	5.92	2.18**	-0.75	1.1	3.22	1.24	-4.73	-0.53
S^{BW}	-0.9	0.02	-3.84	-1.04	-5.77	-1.23	-3.13	0.55	-1.26	1.75**	-5.89	-0.64	-7.54	-1.6	-22.32	-1.5
S^{PLS}	1.55	2.13**	4.49	3.65***	-0.76	1.32*	1.56	1.38*	5.74	1.58*	-7.02	-0.24	-8.62	-1.16	-21.6	-1.87
MS	-0.95	-1.43	-2.68	-0.29	-5.23	-0.75	-8.58	-0.66	-10.03	-0.26	-13.77	0.04	-19.73	0.2	-18.83	1.08
CCI	-1.92	-0.39	-1.9	0.61	-1.38	0.93	2.19	1.38*	7.38	1.61*	3.53	1.35*	10.05	1.44*	23.21	1.83**
	Panel B: Recession period															
S^{TV}	0.39	0.63	-1.23	-0.53	-5.99	-1.85	-6.88	-1.54	-3.68	-0.61	2.11	1.60*	-19.21	-	-3.95	-
S^{BW}	5.98	1.39*	1.28	0.58	-2.30	-1.97	-7.31	-2.93	-9.91	-2.04	-58.93	-1.73	-40.12	-	0.59	-
S^{PLS}	3.84	1.13	9.70	2.25**	7.06	1.33*	-0.91	0.06	-7.78	-2.76	-44.42	-1.83	-58.00	-	-1.96	-
MS	0.49	1.82**	-1.06	-0.87	-0.90	-1.06	-0.26	-1.22	-12.94	-1.52	-10.64	-1.57	-20.42	-	5.29	-
CCI	2.07	1.61*	-2.37	-0.89	-4.01	-1.13	-9.51	-1.50	-13.00	-1.31	5.15	1.56*	12.39	-	-13.80	-

Notes: This table presents the Campbell and Thompson (2008) R^2_{OS} (%) and the Clark and West (2007) *MSFE-adjusted* statistic of various investor sentiment measures: the time-varying weighted investor sentiment index (S^{TV}), the Baker and Wurgler investor sentiment index (S^{BW}), the aligned investor sentiment index (S^{PLS}), the University of Michigan Consumer Sentiment Index (MS) and the Conference Board Consumer Confidence Index (CCI) under the restrictive regression framework. Panel A reports the forecasting performance of each sentiment measure in expansion periods; Panel B reports the forecasting performance of each sentiment measure in recession periods. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively, based on Newey-West *t*-statistic for *MSFE-adjusted* test. The in-sample period covers from December 1968 to November 1983 and out-of-sample period covers from December 1983 to December 2014.

whereas S^{TV} consistently predicts excess market returns from 3-month up to 12-month forecast horizon in the expansion period based on *MSFE-adjusted* statistic.

The asymmetric predictive power of investor sentiment is consistent with the results reported in Aissia (2016) and Chung et al. (2012). Investors become more optimism during market expansion and participate actively in the stock market. Therefore, the predictive power of investor sentiment is more pronounced during expansion periods.

The predictive power of investor sentiment measures in different states of business cycle after imposing the sign restriction are evaluated as well. Panels A and B of Table 4.14 report the forecasting performance of sentiment measures under restrictive regression framework in the expansion and recession period, respectively. The results show that investor sentiment measures again perform better in expansion periods than in recession periods, where the chances of rejecting null hypothesis based on *MSFE-adjusted* statistic are higher in expansion periods, even after the implementation of the restrictive forecast. By constraining the coefficient sign, S^{TV}, however, has lower R^2_{OS} values during expansion periods as compared to the results of S^{TV} under unrestricted model reported in panel A of Table 4.13. The reduction in R^2_{OS} is mainly seen in short-horizon forecasts. In contrast, panel B of Table 4.14 shows that the sign restriction has a relatively little adverse impact on the forecasting performance of S^{TV} during recession periods given that R^2_{OS} remains insignificant according to the *MSFE-adjusted* statistic for most cases, except for h = 24, at which the R^2_{OS} statistic of S^{TV} in panel B of Table 4.13 is significant as well. As we have seen from panel B of Figure 4.4, out-of-sample forecasting performances of investor sentiment measures, especially S^{TV}, do not affected much after imposing the sign restriction in recession periods as compared to expansion periods as shown in panel A of Figure 4.4.

In summary, restricting the coefficient sign of S^{TV} to be a negative value in recession periods could be more appropriate than in expansion periods. During the expansion period, the growing optimism of irrational investors leads to stock overvaluation that is hard to be corrected within a short-term period due to limits to arbitrage[68]. As such, stock prices take a longer time to revert to fundamental values, which is evidenced by the poorer forecasting performance of S^{TV} after restricting the coefficient sign to be negative in short-horizon

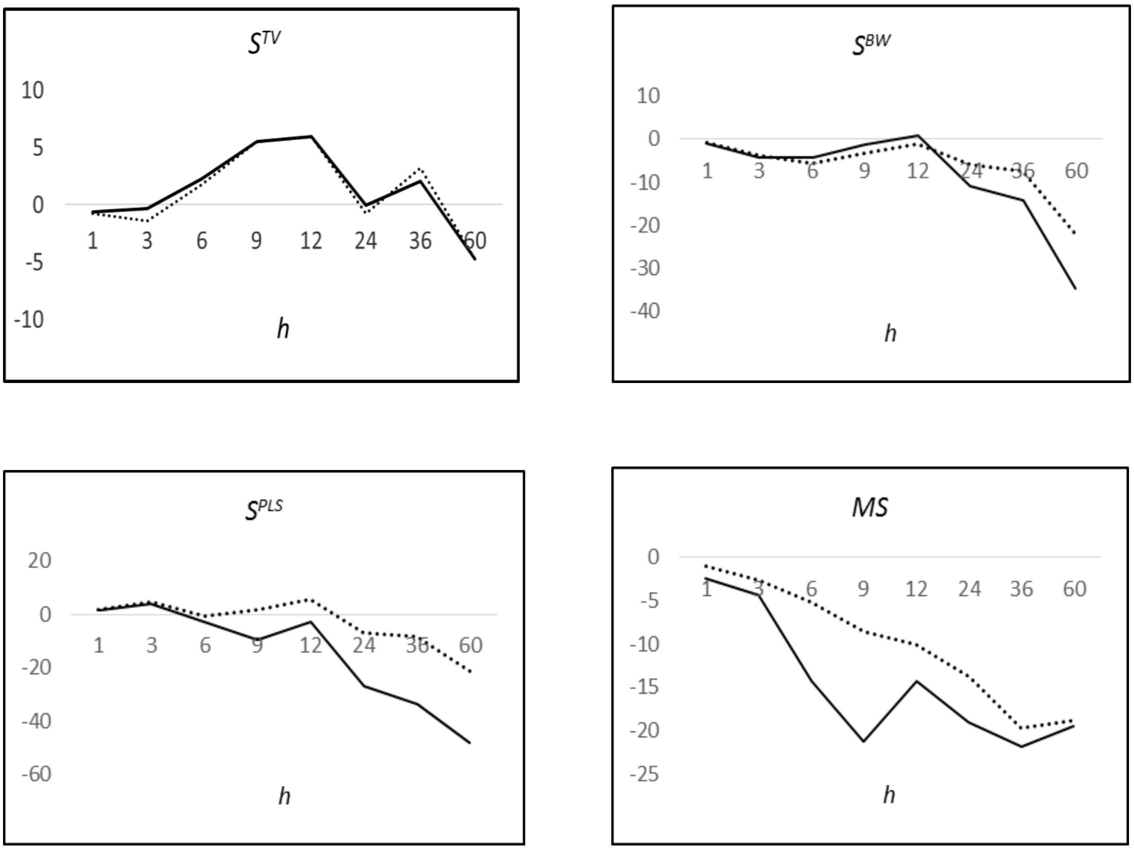
[68] Arbitrage is also easier if buying, but not short selling, is required.

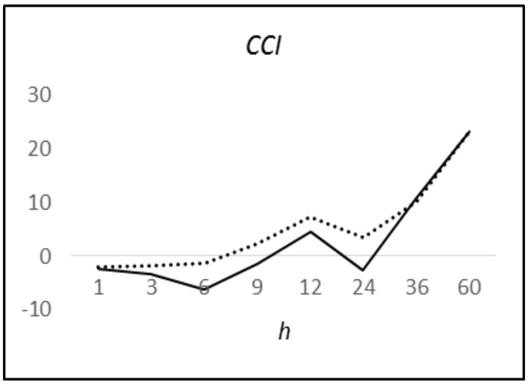
forecasts during expansion periods. These phenomena could explain why R^2_{OS} values over the entire out-of-sample period are being affected slightly, especially for short-horizon forecasts, when the coefficient sign of S^{TV} is restricted to be less than zero. The expansion period has a greater number of observations than the recession period in this study, and hence the predictive performance of S^{TV} in expansion periods has a greater influence on the overall performance of S^{TV} under the restrictive regression framework. This truly reflects a stronger sentiment effect during expansion periods when stock overvaluations resulted from excessive optimism during good market state requires a longer correction period. Therefore, this finding implies that investor sentiment drives the stock market mainly during the expansion period.

Figure 4.4: The R^2_{OS} statistics for each investor sentiment index across different forecast horizons over the business cycle period

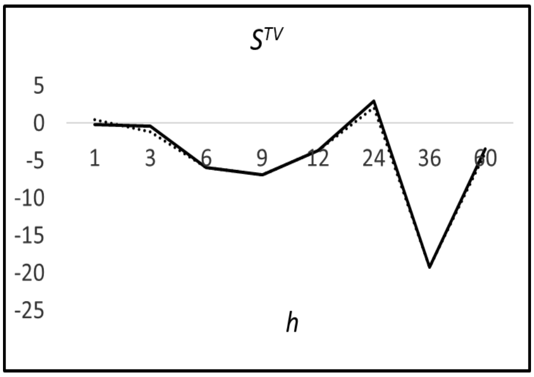
Panel A and B present the R^2_{OS} of investor sentiment indexes during the expansion and recession periods, respectively, occurred in the out-of-sample period. The solid (dotted) line denotes the R^2_{OS} statistics for each investor sentiment index prior to (after) the implementation of sign restriction.

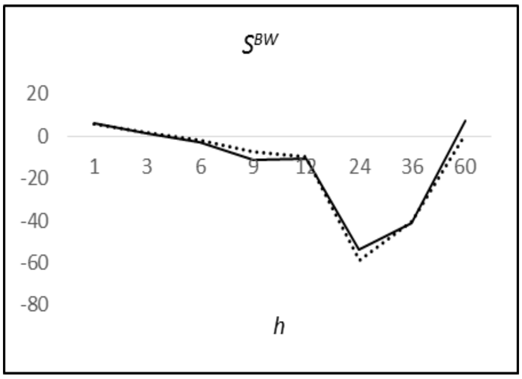
Panel A: Expansion period

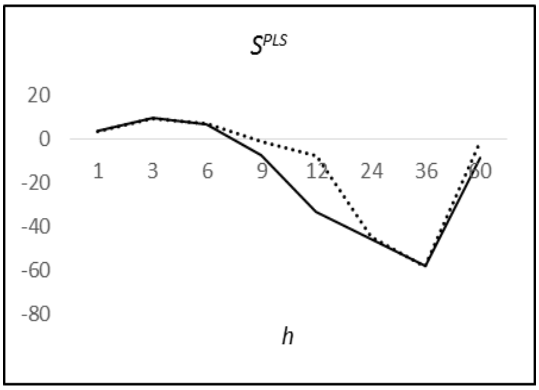


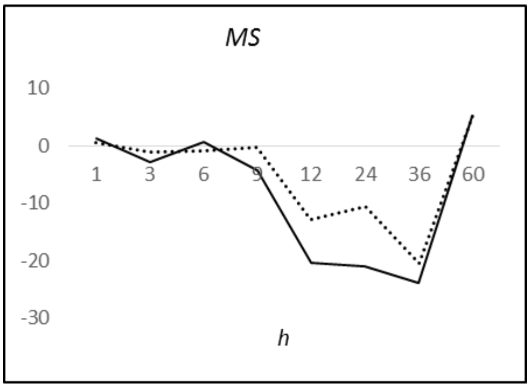


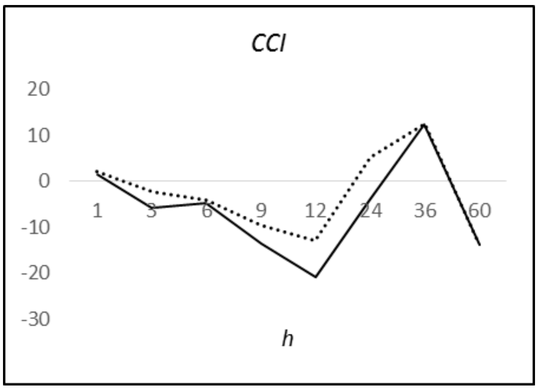
Panel B: Recession period











(II) Predictive power of economic predictors measures in different business cycles

The predictive performance of economic predictors corresponds to unrestricted model in different business cycles is presented in Table 4.15. As usual, panel A demonstrates the predictive performances during the expansion period, and panel B shows the results for the recession period. For the ease of comparison, the performance of S^{TV} is shown in the first row.

Table 4.15 shows that economic predictors perform better during the expansion period than during the recession period, with greater R_{OS}^2 values and the null hypothesis of *MSFE-adjusted* test is being rejected at a higher rate. This result is in contrast to Henkel, Martin and Nardari (2011), Pettenuzzo, Timmermann and Valkanov (2014), Rapach et al. (2010). Two explanations could possibly contribute to this finding. First, the recession period covered in this study is infrequent and hence a relatively limited observation (i.e. 34 months) corresponds to the recession period is available for this study as compared to previous studies. Pettenuzzo et al. (2014) has a total recession period of 122 months in the out-of-sample evaluation. Similarly, a higher number of recession period is used in the study of Rapach et al. (2010). Second, the underlying causes of the recession will probably affect the conclusion drawn. Although Henkel et al. (2011) has about the same number of recession period as in this study for the out-of-sample evaluation, the subprime crisis in 2007/2008, which can be partially explained by investor irrationality (see Barberis, 2013; Hoffmann, Post and Pennings, 2013), has been excluded in their study. Contrarily, they included the tight monetary policy triggered recession in 1980s, which occurred before the out-of-sample period considered in this study.

The economic predictors also predict well during the expansion period under the restrictive regression framework as shown in Table 4.16, which is consistent with the results of unrestricted regression model. In addition, a massive improvement in terms of R_{OS}^2 and *MSFE-adjusted* statistics is shown in panel A of Table 4.16 after the sign restriction has been imposed on the coefficient of economic predictors. The number of significant *MSFE-adjusted* statistics has increased across different forecasting horizons with the improvement highly focuses at 9-month and 12-month forecast horizons. However, the sign restriction does not have much effect on the economic predictors during the recession period.

Table 4.15: Out-of-sample forecasting results for conventional regression in different business cycles: S^{TV} vs. economic predictors

	h = 1		h = 3		h = 6		h = 9		h = 12		h = 24		h = 36		h = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
	Panel A: Expansion period															
S^{TV}	-0.6	0.05	-0.3	1.89**	2.25	1.40*	5.49	2.27**	5.92	2.18**	-0.01	1.16	2.04	0.98	-4.73	-0.53
DP	1.12	1.86**	6.45	2.55***	9.45	1.87**	2.67	1.50*	-11.63	1.02	-42.67	0.02	-74.92	-0.49	-106.63	-0.34
DY	-0.48	0.49	3.3	1.76**	6.73	1.75**	2.95	1.48*	-10.39	1.16	-42.85	-0.06	-79.51	-0.61	-134.55	-0.61
EP	-1.04	0.05	-1.04	-0.25	-24.65	-0.74	-41.9	-0.61	-42.05	-0.62	-49.75	-1.4	-70.07	-1.27	-120.53	-2.02
DE	-1.12	0.01	-0.88	0.84	-13.72	-0.46	-6.46	0.39	4.13	1.11	-38.17	0.3	-52.5	-0.06	4.63	1.72**
SVAR	-6.92	-0.75	-35.44	0.96	-120.87	-0.51	-147.25	0.37	-68.25	1.91**	-17.85	1.32*	-1.72	0.3	-29.46	-1.07
BM	-0.73	-1.09	-0.46	1.07	-0.78	1.22	-12.38	0.57	-25.81	0.3	-39.06	-0.5	-49.72	-1.29	-92.8	-1.19
NTIS	-1.82	0.66	-7.24	0.61	-18.76	0.55	-33.26	0.5	-35.2	0.91	-30.44	1.06	-28.26	1.05	-64.77	0.46
TBL	-1.66	-0.46	-4.32	-0.4	-11.74	-1.12	-9.46	-0.33	2.5	0.96	11.5	1.25	9.54	1.06	-26.94	-1.41
LTY	-2.17	-0.5	-2.87	0.84	-7.87	0.15	-4.87	0.64	-1.89	0.88	-15.34	0.45	-34.97	-0.88	-70.66	0.25
LTR	-11.2	0.06	0.84	1.72**	1.95	2.30**	4.53	1.97**	8.68	3.10***	2.78	1.15	2.2	0.89	-1.63	-0.56
TMS	-1.57	-0.18	-4.89	-0.08	-6.23	-0.68	3.77	1.88**	5.84	1.92**	-0.51	0.59	18.29	2.1	21.58	2.31**
DFY	-2.11	-0.93	-10.21	-1.16	-59.23	-1.07	-128.3	-1.07	-74.34	-0.88	-36.58	-1.22	-17.22	-1.69	-21.34	-1.15
DFR	-5.56	1.21	-5.86	-0.54	-0.04	0.84	4.74	1.80**	5.02	2.15**	-1.44	0.37	1.17	0.62	-1.43	-0.31
INFL	-0.35	-0.12	-0.54	0.51	0.63	0.91	6.87	2.33**	7.13	2.07**	0.68	0.45	-1.55	-0.08	-7.83	-1.18
OG	-1.03	1.01	-2.48	1.80**	0.73	2.17**	0.17	2.43***	-6.62	2.26**	-90.24	1.08	-121.33	0.66	44.96	2.23**
SCR	-1.48	-1.01	-10.33	-0.66	-83.19	-1.08	-120.90	-0.95	-107.05	-0.92	-76.79	1.11	-282.00	1.21	-108.45	1.14
CAY	-0.29	1.27	-6.97	-0.32	4.37	2.24**	5.12	2.51***	5.07	2.91***	4.07	2.00**	11.4	2.14**	-19.03	1.33*
PC-ECON	-0.82	-0.49	1.49	1.58*	3.51	1.69**	8.20	1.74**	5.57	1.54*	-59.92	1.05	-75.97	0.75	-90.00	0.26

Table 4.15 (Continued):

	h = 1		h = 3		h = 6		h = 9		h = 12		h = 24		h = 36		h = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
	Panel B: Recession period															
S^{TV}	-0.22	-0.14	-0.38	0.14	-5.99	-1.85	-6.88	-1.54	-3.68	-0.61	2.88	2.21**	-19.21	-	-3.41	-
DP	0.75	0.5	-1.78	0.04	-9.86	-0.78	-16.08	-1.23	-15.78	-1.52	-35.32	-2.09	23.58	-	44.98	-
DY	-2.74	-0.42	-0.37	0.18	-12.42	-1.23	-17.38	-1.64	-17.36	-2.12	-51.46	-2.25	15.14	-	50.79	-
EP	-24.9	-0.84	-9.42	-0.27	1.04	0.87	-0.17	0.14	-7.29	-0.91	-51.63	-0.99	-118.8	-	-7.07	-
DE	4.28	0.87	3.45	0.73	4.28	0.55	-2.14	0.02	-17.33	-1.57	-23.69	-2.11	19.26	-	40.16	-
SVAR	-3.99	0.48	-17.63	-1.87	-2.54	0.61	-4.3	-2.86	-7.25	-3.31	-5.37	-0.9	-121.93	-	-16.41	-
BM	0.3	0.32	-0.24	0.1	-5.13	-1.51	-6.86	-2.61	-8.49	-2.52	-29.02	-4.08	-24.87	-	-12.63	-
NTIS	4.78	0.95	8.58	0.95	25.1	1.36*	26.3	1.17	20.25	1.02	27.46	1.62*	40.98	-	-0.07	-
TBL	1.19	0.47	4.08	0.81	8.66	1.38*	3.15	0.6	-3.95	-1.18	-15.62	-1.18	-9.04	-	-160.75	-
LTY	0.39	0.27	2.49	0.8	4.81	1.15	5.39	1.14	2.48	0.59	12	2.43**	48.83	-	33.84	-
LTR	0.54	0.59	-7.75	-1.26	-3.92	-2.18	-5.13	-2.2	-6.11	-2.5	-2.25	-0.8	4.22	-	-7.65	-
TMS	0.89	0.62	-0.6	-0.29	-5.29	-2.71	-11.54	-3.56	-14.29	-3.91	2.86	5.92	48.82	-	-110.16	-
DFY	-4.01	0.62	-24.03	0.61	2.92	1.5	24.49	1.38	8.74	0.98	-2.28	-0.93	3.35	-	-3.63	-
DFR	-58.88	0.08	-18.02	-0.94	-11.59	-1.73	-9.74	-2.43	-10.59	-2.18	-0.4	-0.07	-4.36	-	-3.73	-
INFL	0.75	0.36	-3.87	-1.03	-4.59	-2.84	-4.89	-2.22	-6.29	-3.2	-4.4	-0.87	-10.78	-	-12.2	-
OG	2.20	1.42*	1.40	0.47	-6.62	-1.82	-9.44	-2.00	-14.41	-1.15	-58.23	-0.96	12.97	-	62.37	-
SCR	-9.88	0.47	-28.77	-0.15	1.91	1.02	-11.22	-1.3	-41.09	-1.68	-7.64	-0.68	9.54	-	-2.20	-
CAY	-0.18	-0.33	0.19	0.19	-2.76	-0.37	2.22	0.71	14.31	2.83***	70.77	2.31**	58.35	-	54.05	-
PC-ECON	-5.82	-1.09	-8.52	-0.99	-1.73	0.59	0.62	0.27	3.05	0.55	18.78	1.01	49.07	-	56.24	-

Notes: This table presents the Campbell and Thompson (2008) R^2_{OS} (in percentage) and the Clark and West (2007) *MSFE-adjusted* statistic of the time-varying weighted investor sentiment index (S^{TV}) and economic predictors (as listed in Section 4.3). Panel A reports the forecasting performance of each sentiment measure in expansion period; Panel B reports the forecasting performance of each sentiment measure in recession period. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively, based on Newey-West *t*-statistic for *MSFE-adjusted* test. The in-sample period covers from December 1968 to November 1983 and out-of-sample period covers from December 1983 to December 2014.

Table 4.16 Out-of-sample forecasting results for restrictive regression in different business cycles: S^{TV} vs. economic predictors

	h = 1		*h* = 3		*h* = 6		*h* = 9		*h* = 12		*h* = 24		*h* = 36		*h* = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
	Panel A: Expansion period															
S^{TV}	-0.73	-0.17	-1.44	1.43*	1.77	1.35*	5.49	2.27**	5.92	2.18**	-0.75	1.1	3.22	1.24	-4.73	-0.53
DP	2.13	2.87***	6.45	2.55***	9.16	1.81**	3.26	1.52*	-8.84	1.15	-18.29	0.87	-18.28	0.7	-0.71	1.34*
DY	-0.23	0.63	3.64	1.85**	7.45	1.76**	4.71	1.56*	-6.42	1.32*	-11.84	0.99	-10.86	0.76	1.78	1.25
EP	-0.82	-0.03	-5.77	-0.15	-24.88	-0.75	-41.9	-0.61	-43.33	-0.69	-44.76	-1.14	-69.86	-1.3	-102.09	-1.54
DE	-0.56	0.19	0.35	0.9	-2.35	0.36	1.42	0.94	9	1.33*	-19.23	0.85	-27.96	0.87	8.39	1.78**
SVAR	-4.03	-1.01	-35.05	1.06	-117.96	0.1	-139.02	1.66**	-67.6	2.05**	-16.8	1.56*	0.02	0.39	-2.81	0.19
BM	-0.21	-0.72	-0.88	0.85	-0.69	1.22	-11.25	0.64	-22.36	0.48	-19.15	0.28	-20.26	-0.44	-44.28	-0.15
NTIS	-0.7	1.34*	-1.82	1.58*	-1.28	1.97**	0.25	1.73**	0.52	1.53*	2.58	1.18	0.53	1.02	-1.1	0.97
TBL	-0.26	0.83	2.27	2.49***	0.66	1.05	4.79	1.70**	9.1	1.63*	15.23	1.47*	14.69	1.41*	-23.42	-1.51
LTY	-0.69	0.76	0.01	1.77**	5.33	2.13**	8.12	1.65*	10.04	1.43*	1.27	0.78	-11.26	-1.03	-30.13	-1.3
LTR	-9.65	0.19	0.69	1.61*	1.77	2.16**	5.28	2.52***	8.42	3.23***	1.86	1.03	-1.02	-0.52	-0.38	-0.38
TMS	-0.92	0.1	-2.05	0.27	-1.47	0.24	4.59	2.07	8.17	2.40***	4.39	1.28	19.96	2.31**	23.92	2.58***
DFY	-0.92	-0.33	-2.05	-0.25	-1.47	0.61	4.59	0.9	8.17	1.44	4.39	0.29	19.96	-0.47	23.92	-0.75
DFR	-5.35	1.26	0.38	0.81	-0.93	-0.77	3.35	1.70**	2.93	1.67**	1.91	0.84	3.76	1.38*	-0.63	-0.22
INFL	-0.01	0.41	0.11	0.92	1.03	1.12	5.66	2.20**	6.74	1.95**	3.59	1.58*	4.32	1.84**	0.95	1.07
OG	0.14	1.51*	0.50	2.03**	7.32	2.14**	9.41	2.37***	8.17	2.29**	-49.18	1.71**	-58.04	1.40*	45.06	2.23**
SCR	-0.18	-0.07	0.29	1.47*	2.29	1.49*	5.55	1.69**	2.63	0.93	-75.72	1.13	-283.13	1.2	-108.45	1.14
CAY	-0.09	-0.17	-1.54	0.59	3.05	1.92**	4.99	2.49***	5.07	2.91***	4.07	2.00**	11.4	2.14**	-14.36	1.55*

Table 4.16 (Continued):

	h = 1		*h* = 3		*h* = 6		*h* = 9		*h* = 12		*h* = 24		*h* = 36		*h* = 60	
	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*	R^2_{OS}	*MSFE-adjusted statistic*
	Panel B: Recession period															
S^{TV}	0.39	0.63	-1.23	-0.53	-5.99	-1.85	-6.88	-1.54	-3.68	-0.61	2.11	1.60*	-19.21	-	-3.95	-
DP	0.58	0.43	-1.78	0.04	-9.86	-0.78	-15.84	-1.20	-10.17	-0.81	0.39	3.15***	23.58	-	44.98	-
DY	-2.74	-0.42	-0.37	0.18	-12.19	-1.20	-14.68	-1.26	-9.39	-0.91	-0.45	0.41	14.87	-	50.79	-
EP	-24.76	-0.83	-9.48	-0.28	1.31	0.97	-0.17	0.14	-7.29	-0.91	-51.63	-0.99	-118.80	-	-4.35	-
DE	0.01	0.12	0.79	0.93	-2.10	-0.91	-2.04	-1.27	-0.76	-1.17	0.39	0.70	26.45	-	51.05	-
SVAR	0.00	N/A	-12.94	-1.49	-1.31	-1.24	-1.87	-4.42	-7.25	-3.31	2.52	2.28	-104.97	-	-1.54	-
BM	0.09	0.18	-0.14	0.12	-4.90	-1.41	-4.56	-1.44	-3.26	-0.94	-16.37	-1.70	-24.87	-	-12.69	-
NTIS	0.34	0.79	-0.51	0.00	-3.07	-1.23	-7.65	-1.49	-11.20	-1.21	-4.26	-1.03	-3.16	-	-3.79	-
TBL	0.12	0.27	0.12	0.43	0.00	0.00	-0.37	-1.19	0.00	N/A	0.93	2.12**	-5.43	-	-159.47	-
LTY	-0.39	-0.36	0.00	N/A	-1.61	-1.50	-1.36	-1.47	-2.64	-1.56	-0.20	-1.26	0.00	-	-4.69	-
LTR	1.36	0.81	-7.50	-1.21	-3.92	-2.18	-4.99	-2.09	-5.25	-1.82	-3.66	-1.68	2.65	-	0.00	-
TMS	0.42	1.33*	0.61	0.88	-1.58	-0.86	-3.80	-1.16	-2.62	-1.03	1.35	2.37**	48.82	-	-106.02	-
DFY	1.04	1.24	0.92	0.66	1.42	1.02	0.86	1.24	0.78	1.16	0.08	1.10	0.21	-	-0.31	-
DFR	-58.87	0.08	-0.91	-1.89	-0.86	-0.99	-1.72	-1.90	-0.09	-1.12	2.49	2.15**	1.87	-	-5.28	-
INFL	-1.95	-1.11	-3.26	-0.85	-0.76	-1.82	-4.02	-1.99	-5.91	-3.49	-4.40	-0.87	1.43	-	0.01	-
OG	2.20	1.42*	1.46	0.48	-4.05	-0.99	-2.75	-0.93	2.14	1.02	17.46	1.68*	37.10	-	62.43	-
SCR	0.08	0.23	-3.30	-1.51	-2.84	-1.40	-13.85	-1.92	-39.44	-1.55	-8.76	-0.85	8.37	-	-2.20	-
CAY	-0.06	-0.19	-0.25	0.08	-2.76	-0.37	2.22	0.71	14.31	2.83***	70.77	2.31**	58.35	-	54.11	-

Notes: This table presents the Campbell and Thompson (2008) R^2_{OS} (in percentage) and the Clark and West (2007) *MSFE-adjusted* statistic of the time-varying weighted investor sentiment index (S^{TV}) and economic predictors (as listed in Section 4.3) for restrictive regression. Panel A reports the forecasting performance of each sentiment measure in expansion period; Panel B reports the forecasting performance of each sentiment measure in recession period. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively, based on Newey-West *t*-statistic for *MSFE-adjusted* test. The in-sample period covers from December 1968 to November 1983 and out-of-sample period covers from December 1983 to December 2014.

4.6 Conclusion

This study sheds light on the main driver – investor sentiment or fundamental economic predictors – of the stock market movements. Whilst fundamentalists proposed different fundamental predictors capturing the business cycle risk and changing risk aversion, behaviourists introduced various measures of investor sentiment that aim to improve the way the sentiment is being captured. Although different return predictors might capture different information, proponents from both sides have the same objective: predict stock market returns with their newly introduced predictor. However, less is known about whether investor sentiment or economic predictor has a greater influence on stock market fluctuations. Therefore, this study tackles this question by performing a horse race on the return predictability by investor sentiment and economic predictors.

The predictive power of S^{TV} against economic predictors for stock market returns has been assessed thoroughly based on both statistical and economic measures. Out-of-sample findings reaffirm that S^{TV} is a superior sentiment measure since it generates superior out-of-sample forecasts as compared to alternative sentiment proxies in forecasting stock market returns. Besides that, return forecasts produced by this superior sentiment measure, S^{TV}, dominate the fundamental-based forecasts, implying that sentiment possesses unique information about future stock market movements that are not contained in most of the popular economic predictors. Lastly, our sentiment index generates economically, not only statistically, significant forecasts, consistently outperforming fundamental competitor variables especially for investors with higher level of risk aversion. These results imply that the stock market is mainly driven by investor irrationality or sentiment.

This study has a great relevance to the intense debate between proponents of efficient market and behaviourists. Previous studies contended that predictability of stock returns based on economic predictors does not necessary imply that stock market is inefficient (e.g. Balvers, Cosimano and McDonald, 1990; Campbell and Cochrane, 1999; Fama and French, 1988a), rather stock returns adjusted to incorporate new fundamental information (Van Nieuwerburgh and Koijen, 2009), time-varying risk (Bansal and Yaron, 2004; Malkiel, 2003), or it could be due to the flaw of methodology adopted (Fama, 1998). Having said that, the superior performance of S^{TV} over fundamental economic predictors is inconsistent with the market efficiency view. Indeed, the stronger predictive power of S^{TV} confirms that investor sentiment has overriding influence to stock market movements and the findings lean towards the notion that price reversal is mainly caused by mispricing of assets.

Chapter 5. The Sentiment Effect through Cash Flow and Discount Rate Channels

5.1 Introduction

This chapter investigates whether it is the cash flow (CF) and/or discount rate (DR) channel, through which investor sentiment affects stock returns. This chapter builds on the superior predictive ability of investor sentiment, captured by S^{TV}, on the stock market returns as documented in Chapter 3 and 4. Whilst Campbell, Polk and Vuolteenaho (2010) assume investor sentiment is transmitted only through the discount rate channel, Huang et al. (2015) conversely argue transmission is only through the cash flow channel. Therefore, a more comprehensive examination on these conflicting views is required. Although the two-beta model of Campbell and Vuolteenaho (2004, henceforth CV) decomposes the capital asset pricing model (CAPM) beta into cash flow and discount rate betas, their model does not distinguish between the effects of rational and irrational expectations of cash flows and discount rates on the stock prices. Irrational investors who trade based on their sentiment tend to form irrational expectations about future cash flows and returns, affecting stock prices and returns. Hence, this chapter revisits and extends their two-beta model to a four-beta model that explicitly acknowledges the role of irrationally and rationally expected future cash flow and discount rates[69] on the stock prices given that previous literature has documented the role of irrational expectations in both channels[70]. The four-beta model provides a mean to evaluate the source of return predictability with investor sentiment, i.e. CF and/ or DR.

Traditional finance theory is built on the assumption that investors discount the rationally expected cash flow at an appropriate discount rate. This gives rise to the return decomposition framework of the Campbell and Shiller (1988a) and Campbell (1991), where unexpected stock market returns consist of the market cash flow news (N_{CF}) and the market discount rate news (N_{DR})[71]. Building upon this framework, CV (2004) decompose the CAPM beta into 'good' discount-rate beta ($\beta_{i,DR}$) that measures the response of stock to the N_{DR}, and

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[69] Investor irrationality is a broad term in that it is a reflection of different types of investor psychology. Thus, the whole magnitude of investor irrationality in the stock market is unknown. Since investor sentiment has been well recognised as a proxy to investor irrationality, sentiment-induced expectations are termed as irrational expectations throughout this chapter.

[70] The review of literature on the impact of irrational expectations on both channels is given in Section 5.2.

[71] N_{CF} (N_{DR}) is the change in expectations about the future cash flow (future stock returns).

‘bad’ cash-flow beta ($\beta_{i,CF}$) that measures the reaction of stock to the N_{CF}. The terminology of ‘bad’ and ‘good’ beta is used since, as explained by those authors, a long-term risk averse investor would require a greater premium on stocks that are more sensitive to the N_{CF}, which causes a permanent and irreversible effect, than the stocks that are more sensitive to the N_{DR}, which tends to be only a transitory effect.

Whilst their two-beta model improves the explanatory power of CAPM proposed by Sharpe (1964) and Lintner (1965) on the cross-section of stock returns, their model is silent on differentiating the irrational expectation from the rational expectation of future cash flow and discount rates. Unlike CV (2004), Campbell, Polk and Vuolteenaho (2010, CPV hereafter) distinguish the fundamental and sentiment view based on the cash flow and discount rate movement of firms with the market news. Specifically, the systematic risks[72] of stocks are said to be driven by fundamental factors if the co-movements of stock returns with market news are caused by their cash-flow movements. Otherwise, investor sentiment is said to play an important role in explaining the systematic risks of stocks if the discount rates of stocks mainly drives those systematic risks. Their assumptions are built on the basis that investor sentiment has a direct impact on the discount rates, but has an indirect impact on the cash flow, based on the work of Subrahmanyam and Titman (2001). They found that the systematic risks of value and growth stocks are mainly driven by their cash flow news, and hence claim that the systematic risks of growth stocks are driven by their fundamentals instead of sentiment, as claimed in previous studies[73].

Other studies, such as Da and Warachka (2009) and Koubouros, Malliaropulos and Panopoulou (2010), which do not aim to distinguish between the fundamental and sentiment view tend to perceive that the cash flow risk is linked to the fundamentals. Chen and Zhao (2009) also mention that N_{CF} is link to fundamental factors and N_{DR} could be caused by a change in sentiment or risk aversion.

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[72] The systematic risk measures adopted in CPV (2010) are the bad and good betas of CV (2004), which claim that value (growth) stocks have higher bad cash flow (good discount rate) beta. Nevertheless, such a pattern of bad and good betas is not documented for value and growth stocks in this study, which has a different sample period, and therefore allowing for both rational and irrational expectation to play a role in both cash flow and discount rate channels would be more appropriate.

[73] Since assets’ cash flow news (discount rate news) is correlated to the markets’ cash flow news (discount rates news) (Pettit and Westerfield, 1972), the claim of CPV (2010) made at the stock-level also implicitly implies that the changes in the market-wide cash flow expectations is driven by fundamental factor; changes in market discount rates are driven by investor sentiment.

Despite these assumptions, the changes in expectations about the future cash flows and discount rates can, however, reflect both rational and irrational expectations of investors, and stock prices react to both rational and irrational components in each shock. Indeed, as defined in Baker and Wurgler (2007), investor sentiment is the expectation about future cash flow and risk that is not justifiable by fundamental information. Hence, a change in investor sentiment could reflect a change in the irrational expectations of future cash flow and/ or returns, which would then lead to an unexpected move in the stock price. As shown in the simple model by Brown and Cliff (2005), the stock price is the weighted average of prices formed based on rational and irrational expectations of future cash flows and future returns[74]. Therefore, unexpected returns could be result from revisions in both the rational and irrational expectations of future cash flows and/ or discount rates.

Empirically, the phenomenon of investors forming irrational expectations about future cash flows is well documented in the literature (*e.g.* Barberis, Shleifer and Vishny, 1998; Cooper, Gullen and Schill, 2008; Engelberg, Mclean and Pontiff. 2018; Hribar and Mlcnnis, 2012; Lakonishok, Shleifer and Vishny, 1994 (LSV henceforth); Piotroski and So, 2012). Stock prices could be greatly affected if investors form systematic expectation errors of future cash flows. Lamont and Thaler (2003b, p.201) question that "During the Nasdaq bubble of the late 1990s, approximately $7 trillion of wealth was created and then destroyed. Was this a rational process of forecasting the future cash flows of new technology or an investing frenzy based on mob psychology?". Indeed, past studies mention that investors' irrational expectations of earnings growth led to the formation of the Dot-com bubble (Ofek and Richardson, 2002[75]) and the overvaluation of internet-based IPOs (Loughran and Ritter, 1995; Ritter 1991). Therefore, irrationally expected cash flows should not be completely ruled out from an asset pricing model even though CPV (2010) claim that investor sentiment can only have an indirect effect on the cash flow. Furthermore, investor sentiment is highly persistent, current expectations about future cash flows could be affected by a prolonged history of sentiment, and hence it is hard to claim that N_{CF} links solely to fundamental factors.

[74] Such pricing model, i.e. asset prices are determined as the weighted average of expected payoffs formed by heterogeneous investors, can be traced back to Diether, Malloy and Scherbina (2002), Lintner (1969) and Miller (1977).

[75] They reported that 6% of total market capitalization in the US stock market is represented by internet-based stocks even though these stocks have negative earnings, which are priced in the market, before the burst of Dot-com bubble. Similar evidence is presented by Schultz and Zaman (2001, p.354).

As opposed to the sentiment view of CPV (2010) on the discount rates, other studies show that discount rate news could have rational explanations. Changes in the discount rates could reflect the compensations for the time-varying risk (*e.g.* Bansal and Yaron, 2004; Bollerslev, Tauchen and Zhou, 2009) and/ or the risk aversion (*e.g.* Campbell and Cochrane, 1999; Cochrane, 2011). In his presidential address, Cochrane (2011) argued that discounting the future payoffs at a risk-free rate with distorted probability is simply equivalent to discounting the future payoffs at a different discount rate. Having said so, behavioural explanations have been proposed to explain the variation in expected returns[76]. As Cohen, Gompers and Vuolteenaho (2002) argue that discount rate news can be treated as the mispricing news as well as a change in the firm's risk. Hence, it is important to account for both rational and irrational expectations of future discount rate in an asset pricing model.

Given that both rational and irrational expectations could have affected both cash flow and discount rate channels, this study constructs a four-beta model that decomposes the cash flow and discount rate betas into rational and irrational components in order to empirically evaluate the source of the predictive ability of investor sentiment on stock market returns. Each beta in the four-beta model measures the covariances of asset returns with one of the news series – irrational cash flow news (N_{CF}^{IR}), rational cash flow news (N_{CF}^{R}), irrational discount rate news (N_{DR}^{IR}), and rational discount rate news (N_{DR}^{R}). Furthermore, this study also empirically evaluates the assumptions made by CPV (2010) with the use of this four-beta model. If their assumptions are correct, then the covariances of an asset's returns with the irrational cash flow news and the rational discount rate news would not be significantly different from zero. That is to say, asset prices will not react to, for instance, the changes in the irrational expectations of market cash flows, which consists of the irrational cash flow news from individual stocks, if N_{CF} is mainly driven by fundamental factors. If both rational and irrational expectations significantly affect stock prices, is the covariance of stock returns with the shocks in both expectations significantly priced across different stocks? Hence, this study investigates whether each component in the four-beta model is a systematic risk factor that is priced in the cross-section.

Methodologically, unexpected returns are first disentangled into cash flow news and discount rate news by using the Vector Autoregression (VAR) approach following Campbell (1991) and CV (2004). However, unlike CV (2004) who assume the true VAR parameters are

76 Refer to Section 5.2 for a detailed discussion.

constant over the full sample period, the parameter estimate of each state variable is allowed to vary over time since the literature has argued that parameter instability is accountable for the time-varying predictive strengths of the state variables on future stock market returns (see Lettau and van Nieuwerburgh, 2008; Henkel, Martin and Nardari, 2011; Pesaran and Timmermann, 2002). By doing so, the news series could more precisely reflect the shocks in stock returns over time. This approach is termed as the time-varying VAR (TV-VAR) throughout this chapter[77]. To investigate the pricing of the four factors, this study performs the Fama-Macbeth (1973, henceforth FMB) regression to obtain the estimated risk premium of each risk factor.

Asset pricing theory states that only the risk factors that systematically affect all stocks are priced. Whilst different fundamental risks have been considered and priced in the rational asset pricing models (*e.g.* Campbell and Cochrane, 2000; Engle and Mistry, 2014; Lettau and Ludvigson, 2001b; Jagannathan and Wang, 1996), behavioural studies also found that systematic trading from irrational investors (Barber, Odean and Zhu 2009), and so their sentiment and irrational expectations, can generate systematic risk (see Lee, Jiang and Indro, 2002; Piotroski and So, 2012), which are priced (*e.g.* Liang 2018; Piotroski and So, 2012; Shefrin, 2008; 2015). Therefore, the risk premium in the market could contain both a rational and an irrational premium. Since Liang (2018) and Fong and Toh (2014) report a negative risk premium for sentiment factor in the cross-section of stock returns, this study conjectures that irrational risk factors in this study would command a negative risk premium[78].

Empirical results from the four-beta model are consistent with the findings of Huang et al. (2015) in that changes in the irrational expectation of cash flow is the main underlying source of the sentiment-return relationship. Besides that, the findings confirm that stocks are not immune to the variations in the irrational cash flow expectations and rational discount rate expectations since the irrational cash flow beta and rational discount rate beta estimates are significant across different portfolios. Hence, the null hypothesis that the covariances of an asset's returns with the irrational cash flow news and the rational discount rate news would not be significantly different from zero is rejected by the four-beta model. The results from

[77] As Chen and Zhao (2009) show that the news series estimated from different sample periods alter the conclusion of beta trend (i.e. $\beta_{i,CF}$ has an increasing trend moving from growth stocks to value stocks) documented in CV (2004), which can be seen also in Section 5.6.2. Hence, we adopt a time-varying VAR approach to estimate the news series. Although our baseline results come from the TV-VAR, we also provide the results derived from a VAR for comparison.

[78] The rationale of the negative risk premium associated with the irrational betas are discussed in Section 5.6.5.

the full sample VAR estimation further supports the findings obtained from the TV-VAR estimation, where only the irrational cash flow news and rational discount rate news are found to significantly affect the stock price under different estimation frameworks. As for the asset pricing test, the results demonstrate that the four-beta model improves the explanatory power of the CAPM and CV's two-beta model in describing the cross-sectional variation of average excess returns since the four-beta model delivers a higher adjusted cross-sectional R^2 statistic and a lower pricing error. In line with the prediction, the irrational betas are significantly and consistently priced in the cross-section of stock returns and demand a negative risk premium. On the other hand, covariances of asset's returns with the news of rational expectations earns a positive risk premium. However, the risk premium estimates associated with the rational cash flow and discount rate betas have lower magnitude in the absolute terms.

A popular issue documented in the asset pricing literature is that the market beta is varying over time (see Jagannathan and Wang, 1996; Merton, 1973), and hence a time-varying beta is widely employed in the literature (*e.g.* Adrian and Franzoni, 2009; Botshekan, Kraeussl and Lucas, 2012; Petkova and Zhang, 2005). In view of the fact that the beta is non-constant, this study also performs the sub-sample analysis in order to investigate if the beta estimates produced under the TV-VAR framework change across different sub-samples, and how these changes affect the pricing of each beta risk. In particular, this study employs a structural break test to identify the structural shifts in the four betas[79].

The sub-sample analysis reveals that the changes in the irrationally expected cash flows significantly affect most of the assets' returns in the second sub-sample period (February 1998 to December 2014), but not in the first sub-sample period (December 1969 to August 1997). In contrast, irrational discount rate betas are insignificant across both sub-sample periods, confirming that the predictive power of investor sentiment is transmitted through the cash flow channel. The rational discount rate betas do, however, remain highly significant, across all portfolios in both sub-sample periods. These findings are again calling into question the assumptions of CPV (2010). Meanwhile, the positive sign on the irrational cash flow beta and rational discount rate beta estimates also remain unchanged across both periods. As for the pricing of risk, consistent with the full sample results, both irrational cash

[79] To be able to estimate the risk premia associated with the four betas, a consistent break point is required for each of the four betas. Although multiple break points could have incorporated in this study, but the test for multiple breaks reveals inconsistent break points across different betas and this complicates the analysis. Hence, for simplicity, a single break test is adopted to identify the main structural break in the sample period considered.

flow and irrational discount rate betas are significantly priced and investors are willing to pay a premium for the irrational risk factors across sub-sample periods.

This study contributes to the literature in several aspects. First, this study adds to the literature of behavioural finance in that it provides a deeper understanding on the economic source underlying the sentiment-return relation. Most of the behavioural literature examined the effect of irrational expectation on only either the future cash flow or the expected returns, separately[80]. This chapter fills the gap by integrating irrational expectations in both cash flow and discount rate channels into one model since the stock valuation could be affected by the expectations errors about the future cash flow and discount rates concurrently. The newly constructed model permits a better comparison of the relative importance of the sentiment-induced irrational cash flow and discount rate expectations on the asset's returns.

Although Huang et al. (2015) also examine the predictive power of sentiment on stocks' cash flow and discount rates, their investigation focused on the one-period model as shown in the equation (2') of Campbell and Shiller (1988a). In contrast, this study considers a multi-period model, which is modelled through the VAR specification, on the ground that we are evaluating the behaviour of the long-lasting securities, and that the sentiment exerts stronger predictive power on stock market returns of longer horizons as shown in Chapter 2 and Chapter 3. Besides that, their study provides an indirect link in this subject since the sentiment is used to forecast only the CF and DR, but does not directly link the sentiment-induced CF or DR news to stock returns. This study, however, provides a direct link as the returns of 25 size- and value-sorted portfolios, which represent the stock market returns, are regressed on the sentiment-induced CF and DR news series.

Second, this study critically investigates the assumptions that are commonly applied in the literature, especially those made in CPV (2010). Often, cash flow news is claimed to be driven by fundamental factors, but no study has split the cash flow news into rational and irrational components in order to examine if the fundamental factor is the only driver for the cash flow news. This study provides the first examination of the assumption made with respect to the cash flow news. Similarly, CPV (2010) made a definite claim on the discount rate news that it is driven mainly by the sentiment. Again, no study has tested whether discount rate news is truly driven by investor sentiment only, or rational expectation does play

[80] See Section 5.2 for a review.

a role as well. Thus, this study fills this gap, verifying the assumptions of cash flow and discount rate news by using the four-beta model constructed in this study.

Lastly, to the best of our knowledge, no one has developed a four-beta model that decomposes the cash flow and discount rate betas into rational and irrational components, in order to examine the pricing of those betas in the cross-section of stock returns. CV (2004) mention that their model remains important in understanding how a long-term risk-averse investor prices the cash flow and discount rate risks even though investor irrationality could have affected the stock prices. However, investor irrationality has not been given credit explicitly in their model. Therefore, extending their two-beta model to a four-beta model that accounts for both rational and irrational expectations could further enhance our understanding towards the pricing properties of rational and irrational risks in both cash flow and discount rate channels.

This chapter is organized as follows. Section 5.2 reviews the literature and Section 5.3 presents the framework of return decomposition. Section 5.4 discusses the empirical methodology employed in this study, which includes the approaches used to decompose stock market returns, the computation of the four-beta model, and the pricing of the four betas. Section 5.5 presents the data and descriptive statistics of data, followed by the empirical findings in Section 5.6. Section 5.7 presents the robustness checks on the asset pricing test and Section 5.8 performs the equity anomalies test. Last section concludes.

5.2 Literature review

5.2.1 Different beta risks

The seminal work of Campbell and Shiller (1988a) propose the dividend-ratio model that decomposes the dividend-price ratio into two components, which are the shocks in expected future dividend growth rates (*i.e.* cash flow shock) and in discount rates, under a framework with time-varying discount rates. Given that both expected future cash flows and discount rates are unobservable, they employ the vector autoregressive model (VAR) to operationalize the concept of log dividend-price decomposition. While the returns forecast in Campbell and Shiller (1988a) is implied by the forecasts estimated from log dividend-price ratio and dividend growth rates, Campbell (1991) models the returns forecast explicitly to obtain a return decomposition model.

Following the introduction of the return decomposition model, some studies have investigated whether N_{CF} or N_{DR} plays a dominant role in the variation of stock returns. Studies which argued that N_{DR} plays a more important role than N_{CF} in explaining the movement of stock returns at aggregate level include Campbell (1991), Campbell and Ammer (1993) and Campbell and Vuolteenaho (2004); whereas the opposite finding is reached at the cross-sectional level (see Lochstoer and Tetlock, 2018; Vulteenaho, 2002). Meanwhile, Chen, Da and Zhao (2013) claim that N_{CF} can explain stock returns at both individual stock and aggregate market level. There are studies which claimed that N_{CF} has a more important role in the return predictability if a different measure of N_{CF} is employed (see Chen, Da and Priestley, 2012; Chen, Da and Zhao, 2013; Chen and Zhao, 2009; Garrett and Priestley, 2012).

Another application of return decomposition model can be seen in the market risk decomposition of Campbell and Vuolteenaho (2004) who assess the sensitivity of stock returns with respect to the market N_{CF} and N_{DR}, measured by $\beta_{i,CF}$ and $\beta_{i,DR}$. Their two-beta model successfully explains the cross-sectional of average stock return. Concretely, they documented that a higher reward is awarded to a long-term risk averse investor for bearing the cash flow risk given that an undesirable move in the expected cash flows brings permanent effect to investors[81]. Therefore, stocks with returns that are highly correlated with the market N_{CF} receive a higher risk premium, for instance, small and value stocks. Contrarily, stocks that are more sensitive to the market N_{DR} have a relatively lower risk premium, *e.g.* large and growth stocks.

Building on the market risk decomposition of CV (2004), several studies also developed different asset pricing models with market risk being decomposed into different components in order to shape further understanding towards the variation in stock returns at the cross-sectional level. While some studies focused on different measures of N_{CF} when computing the $\beta_{i,CF}$, other studies proposed new types of beta in addition to $\beta_{i,CF}$ and $\beta_{i,DR}$.

As mentioned earlier, some studies argued that the measure used to model N_{CF} is important in revealing the role of the N_{CF} in the return variability. Likewise, $\beta_{i,CF}$ computed from a different measure of N_{CF} also led to a different explanation for the cross-sectional of

[81] Using a VAR model, Cochrane (1994) shows that stock returns is predictable by price/dividend ratio and the dividend resemblance a random walk series. Therefore, dividend will not revert to its mean following a dividend shock (i.e. cash flow news) holding expected returns constant, and thus bring permanent effect to the stock price as price moves to a new level. Contrarily, a price shock (i.e. discount rate news) holding dividend constant triggers a transitory effect on the stock returns since returns will revert to its mean level.

stock returns. Instead of modelling the N_{CF} as the residual of unexpected returns and N_{DR}, Chen and Zhao (2009) model the N_{CF} directly in the VAR based on two proxies, which are the dividend growth rate and return on equity. A noise beta, $\beta_{i,Noise}$, in addition to $\beta_{i,CF}$ and $\beta_{i,DR}$ is then introduced to capture the news explained neither by CF nor DR. The 'noise' in their model is simply the difference between the N_{CF} retrieved from the VAR of CV (2004) and the direct modelled N_{CF}. The direct modelling of N_{CF} reveals that value stocks have lower $\beta_{i,CF}$ and $\beta_{i,DR}$, but a higher $\beta_{i,Noise}$ as compared to growth stocks. Excluding price-earnings ratio as a state variable, they found that the positive risk premium associated with the $\beta_{i,CF}$ is applicable only to the size effect (*i.e.* small stocks earns higher returns), but not related to the value effect (*i.e.* value stocks have higher returns), contradicting the findings of CV (2004). Meanwhile, the $\beta_{i,DR}$ commands a negative risk premium.

An extension to their work can be seen from Garrett and Priestley (2012), where they employed a new predictor to forecast the dividend growth, which is then used to compute the N_{CF} directly from the VAR. Similarly, they found that value stocks have a higher β_{Noise}. Their cross-sectional regression shows that the cash flow and noise beta risks are consistently and positively priced, but discount rate beta risk is not significantly priced across stocks. Da and Warachka (2009) also report that their earnings beta (i.e. cash flow beta) computed from the revision in analysts' earnings forecasts can explain more than half of the cross-sectional variation of stock returns. Nevertheless, the discount rate beta risk is ignored in their cross-sectional regression model.

There are a few studies which accounted for the second moment of return distribution when they decomposed the market risk (see Campbell, Giglio, Polk and Turley, 2018; Koubouros, Malliaropulos and Panopoulou, 2007; Koubouros, Malliaropulos and Panopoulou, 2010). Koubouros et al. (2007) decompose the market beta into four betas that measure the co-movement of firm-specific cash flow and discount rate news with the market cash flow and discount rate news. They differentiate their four-beta model from, but closely related to, the four-beta model of CPV (2010) by considering the heteroscedasticity in return residuals. The news series is modelled as a function of standardized residual, which is computed as the VAR residuals over the conditional covariance matrix of the residuals. As such, the more volatile shocks have lesser impact on the new series. Their findings reconcile the findings of CV (2004), in which value and small stocks have lower $\beta_{i,DR}$ but higher $\beta_{i,CF}$. Unlike CV (2004), their model produces a relatively stable beta estimates over time. Koubouros et al.

(2010) show that this four-beta model has been found to price the average asset returns at the cross-sectional level, and performs even better than the two-beta model of CV (2004).

Recently, Campbell, Giglio, Polk and Turley (2018) propose a three-beta model that captures the sensitivity of stock returns with respect to the N_{CF}, N_{DR} and a market risk news (N_{Risk}) given that a long term investor will hedge against not only the decrease in expected stock returns, but also the increase in the volatility of stock returns. Their model shows that large and growth stocks have higher discount rate and variance betas, and that these two betas provide much lower risk premium as compared to cash-flow beta, and hence explain the lower average returns of these stocks.

Meanwhile, Botshekan, Kraeussl and Lucas (2012) decompose the market risk into four different components conditional on the market ups and downs. Their idea is built on the framework of prospect theory, where they argued that long-term loss averse investors perceive losses caused by unexpected decrease in cash flows worse than unexpected increase in discount rates during the market downturns, and thus require a higher premium for bearing the downside cash flow risk. Their result is consistent with their intuition in that the downside $\beta_{i,CF}$ receives the largest premium even though all four betas are significantly priced across different assets.

Despite studies in this research area are still counting, to the best of our knowledge, no study has decomposed the cash flow and discount rate betas into the rational and irrational components. The most closely related work would be CPV (2010). Nevertheless, their claim on the rational and irrational views is rather restrictive in the sense that the sensitivity of stock returns with market news driven by firms' cash flow movement is claimed to be due to fundamental factors; whereas investor sentiment drives the discount rate movements of an asset with the market news. Given that stock markets constituted from individual stocks, their assumptions of the rational and irrational views applied to every stock also implicitly implies that unexpected moves of the market-wide cash flows and discount rate are also driven by fundamental factors and investor sentiment, respectively. Besides that, they left an open question in their study: Are their four betas priced in the cross-section of stock returns?

In spite of CPV's assumptions, both rational and irrational views co-exist in the stock markets, and the interplay between the rational and irrational expectations could have affected the stock prices through both cash flow and discount rate channels. Next, the literature focus on the expected cash flows is reviewed, followed by the literature on the expected return.

5.2.2 *Expectations of future cash flows*

Different measures have been used as a proxy for the expected cash flows, such as profitability, asset growth, stock repurchase, net stock issue, and accruals, and the review of the effect of each variable on stock returns is given in Fama and French (2008). In particular, profitability and asset growth, which have wide applications, tend to predict positively and negatively, respectively, the expected returns (see, for example, Cohen, Gompers and Vuolteenaho, 2002; Fama and French 2006; 2008; Fairfield, Whisenant and Yohn, 2003; Haugen and Baker, 1996; Hou, Xue and Zhang, 2015; Novy-Marx, 2013). Although the profitability and investment effects[82] are in line with the prediction of the dividend discount model (DDM)[83], the DDM does not distinguish between the rational and irrational pricing since the model is unable to differentiate if the forecasts of future cash flows are rational or irrational (Fama and French, 2006; 2008), which is a highly debated issue.

From the rational view, if investors fully understand the profitability information, a rational expectation about the future cash flows could be formed based on that information. Fama and French (FF, 1995) examine whether the price behaviours of different stocks is consistent with their earnings behaviours. They reported a negative relationship between the profitability and book-to-market ratio, i.e. high *BE/ME* stocks (so-called value stocks), which usually have higher average returns, persistently have lower profits than low *BE/*ME stocks (i.e. growth stocks), which have lower average returns (see also Penman 1991; 1996). Contrary to LSV (1994), who claim that the market corrects the mispricing of value and growth stocks after the unraveling of actual growth rates, FF argued that market rationally estimates the future growth rates of earnings and understand about the convergence of the growth rates between these two types of stocks after portfolio formation period, which leads to high (low) average returns for value (growth) stocks.

Studies supporting the view that both profitability and investment effects are mainly driven by the rational pricing adopt *q*-theory of investment in their justifications and present evidences that rational explanation dominates the behavioural biases. Both effects are closely

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[82] Profitability, which is commonly measured as earnings on book equity or gross profit to assets, embeds the information about the future cash flows. Dechow, Kothari and Watt (1998), Greenberg, Johnson and Ramesh (1986) and Kim and Kross (2005) claim that future cash flows are more predictable by current earnings instead of current cash flows, supporting the assertion of the Financial Accounting Standards Board (see also Barth, Cram and Nelson, 2001). Investment is measured by the asset growth, which is the change in book equity.

[83] As shown in Fama and French (2006, 2015), the expected dividend in the dividend discount model can be expressed as expected earnings minus the asset growth under the clean surplus accounting principle.

linked under this theory. According to the *q*-theory, producer determines the optimal investment level to maximize the market value of the firm by evaluating the expected future cash flows against the current cash flows. Discounting the expected future cash flows at a high cost of capital leads to a low net present value and hence a low investment. As such, if the marginal profitability of investment (discounted to time 0) is greater than the marginal cost of investment at time 0, of which occurred when the discount rate is low, the firm will invest more. The investment demand will be adjusted until it achieves an optimality condition where the discount rate is sufficiently high to offset the high profitability of the investment. At this point, the marginal benefit equals to the marginal cost of investment, or the discount rate is equal to the marginal investment return (i.e. marginal benefit to the marginal cost of investment). Hence, high (low) profitability should project high (low) expected returns for a given level of investment. Also, the profitability premium is higher for the firms with less friction (Jiang, Qi and Tang, 2018) and in developed markets (Chen, Sun, Wei and Xie, 2018)[84].

As for the investment effect, the decreasing return to scale indicates that lower marginal benefit of investment is realized when more investments are undertaken. Equivalently, the expected returns, which equals to the marginal benefit to marginal cost of investment, also decrease with investment. Meanwhile, the discount rate effect claims that large investments are made when the discount rate is low. Both effects predict a negative expected return–investment relationship. Based on the cross-country analysis, Titman, Wei and Xie (2013) and Watanabe, Yu, Yao and Yu (2013) find that investment effect is more prevalent in the developed markets, showing that the effect of investment on the expected future cash flows and expected returns is correctly priced in the markets.

Ball, Gerakos, Linnainmaa and Nikolaev (2015; 2016) provide rational explanation of the profitability effect without relating it to the *q*-theory. They revealed that the predictive power of profitability on future returns persists up to ten years, and hence claim that both profitability and expected returns have common underlying risk, and that the mispricing cannot be an explanation in this case[85]. Nevertheless, the type of risk shared by these two variables is unknown in their papers, but is proposed in other studies. Bansal, Dittmar and

[84] Managers in developed markets, which have lower investment frictions, tend to maximize the firm value by practicing capital budgeting, consistent with the *q*-theory of investment model.

[85] They argued that mispricing will not last that long.

Lundblad (2005), Bansal, Ditmar and Kiku (2009) and Hansen, Heaton and Li (2005) show that the aggregate consumption risk is reflected in the assets' cash flows and their cash flow beta explains the variation in the cross section of stock returns.

From the behavioural standpoint, the profitability effect could be observed as a result of investors' misinterpretation of current profitability that leads to the expectation errors in future cash flow estimates. A horse race between the rational and irrational explanations in Lam, Wang and Wei (2015) and Wang and Yu (2013) suggests that the profitability effect is ensued from the misperception of current profitability of the firm that leads to the expectation errors in the future cash flow estimates. Both also reported that stronger profitability premium (*i.e.* return spread between the most profitable and the least profitable firms) is seen after the high sentiment period.

Similarly, the findings of Cooper, Gullen and Schill (2008) and Titman, Wei and Xie (2004) lean towards the behavioural bias. Cooper et al. (2008) find that investors overreact to the previous growth rates and the reactions of low asset growth and high asset growth stocks to the earnings announcements is consistent with the expectational errors hypothesis. Titman, Wei and Xie (2004) explain the negative relationship between the investment and average returns on the ground of overinvestment and investor misperception. Firms may overinvest but investors who are unaware of this unfavourable managerial action may irrationally expect higher future cash flows to be realized based on the high investment. The lower future returns simply reflects the correction of mispricing.

The abovementioned studies documented the fact that expected cash flows are irrationally formed through distinguishing the underlying explanations – rational vs. irrational – of the profitability and investment effects, other studies provided direct evidence on irrational expectations of future cash flows based on the irrational earnings forecasts produced by analysts. Specifically, Hribar and Mclnnis (2012) find that analysts' forecasts tend to be more optimistic (pessimistic) when investor sentiment is high (low) and thus forecast errors are higher (lower) during high (low) sentiment period. Furthermore, the result of Seybert and Yang (2012) also implies that analysts form irrational earnings forecasts since the management earnings guidance corrects the sentiment-induced mispricing.

Apart from investigating the expectation errors made by analysts, other supporting literature in this strand focus on the dispersion (or disagreement) of analysts' forecasts, which reflects different earnings forecasts produced by optimistic and pessimistic analysts. Hong and Sraer (2016) show that high-beta stocks are overpriced when there is a high disagreement about future cash flows since only optimists' opinions are reflected in the stock prices, but pessimists stand on the sideline in the presence of short-sale constraint. Similar evidence also documented for small and loser stocks (see Diether et al., 2002). Using *BE/ME* sorted portfolio as a test instrument[86], Yu (2011) also find that growth stock mispricing is stronger when there is a high disagreement about the future cash flows, which can be interpreted as only optimists' views are reflected in the stock prices when there is a high disagreement. Optimists are badly informed investors (Miller, 1977) since analysts produce optimistic forecasts during high sentiment periods (Bergman and Roychowdhury, 2008; Walther and Willis, 2013). In fact, Kim, Ryu and Seo (2014) reveal that significant mispricing induced by high disagreement can only be found in high sentiment period. Therefore, high disagreement about future payoffs, which is measured by the analysts' forecasts dispersion, is a proof that analysts form irrational expectations about future cash flows.

Instead of examining the analysts' forecasts dispersion in different states of investor sentiment, a few studies investigated whether investor sentiment predicts future cash flows. There is a vast literature documented that investor sentiment predicts negatively future stock returns, where the current overvaluation or undervaluation is being corrected by arbitrageurs in the future[87]. This predictive power of investor sentiment could stem from the correction of biased beliefs about future cash flows and/ or expected returns made in the past. Huang et al. (2015), who seek to find out the channel through which investor sentiment affects future stock returns, reveal that the return predictability of investor sentiment is a manifestation of investors' biased beliefs about future cash flows where investor sentiment predicts negatively future cash flows. A similar conclusion is also documented by Ma, Xiao and Ma (2018).

Investor sentiment is not the only underlying source of irrationality, literature also found that other investor psychology could have played a role in the formation of irrationally expected cash flows. One of the common biased expectations documented in the literature is the extrapolative bias. Extrapolation is a process whereby investors tend to overweight the recent past information and extrapolate it into the future. The law of small number (a version

[86] Growth stocks (*i.e.* low *BE/ME*) tend to be overpriced during the optimism period. Hence, Yu (2011) employs growth (value) stocks to represent optimistic (pessimistic) view of investors.

[87] See Chapter 2 for a review of literature on the predictive power of investor sentiment on future stock returns.

of representativeness heuristic) is the root of this extrapolation process, where investors generalise from a small sample of observations to the population properties.

As early as Barsky and De Long (1993), investors are found to form the expected dividend growth by extrapolating the dividend growth from the recent past. Cross-sectionally, LSV (1994) find that systematic errors made by naïve investors in forming their expectations about future earnings growth leads to an undervaluation (overvaluation) of value (growth) stocks. Specifically, investors extrapolate the past growth in forming overoptimistic expectations about future earnings/ cash flow growth rates of growth stocks, and inflate the current prices. The opposite is seen for value stocks. Hence, the average stock returns of growth (value) stocks will be lower (higher) when the realized earnings of growth (value) stocks are worse (better) than expected and investors corrected for their errors. Studies which support this view include Piotroski and So (2012)[88] and De Bondt and Thaler (1985; 1987) for momentum sorted portfolios. Considering a wider set of cross-sectional stocks, Chan, Karceski and Lakonishok (2003) claim that the low realized growth rate simply does not justify the high PE ratio, and that the long-term realized earnings growth rate is of little predictability, yet, investors and analysts extrapolate the recent past growth rates far into the future[89]. They also found that the Institutional Brokers' Estimate System's (IBES) growth estimates are found to be too optimistic in the long horizons.

Meanwhile, Chopra, Lakonishok and Ritters (1992), La Porta (1996), La Porta, Lakonishok, Shleifer and Vishny (1997) investigate the market's responses to the earnings announcements. Collectively, they found that returns of growth (winner) stocks are significantly lower than those of value (loser) stocks around the earnings announcement dates once investors learn the actual earnings. These evidences are consistent with the errors-in-expectation hypothesis, where investors formed overly optimistic (pessimistic) forecasts of earnings for the growth and winner (value and loser) stocks. La Porta (1996) reveals that the extreme growth expectations from the IBES is partially attributable to the extrapolative bias. He found that the high returns of value stocks cannot be fully explained by extrapolative bias, but other behavioural biases could play a role. Based on a large set of equity anomalies and a horse race of different explanations, Engelberg, Mclean and Pontiff (2018) confirm that

[88] Piotroski and So (2012) document the largest return for the value-minus-growth strategy during high sentiment periods and vice versa.

[89] They analyse different subsets of stocks include technology, value, growth, large, mid-capitalization and small stocks apart from the analysis that consists all firms.

investors extrapolate the past growth, forming optimistic and pessimistic forecasts, which are then corrected on the earnings announcement days, and subsequently unfolding the predictability of the cross-sectional stock returns.

Besides that, a few papers proposed theoretical models that revolve around the extrapolative bias in the formation of cash flow expectations. Fuster, Herbert and Laibson (2011) employ the quasi-rational model developed by Fuster, Laibson and Mendel (2010) with a zero weight is being assigned to the rational expectations, *i.e.* investors employ a parsimonious model (AR model), to explain a set of empirical implications. Their model argued that investors extrapolate the past earnings in forming their forecasts, overly optimistic during the good time and vice versa, and hence underestimate the long-run mean reversion in earnings. Recently, Alti and Tetlock (2014) propose a model that explains the differences in asset returns across firms on the basis of investors' expectation errors ensued from overconfidence and extrapolation. In contrast to overconfident agents, extrapolative investors overly depend on the past cash flows in forecasting the future productivity.

In addition to the extrapolative bias, conservatism bias is another source for the irrational expectations of future cash flows. Conservatism bias asserts that individuals overweight prior believes but underweight new evidence, leading them to adjust their beliefs slowly. Investors who are prone to this bias tend to underestimate the useful earnings announcements that contradict their prior beliefs and hence revise expected future cash flows in response to the announcements slowly. Therefore, stock prices do not react sufficiently to incorporate news. Barberis et al. (1998) construct an investor sentiment model that is consistent with both the conservatism and extrapolative biases, showing how the investors form biased beliefs about future earnings in two different earnings regimes. For the conservatism bias, investors in their model think that earnings are mean-reverting. As such, they underreact to the latest earnings announcement and formed biased expectations about future cash flows. In contrast, other investors believe that earnings have a trend in another regime. They tend to extrapolate past growth of stocks after a series of good and bad earnings news (*i.e.* extrapolative bias), resulting in overreaction. They assumed the expected returns to be constant in the model, and hence all mispricing is attributable to the expectation errors in the cash flows. Their simulation results render support to their model.

5.2.3 Expectations of future returns

Extrapolation occurs not only through the cash flow channel, but also through the discount rate channel, where investors extrapolate from past price changes in forming their expected returns. Early studies by Barberis and Shleifer (2003), Cutler, Poterba and Summers (1990), De Long, Shleifer, Summers and Waldmann (1990), and Hong and Stein (1999) present theoretical models showing how the asset price is determined through the interaction between rational investors, who base their expected returns to the fundamental news, and extrapolators, who form their expected return based on past price changes. Generally, their models demonstrate that extrapolators become more bullish by extrapolating positive past price changes, and hence form the optimistic expectation about future returns, leading the stock price to deviate further from its fundamental value. The mispricing is hard to be corrected by rational investors within short-term period in the presence of extrapolators.

Recently, Barberis, Greenwood, Jin and Shleifer (2015, henceforth BGJS) develop a new consumption-based asset pricing model at the aggregate stock market level by taking into account of the expectations formed by extrapolators. Unlike studies mentioned above, the role of investor sentiment is explicitly spelled out in their model in order to formalize the concept of extrapolation. Specifically, the high sentiment level, which is built upon the positive past price changes, leads to a more bullish expectation of future stock returns to be formed by extrapolators. Their model shows that the expectations formed by less rational investors could cause the stocks to be overvalued, and BGJS (2018) demonstrate that expected returns formed by extrapolating past price changes could lead to a bubble, even in a market where both rational traders and extrapolators co-exist. Therefore, irrational expectations about future stock returns should be given a credit in the asset pricing model.

Whilst theoretical research studied the implication of the interaction between heterogeneous agents has on the asset prices, empirical research provided evidences on the existence of investors' irrational expectations about future stock returns, for instance, Cassella and Gulen (2018), Greenwood and Shleifer (2014), Vissing-Jorgensen (2004). These studies employed the survey-based investor expectation data, such as UBS/Gallup investor survey, American Association of Individual Investors, Investors' Intelligence and etcetera [90], to measure the investors' expectations of future stock market returns.

[90] These indexes are also used as measures of investor sentiment in other literature (*e.g.* Qiu and Welch, 2004; Fisher and Statman, 2000; Brown and Cliff, 2004; 2005).

Using only the Investor Optimism Index from UBS/Gallup as a measure of investor belief, Vissing-Jorgensen (2004) find that investors hold irrational expectations since investors expected a higher future returns during market boom, which is contradicting to the rational expectation model. Their beliefs are not corrected immediately even though investors are aware of the stock market overvaluation. Their findings that investors form irrational expectations was reinforced by Greenwood and Shleifer (2014) who provide a more comprehensive investigation on the existence of bias in investors' expectations by employing various survey data of investor expectations. Greenwood and Shleifer (2014) reveal that investor expectations retrieved from different measures are highly correlated, but are negatively correlated with the 'true' model-based expected returns. These widely shared and biased beliefs have been found to predict negatively future stock returns, which, is not in line with the rational expectation model, but is consistent with the sentiment view that investor optimism lifts the current stock prices due to their high expected returns, leading to lower future stock returns.

Building upon the works of Greenwood and Shleifer (2014) and Barberis et al. (2015), Cassella and Gullen (2018) propose a measure – *degree of extrapolative weighting* (DOX) – to quantify the degree to which investors rely on more recent returns in forming their expectations, and find that the predictive power of price-scaled variables, *e.g.* dividend-price, book-to-market, and earnings-price ratios, could be explained by time-varying irrational expectations.

Under the efficient market hypothesis framework, different rational explanations are proposed to account for the change in expected returns formed by rational agents. The time-varying returns required by rational investors could simply represent (1) time-varying risk-aversion (Bekaert, Engstrom and Xing, 2009; Campbell and Cochrane, 1999; Cochrane, 2011), (2) time-varying risk (Bansal, Kiku, Shaliastovich and Yaron, 2014; Bansal, Kiku and Yaron, 2012; Bansal and Yaron, 2004; Bollerslev, Tauchen and Zhou, 2009), (3) disaster (*e.g.* Great Depression and wars) risk (Barro, 2006; Gabaix, 2012; Watcher, 2013), and (4) time-varying firm's asset portfolio and interest rates (Berk, Green and Naik, 1999).

Campbell and Cochrane (1999, CC) build a habit formation type of consumption-based asset pricing model by allowing the risk aversion to vary over time. According to their theoretical model, investors become more risk averse as the consumption tends towards the habit level[91], which is measured by the surplus consumption ratio (SCR)[92], during the recession period. Consequently, expected returns (*i.e.* discount rate) increase and current stock prices decrease. Cochrane (2011) depicts graphically that the SCR covaries with the price-dividend ratio, reinforcing the idea that time-varying risk aversion alters the investors' expected returns. Despite the consumption-wealth ratio (CAY)[93] model of Lettau and Ludvigson (2001a) is not built upon the framework of time-varying risk aversion, they, however, indirectly interpreted the comovement of CAY with expected returns using the concept of time-varying risk aversion. A decline in CAY reflects lower expected returns in the future is consistent with the time-varying risk-aversion framework. The CC model argues that the consumption exceeds the habit level during expansion periods and investors become less risk averse, leading to an increase in the asset demand but a decrease in the expected returns. Despite the consumption boom, asset wealth will increase at a much higher rate as compared to consumption, leading to a lower CAY that reflects lower expected returns. Bekaert et al. (2009) develop a model that accounts for both time-varying risk aversion and time-varying risk explanations, but found that the fluctuation in expected returns is driven mainly by the time-varying risk aversion.

With respect to the risk channel, Bansal and Yaron (2004, henceforth BY) propose a long-run risk model to explain the variation in discount rates. Their model implies that the variation in stock prices is a response to the variation in long-run expected growth and consumption volatility. They showed that the discount rate news is largely attributable to the time variation in the aggregate consumption risk, where an increase in the consumption volatility is associated with an increase in the discount rates. The relationship between volatility news and discount rate news has been further emphasized in the works of Bansal, Kiku and Yaron (2012), who provide empirical evidence to support BY's model, and Bansal, Kiku, Shaliastovich and Yaron (2014), who focus on the fluctuations of macroeconomic volatility. Meanwhile, the variance risk premium of Bollerslev, Tauchen and Zhou (2009), which is measured as the difference between implied and realized volatility, predicts positively expected returns.

[91] The habit in their model is governed by the aggregate consumption.

[92] A lower SCR indicates that the consumption approaches habit level.

[93] CAY measures the short run deviations of aggregate consumption, asset holdings, and labour income from their common trend. To shield the future consumption from the time-varying expected returns, investors will adjust their consumption level based on their expected future stock returns, resulted in a temporary deviation of the consumption from the shared trend, either move above (*i.e.* high CAY) or below (*i.e.* low CAY) the trend.

The disaster, such as Great Depression and wars, are events that do not happen very often but the impact brought by these events are huge in magnitude. Therefore, investors should be highly compensated for the risk ensued from the disaster (Rietz, 1988). Relax the low-probability disasters of Rietz, the time-varying probabilities of disaster explains the time-varying risk premium (Barro, 2006; Gabaix, 2012; Watcher, 2013). Apart from the macro perspective (*i.e.* interest rates in their model), Berk et al. (1999) also look into the micro perspective (*i.e.* firm's asset portfolio in their model), and tie both perspectives in explaining the time-series dynamic behaviour of conditional expected returns. They showed that increase in interest rates leads the firms to undertake lower risk projects lately as well as in the near future. Since the expected risk associated with receiving anticipated cash flows is decrease, the expected return is decrease.

5.2.4 Summary

The review of literature shows that most papers studied the expectations of future cash flows and discount rates in isolation with some even focused solely on the rational or irrational expectations in a particular channel. Studying the effect of each expectation on asset prices separately implicitly assumes the other expectations to hold constant. Nevertheless, some information about asset returns captured by one expectation could have been omitted by the other. Asset pricing model that considers only on the changes in one expectation may not truly reflects the effect of each expectation on asset prices as the model does not control for other expectations. Therefore, a more comprehensive view is provided by integrating the four expectations – irrational expectations of future cash flows and discount rate, and rational expectations of future cash flows and discount rate – into one model. As discussed earlier, different beta risks expanding from the work of CV (2004) have been proposed in the literature. However, to the best of our knowledge, none of them distinguish between irrational and rational beta risks. Thus, this study fills in this gap by evaluating the responsiveness of stock returns to changes in each of the four expectations. This enables us to evaluate the relative importance of irrational expectations and rational expectations risks in each cash flow and discount rate channel.

5.3 Return decomposition framework

Based on the present value concept, stock prices change because of a change in the expected cash flows and/ or discount rates. An increase in the expected future cash flows will lead to an increase in stock prices; an increase in the discount rates will cause a drop in stock prices. This simple concept leads to the development of the return decomposition framework introduced by Campbell and Shiller (1988a) and Campbell (1991). The framework starts with the log-linear approximation of the present value approach (Campbell and Shiller, 1988a), where the next-period stock returns approximate to the log-linear returns around the average of log dividend-price ratio which can be expressed as $r_{t+1} \approx k + \rho p_{t+1} + (1-\rho) d_{t+1} - p_t$. The lowercase letters r_t, p_t and d_t denote the log transformed stock returns (R_t), stock price (P_t) and dividend (D_t), respectively. k is a constant term expressed as $k = -\log \rho - (1-\rho)\log(1/\rho - 1)$ and the discounting coefficient, ρ, is assumed to be 0.95 per annum.

Iterating the one-period log-linear return approximation forward with $\lim_{j\to\infty} \rho^j (d_{t+j} - p_{t+j}) = 0$ yields the following linearized present value identity, which is an ex-ante measure using an expectation notation:

$$p_t - d_t = \frac{k}{1-\rho} + E_t \sum_{j=0}^{\infty} \rho^j [\Delta d_{t+1+j} - r_{t+1+j}] \tag{5.1}$$

where E_t denotes the expectations made at time t. This model implies that the increase in the expectation of future log dividend growth, Δd_{t+1+j}, and/ or a drop in the expectation of future stock returns, r_{t+1+j}, will produce a high log price-dividend ratio, $p_t - d_t$. The assumption of $\lim_{j\to\infty} \rho^j (d_{t+j} - p_{t+j}) = 0$ implies that the mean reverting (or non-explosive) condition holds for the terminal value of log price-dividend ratio.

Instead of employing the above present value identity to imply the forecasts of stock returns, Campbell (1991) explicitly forecast the stock returns. He decomposed stock returns into the expected cash flow and expected return components, and derived the equation for unexpected stock returns as follows:

$$r_{t+1} - E_t(r_{t+1}) = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j} \tag{5.2}$$

$$r_{t+1} - E_t(r_{t+1}) = \Delta E_{t+1}\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - \Delta E_{t+1}\sum_{j=1}^{\infty} \rho^j r_{t+1+j} \tag{5.3}$$

where E_t represents the expectations made at time t. The unexpected stock returns, $r_{t+1} - E_t(r_{t+1})$, at time t+1 is simply the combination of the change in expectations, E_{t+1}

– E_t, of cash flows and discount rates at time t + 1. The shocks in these return components are defined as cash flow news, N_{CF}, and discount rate news, N_{DR}.

$$N_{CF,t+1} = \Delta E_{t+1} \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} \tag{5.4}$$

$$N_{DR,t+1} = -\Delta E_{t+1} \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \tag{5.5}$$

The above equations indicate that a decrease in the unexpected return is a result of a decrease in the current and expected future cash flows and/ or an increase in the discount rates, and vice versa. The negative relationship between the unexpected returns and discount rate news is intuitive. A higher future stock return can only be realised from a lower current stock price (*i.e.* currently suffer from a loss), assuming the dividend growth holds constant. An investor, who is considering adding an additional stock into a well-diversified portfolio, will need to make the decision based on the comovement of that particular stock with the stock market news, which are N_{CF} and N_{DR}, and this leads to the construction of two-beta model in CV (2004). The empirical estimation of N_{CF} and N_{DR} as well as the extension of the two-beta model into four-beta model are presented in the next section.

5.4 Empirical methodology

This section presents four different approaches used to decompose stock market returns into N_{CF} and N_{DR}. The second sub-section presents the construction of the four-beta model, where the procedure of decomposing N_{CF} and N_{DR} into a rational and an irrational component is first discussed. The final sub-section describes the asset pricing test.

5.4.1 Return decomposition approaches

(I) VAR approach

To operationalize equation (5.2), Campbell and Shiller (1988a) and Campbell (1991) propose the use of vector autoregression (VAR) model in decomposing the stock market returns. The main idea of this approach is to extrapolate the short run forecasts of stock market returns into the long run forecasts since the data of the state variables on an infinite period (or long horizon) is hard to obtain. First, stock market returns are assumed to be generated by the first-order VAR model following CV (2004)[94].

$$\mathbf{z_{t+1}} = \mathbf{a} + \mathbf{\Gamma z_t} + \mathbf{u_{t+1}} \tag{5.6}$$

where the stock market return is the first element in an m-by-1 state vector, $\mathbf{z_{t+1}}$, and other state variables constitute any of the variables that are known to predict stock market return. Although studies by Cohen et al. (2002), CPV (2010), and Khimich (2017) employ individual stock returns as the first element in $\mathbf{z_{t+1}}$, this study opts for stock market returns for two reasons. First, this study follows closely the procedure of CV (2004) who decompose stock market returns instead of individual stock returns. Second, the effect of investor sentiment is pervasive in the stock market. This enables us to estimate the irrational component of stock market news.

Whilst the real stock market returns, $r^e_{M,t+1}$, can be retrieved from the vector $\mathbf{z_{t+1}}$ as $r^e_{M,t+1} = \mathbf{e1'z_{t+1}}$, where $\mathbf{e1'} = [\mathbf{1, 0, ..., 0}]$, the one-period unexpected stock market returns can be computed as $r^e_{M,t+1} - E(r^e_{M,t+1}) = \mathbf{e1'u_{t+1}}$. Given that the simple multi-period forecasts of future stock market returns can be generated from the first-order VAR as $E_t r^e_{M,t+1+j} = \mathbf{e1'\Gamma^{j+1}z_t}$, the discount rate news, which is the changes in the discounted sum of future expected returns over the long-run, can be estimated as:

$$N_{DR,t+1} = (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j} \tag{5.7}$$

$$N_{DR,t+1} = \mathbf{e1'}\sum_{\mathbf{j=1}}^{\infty} \boldsymbol{\rho}^{\mathbf{j}}\mathbf{\Gamma}^{\mathbf{j}}\mathbf{u_{t+1}} = \mathbf{e1'}\boldsymbol{\rho}\mathbf{\Gamma}(\mathbf{I} - \boldsymbol{\rho}\mathbf{\Gamma})^{-1}\mathbf{u_{t+1}} = \mathbf{e1'}\boldsymbol{\lambda}\mathbf{u_{t+1}} \tag{5.8}$$

where $\boldsymbol{\lambda} = \boldsymbol{\rho}\mathbf{\Gamma}(\mathbf{I} - \boldsymbol{\rho}\mathbf{\Gamma})^{-1}$, $\mathbf{e1'} = [\mathbf{1, 0, ..., 0}]$, $\mathbf{\Gamma}$ is the point estimates of the VAR matrix, the discounting coefficient, ρ, is set at $0.95^{1/12}$ (see CV, 2004)[95] and $\mathbf{u_{t+1}}$ is the error terms of the

[94] The first-order VAR is chosen since the optimal lag for the return predictive regression is one based on the information criteria of AIC and BIC and it is in line with other studies apart from CV (2004) (see Botshekan et al., 2012; CPV, 2010; Campbell et al., 2018; Garrett and Priestley, 2012). Furthermore, Chen and Zhao (2009) and CPV (2010) also find that their findings are robust to the inclusion of additional VAR lags.

[95] Chen and Zhao (2009) and CV (2004) find that their results are robust to the use of different discounting coefficients, ρ. Hence, this study follows the norm in the beta decomposition literature.

VAR system. The cash-flow news, N_{CF}, is simply the difference between the total unexpected stock market returns and the N_{DR}, and can be computed as:

$$N_{CF,t+1} = (\mathbf{e1'} + \mathbf{e1'\lambda})\mathbf{u_{t+1}} \tag{5.9}$$

This study accounts explicitly for the irrational expectations of the future cash flows and discount rates. Unlike Lof (2015) which allows for a non-zero limiting value of the dividend-price ratio in the short term, this study follows Campbell and Shiller (1988a) and Campbell (1991) that the terminal condition of dividend-price ratio is non-explosive, which is the assumption of equation (5.1). Even though this study accounts for the irrational expectations of the future cash flows and discount rate, the irrational expectations do not always lead to the occurrence of a bubble, rather it does have an impact on the stock prices even during the normal period. Each expectation, therefore, should be decomposed into rational and irrational components for the beta computation.

The return decomposition framework of Campbell and Shiller (1988a) and Campbell (1991) utilizes the financial theory in forming the expected returns since investors' expectations are not directly observable and are extracted from the dynamic relations between the stock market returns and its predictors. Therefore, the expectations formed are rational if and only if the VAR follows the true data generating process as argued by Lof (2015). However, Lof (2015) shows that the VAR does not account for all expectations due from different agents and that the prices produced by irrational contrarian model[96] is closer to the direction of true prices as compared to rational speculator model. Despite Lof (2015) modifying the return decomposition of Campbell and Shiller (1988a) to allow for a rational bubble by relaxing the assumption of non-explosive terminal condition of dividend price ratio, their short-term strategies, however, still based on the rational expectations of speculators. For the irrational contrarian strategy, they take the opposite direction of the expected returns formed by rational speculators. This procedure, however, does not rule out the possibility that some of the contrarian investors are rational. Therefore, it is important to explicitly consider the effect of investor sentiment in forming the irrational expectations.

[96] Lof (2015) defines the contrarian as an investment strategy where the investors trade against the prediction produced by VAR.

(II) Time-varying VAR (TV-VAR)

The constant parameter estimates retrieved from the VAR may not truly reflect or capture the expectations formed by investors through the time. As shown in Neely and Weller (2000), estimating a VAR on a rolling window basis greatly improves the forecasting performance, implying the parameter instability of VAR process. In view of this, this study modifies slightly the constant VAR procedure, constructing the news series from the TV-VAR approach. Specifically, the VAR parameters and the news series are estimated on a rolling window basis with a window size of 72 months[97]. Since the estimation window which produces the news series that best describe the evolution of stock market returns is unknown, the news series are averaged across different windows at each point in time in order to obtain a single series of cash flow and discount rate news. Then, the sentiment-induced irrational component and the rational component from each news series are extracted, producing the four news series, which are the irrational cash flow news, the rational cash flow news, the irrational discount rate news and the rational discount rate news.

There are pros and cons associated with the constant VAR and TV-VAR specifications. The advantage of the constant VAR specification is that retrieving the news series from the full sample is less subject to the small sample bias. However, applying constant weights to state variables may not capture optimally the variation in expected returns, which is well depicted in the Figure 5.1 that plots the estimated coefficients (panel A) of the return predictive regression from the TV-VAR model associated with the *p*-value (panel B) for each state variable on a rolling window basis. Panel A clearly shows that the estimated coefficient of each state variables is changing over time. Moreover, their predictive strengths are not constant through time as depicted in panel B, where each state variable predicts significantly the future stock market returns at certain periods but not the others. Hence, accurately modelling the expected returns over time is important in retrieving the real unexpected returns that will contribute to the construction of the news series. On the other hand, TV-VAR relaxes this restriction, allowing the contribution or weight of each state variable in the VAR specification to change through time. Nevertheless, the potential small sample bias faced by TV-VAR could introduce an upward or a downward bias on the estimates as compared to the constant VAR estimates[98]. As such, it is a trade-off between

[97] The window size is equivalent to a business cycle according to the NBER.

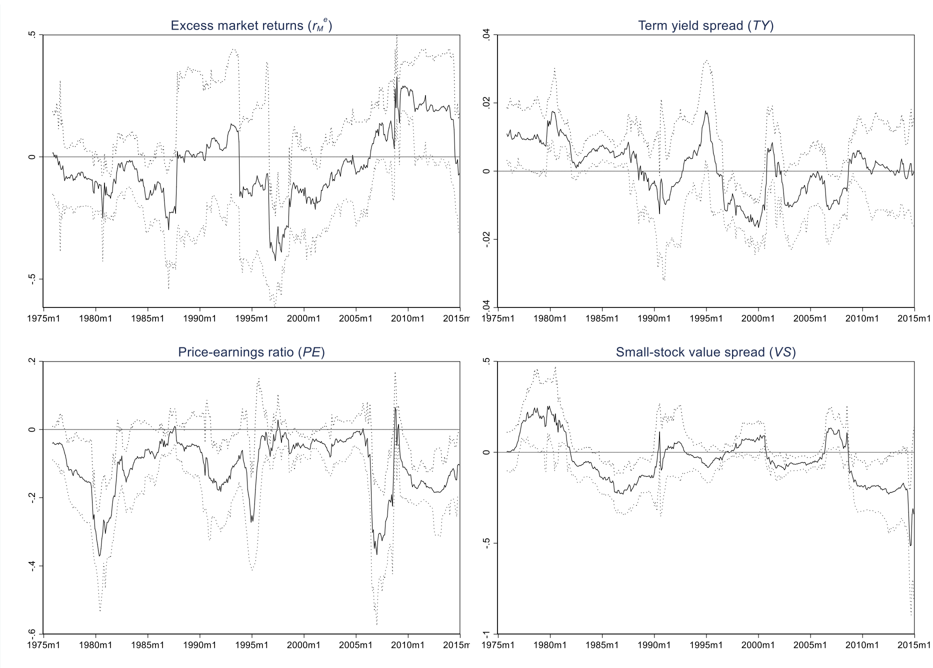
[98] The online appendix of CV (2004) show that the cash flow and discount rate betas in their modern sample period are affected by the small sample bias given that the state variables of the VAR system are highly

"correctness" and small sample bias. Employing a window length of less than 6 years (a full business cycle) could potentially induce severe small sample bias since all state variables are highly autocorrelated. Meanwhile, a longer estimation window length of 15 years has been tested and this longer window length has been found to be less optimal in capturing the variation in expected returns since the adjusted R^2 statistics is lower for the return regression performed on a longer window length, i.e. 15 years. Hence, the window length is chosen to mitigate the small sample bias, yet, is able to uncover the temporal variation in expected returns. If both constant VAR and TV-VAR produce commonality in the betas estimates, the results would be more convincing and reliable. Thus, the beta estimates from both approaches are presented even though the baseline results are derived from the TV-VAR due to its superior model fit as demonstrated in Section 5.6.1.

Figure 5.1: 72-month rolling estimates for return predictive regression

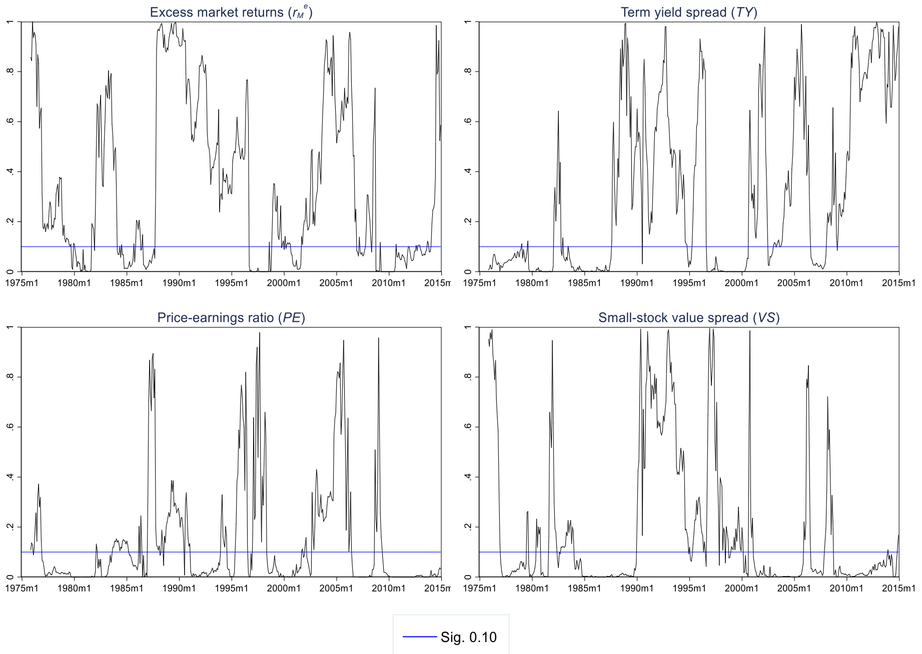
This figure plots the rolling regression estimates for the return predictive regression on a rolling window basis estimated from December 1969 to December 2014. The state variables used to predict the excess market return are the lagged terms of the excess market return (r_M^e), the term yield spread (*TMS*), the price-earnings ratio (*PE*) and the small-stock value spread (*VS*). Panel A depicts the rolling slope coefficient of each state variable associated with its 95% confidence interval represented by dotted lines. Panel B plots the rolling *p*-value for the estimated coefficient of each state variable. The horizontal line in panel B denotes the significance level of 10%.

Panel A: Rolling Coefficient Estimates



persistent. The estimated risk premium associated with the cash flow beta reduces greatly and reverse the conclusion that the cash flow beta earns a higher premium than the discount rate beta.

Panel B: Rolling p-values



(III) Revision in Analysts' Forecasts (AF)

In addition to the VAR-type approach, which is widely used in the literature, this study also considers an alternative approach that is based on analysts' forecasts in constructing the news series. Using the standard return decomposition of Campbell and Shiller (1988a) and Campbell (1991), Khimich (2017) define the N_{CF} as the revision in the analysts' forecasts of the ROE ($FROE$) instead of discounted sum of clean-surplus ROE[99] as proposed in Cohen et al. (2002) and Vuolteenaho (2002), and back out the N_{DR} as the residual, as shown below:

$$r_{t+1} - E_t(r_{t+1}) = (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j ROE_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j}$$
$$r_{t+1} - E_t(r_{t+1}) = \sum_{j=1}^{\infty} \rho^j (FROE_{t+1,t+1+j} - FROE_{t,t+1+j}) - \Delta E_{t+1}\sum_{j=1}^{\infty} \rho^j r_{t+1+j} \tag{5.10}$$

$$N_{CF,t+1} = \sum_{j=1}^{\infty} \rho^j (FROE_{t+1,t+1+j} - FROE_{t,t+1+j}) \tag{5.11}$$

$$N_{DR,t+1} = -\Delta E_{t+1}\sum_{j=1}^{\infty} \rho^j r_{t+1+j} = -\left[r_{t+1} - E_t(r_{t+1}) - N_{CF,t+1} \right] \tag{5.12}$$

[99] Clean surplus accounting requires that the variation in the book value to be calculated by subtracting the net dividends from earnings in order to ensure that gains and losses affecting the earnings are accounted in the computation.

where $\Delta E_{t+1}\sum_{j=1}^{\infty}\rho^{j}r_{t+1+j}$ represents the variation in the discounted sum of expected returns and is computed as the difference between unexpected stock market returns and N_{CF}. The N_{CF} is defined as the discounted sum of the revision in analysts' forecasts, which is the difference between the ROE forecasts generated at time *t* ($FROE_{t,t+1+j}$) and the ROE forecasts produced at time *t* + 1 ($FROE_{t+1,t+1+j}$). Similar to previous approaches, the discounting factor used in this method is assumed to be $0.95^{1/12}$ as well. The ROE forecasts are computed as $FROE_{t+i} = FEPS_{t+i} / BV_{t+i-1}$. Despite cash flow news in equation (5.11) requiring an infinite sum of *FROE*, forecasts of only up to twelve years are used for practical purpose following the works of Gebhardt et al. (2001) and Khimich (2017). The mean of one- and two-year-ahead EPS forecast, *FEPS*, is readily available from the Bloomberg. The three-year-ahead *FEPS* can be computed as $FEPS_{t+3} = FEPS_{t+2}\,(1 + LTG)$, where *LTG* represents the long-term *EPS* growth rate predicted by analysts. In line with other literature, the *FROE* beyond three years is assumed to revert to the median of aggregate *ROE*. As for the book value, *BV*, it can be forecasted based on the clean surplus principle as $BV_{t+i} = BV_{t+i-1} + FEPS_{t+i} - FDPS_{t+i}$, where

$$FDPS_{t+i} = FEPS_{t+i} \times k_t = FEPS_{t+i} \times (D_{t+i-1} / E_{t+i-1}) \tag{5.13}$$

k_t is the current dividend payout ratio computed as a ratio of dividend over earnings. This study accounts for the possibility that the accounting information is publicly available only after forecasts have been made by taking the lagged term of dividend and earnings in the construction of *k*.

This measure reflects the markets' expectation about the future cash flows and hence analysts maybe optimistic in their forecasts. Zhu and Niu (2016) indeed find that investor sentiment does affect the predicted earnings growth rate. Also, Hribar and Mclnnis (2012) reveal that one-year-ahead *FEPS* and *LTG* tend to be more optimistic during high sentiment periods. Meanwhile, Easton and Monahan (2005) claim that the low-quality of analysts' forecasts is the culprit for the lack of reliability of the accounting-based measures as a proxy to the expected returns. They found that accounting-based proxies are less reliable in estimating the expected stock returns when the *LTG* is high. On the other hand, all proxies are positively correlated to the expected returns when the *LTG* is low and *ex-post* analysts' forecasts have lower errors. Their findings are hence a manifestation that analysts' forecasts could be rational at some times but irrational at another times. Since the analysts' forecasts are of low quality and the degree of rationality of analysts' forecasts is varying over time, the analysts' forecasts may not be a good proxy to the cash flow expectations.

(IV) Direct proxy

CPV (2010) employ a direct proxy to measure the market news apart from the VAR approach. Following Cohen et al. (2002), they employed the changes in the discounted sum of *ROE* as a proxy for N_{CF}. For the proxy of N_{DR}, CPV (2010) use the annual changes in market's log smoothed *PE* ratio as follows:

$$N_{DR,t+1} = \sum_{k=1}^{K} \left[\rho^{k-1} \Delta_{t+k} \ln(PE)_M \right] \tag{5.14}$$

where k = examining horizon of 24-, 36-, 48- and 60-month

$\Delta_{t+k} \ln(PE)_M$ refers to the changes in market's *PE* ratio from t + k – 1 to t + k and, as previously, ρ is the discounting coefficient. To be consistent with the VAR approach, ρ = $0.95^{1/12}$. This is done to check for both short-term and long-term fluctuation caused by discount rate news.

While the cash flow proxy may merely reflect accounting information, since historical *ROE* is used in the computation, the direct proxy of the discount rate news may not fully reflect the rational expectations of investors given that stock prices could be affected by investor sentiment. Basu (1977) finds that the *PE* ratio reflects the bias in stock prices (*i.e.* low *PE* stocks have higher risk-adjusted return than high *PE* stocks). This could be due to the optimistic (pessimistic) response of investors towards the information in *PE* ratio causing the overpricing (underpricing) in the high (low) *PE* stocks according to the price-ratio hypothesis (De Bondt and Thaler, 1985). Besides that, Dechow and Sloan (1997) find that the naïve dependence of investors on the analysts' long-term earnings growth forecasts, which are biased, lead them to overvalue the high *PE* stocks that resulted in a future price reversal. On the other hand, other possible risk-based explanations, which are irrelevant to the irrational aspects, have been proposed to study the contrarian strategy as shown by *PE* multiple, such as market friction (Amihud and Mendelson, 1986) and misspecification of the model (Reinganum, 1981). Therefore, both rational and irrational expectations of future returns (i.e. discount rates) could be extracted from the *PE* ratio. Once the N_{DR} is retrieved, the N_{CF} can be computed as a difference between unexpected returns and N_{DR} following the return decomposition as in the equation (5.3).

The direct proxy approach is not prominently applied in the beta decomposition literature apart from CPV (2010). Therefore, only the result summary of the two-beta and four-beta models constructed based on this approach is provided in Section 5.6.4, and the detailed results are not reported.

5.4.2 Four-beta model

Given the estimated N_{CF} and N_{DR}, the rational and irrational components of the market news can be retrieved as either the residuals or fitted values respectively in the following regressions[100]:

$$N_{CF,t} = \alpha + \sum_{i=0}^{12} \beta_i S_{t-i}^{TV} + \varepsilon_t \tag{5.15}$$

$$N_{DR,t} = \varpi + \sum_{i=0}^{12} \gamma_i S_{t-i}^{TV} + \eta_t \tag{5.16}$$

where $N_{CF,t}$ and $N_{DR,t}$ are cash flow and discount rate news, respectively, estimated based on the framework of return decomposition. S^{TV} denotes the time-varying weighted investor sentiment index computed in Chapter 3[101]. As previously stated, the residual series, ε_t and η_t, represent the rational component of the cash flow news, $N_{CF,t}^{R}$, and the discount rate news, $N_{DR,t}^{R}$. The irrational component of the cash flow news, $N_{CF,t}^{IR}$, and the discount rate news, $N_{DR,t}^{IR}$, are simply the fitted values of the above regressions.

[100] A high investor sentiment today is associated with an increase (decrease) in the expectation of future cash flows (discount rate) formed from the period t-1 to t. Hence, investor sentiment is positively correlated with cash flow news (ρ = 0.0239) and is negatively correlated with discount rate news (ρ = -0.0171).

[101] Since investor sentiment is highly persistent, as documented in the Chapter 3, the lagged terms of investor sentiment index have been incorporated in the regressions to avoid the omitted variable bias. Although the lagged terms could have selected based on the information criterion, such as AIC or BIC, but the information criterion tends to select the parsimonious model of up to one lagged term. This may not truly reflect the effect of investor sentiment on unexpected stock market returns given the persistence feature of investor sentiment. The main goal here is to capture as much as possible the sentiment effect in the irrational new series, and to clean out as much sentiment effect as possible from the rational new series. Hence, investor sentiments from the past twelve months are incorporated in equations (5.15) and (5.16). Besides that, capturing the previous twelve months' sentiment could remove (or reduce) any possible seasonal effect of investor sentiment on stock returns.

A four-beta model is then constructed to measure the sensitivity of stock returns to each of these news series. Considering that only one sentiment measure is used to pick out the irrational components in the news series, the model does introduce downward bias against the irrational betas.

CPV (2010) compute the cash flow beta and discount rate beta based on the scaled news series in order to adjust the regression coefficients of different scales to a common scale - variance of excess market return ($Var(r_M^e)$), so that $\beta_{i,CF}$ and $\beta_{i,DR}$ sum up to the market beta. Adapting their approach, each news series is scaled by the ratio of the variance of excess market return, $Var(r_M^e)$, to the variance of each news series as follows:

$$SN_{CF,t}^{IR} = N_{CF,t}^{IR} \times \frac{Var(r_{M,t}^e)}{Var(N_{CF,t}^{IR})} \tag{5.17}$$

$$SN_{CF,t}^{R} = N_{CF,t}^{R} \times \frac{Var(r_{M,t}^e)}{Var(N_{CF,t}^{R})} \tag{5.18}$$

$$SN_{DR,t}^{IR} = N_{DR,t}^{IR} \times \frac{Var(r_{M,t}^e)}{Var(N_{DR,t}^{IR})} \tag{5.19}$$

$$SN_{DR,t}^{R} = N_{DR,t}^{R} \times \frac{Var(r_{M,t}^e)}{Var(N_{DR,t}^{R})} \tag{5.20}$$

where $SN_{CF,t}^{IR}$ and $SN_{CF,t}^{R}$ are irrational and rational scaled cash flow news series; $SN_{DR,t}^{IR}$ and $SN_{DR,t}^{R}$ are irrational and rational scaled discount rate news series. Accordingly, the four betas can be defined as:

$$\beta_{i,CF}^{IR} = \frac{Cov(r_{i,t}, SN_{CF,t}^{IR})}{Var(r_{M,t}^e)} \tag{5.21}$$

$$\beta_{i,CF}^{R} = \frac{Cov(r_{i,t}, SN_{CF,t}^{R})}{Var(r_{M,t}^e)} \tag{5.22}$$

$$\beta_{i,DR}^{IR} = \frac{Cov(r_{i,t}, SN_{DR,t}^{IR})}{Var(r_{M,t}^e)} \tag{5.23}$$

$$\beta_{i,DR}^{R} = \frac{Cov(r_{i,t}, SN_{DR,t}^{R})}{Var(r_{M,t}^e)} \tag{5.24}$$

To empirically obtain these four betas, the following regression is performed:

$$r_{i,t} = \alpha + \beta SN^{k}_{j,t} + \varepsilon_t$$
$$\text{where } SN^{k}_{j,t} = \{SN^{IR}_{CF,t}, SN^{R}_{CF,t}, SN^{IR}_{DR,t}, SN^{R}_{DR,t}\} \tag{5.25}$$

where $r_{i,t}$ represents the portfolio's log returns and $SN^{k}_{j,t}$ denotes one of the four scaled new series computed from equations (5.17) to (5.20). The β is the corresponding beta estimates for each news series depending on which scaled news series is used to perform the above regression.

The following equations show that cash flow beta, $\beta_{i,CF}$, comprises of the irrational cash flow beta, $\beta^{IR}_{i,CF}$, and the rational cash flow beta, $\beta^{R}_{i,CF}$; whereas the discount rate beta, $\beta_{i,DR}$, comprises of the irrational discount rate beta, $\beta^{IR}_{i,DR}$, and the rational discount rate beta, $\beta^{R}_{i,DR}$.

$$\beta_{i,CF} = \beta^{IR}_{i,CF} + \beta^{R}_{i,CF} \tag{5.26}$$

$$\beta_{i,DR} = \beta^{IR}_{i,DR} + \beta^{R}_{i,DR} \tag{5.27}$$

The summation of the cash flow beta and the discount rate beta adds up to the market beta (see CPV, 2010).

5.4.3 Pricing of the four-beta model

If a market is not fully dominated by the long-term risk averse investors but both risk averse and risk seeking investors constitute the market players instead, the rational and irrational risks could carry different premiums. Distinguishing between the sensitivity of stock returns to the rational and irrational components in each channel allows us to answer the question: does the stock market reward investors for bearing both types of risks in each channel? This study performs the FMB regression in order to estimate the risk premium associated with each beta risk in the four-beta model. Concretely, the betas estimated from the previous section are used as explanatory variables (i.e. risk factor) in the following cross-sectional regression at each month *t*.

$$R^{e}_{i,t} = \lambda^{IR}_{CF,t}.\hat{\beta}^{IR}_{i,CF} + \lambda^{R}_{CF,t}.\hat{\beta}^{R}_{i,CF} + \lambda^{IR}_{DR,t}.\hat{\beta}^{IR}_{i,DR} + \lambda^{R}_{DR,t}.\hat{\beta}^{R}_{i,DR} + e_{i,t} \tag{5.28}$$

where $R^{e}_{i,t}$, denotes the simple excess returns on portfolio *i* at month *t*, $\hat{\beta}^{IR}_{i,CF}$ is the estimated irrational cash flow beta on portfolio i, $\hat{\beta}^{R}_{i,CF}$ is the estimated rational cash flow beta on portfolio i, $\hat{\beta}^{IR}_{i,DR}$ is the estimated irrational discount rate beta on portfolio i, $\hat{\beta}^{R}_{i,DR}$ is the estimated rational discount rate beta on portfolio i. $\lambda_{j,t}$ and $e_{i,t}$ are the cross-sectional slope coefficients and the pricing errors, respectively, at month t. The risk premium associated with each risk factor is the time-series average of the cross-sectional slope coefficients, i.e. $\hat{\lambda}_j = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{j,t}$. This study then tests whether this estimated risk premium is significantly different from zero with the use of Newey-West standard errors in order to account for the autocorrelated $\hat{\lambda}_{j,t}$. The pricing performances of the four-beta model, constructed based on different approaches, are compared to the CAPM and the CV's two-beta models, where all models are estimated based on the Fama-Macbeth (FMB) procedure.

As mentioned by Lewellen, Nagel and Shanken (2010), the freely estimated risk premia will inflate the cross-sectional explanatory power, in terms of the cross-sectional R^2 statistic. Therefore, following Campbell et al. (2018) and Ho and Hung (2009), this study imposes theoretical restriction on the asset pricing specification. Particularly, the zero-beta rate[102] is restricted to be equal to the risk-free rate and the risk premium equals the excess returns of the factor.

To assess the performance of each asset pricing model, this study computes the adjusted cross-sectional R^2 statistic that measures the proportion of the cross-sectional variation in the average excess returns that is explained by the model. The higher the adjusted cross-sectional R^2 statistic, the better the model is at explaining the average stock returns at cross-section level. Another evaluation criterion that is widely used in the literature is the pricing errors. Both the root-mean-squared-pricing-error (RMSPE) and the mean-pricing-error (MPE) are computed. A better asset pricing model will deliver relatively lower pricing errors.

5.5 Data and descriptive statistics

The following sub-sections provide the details of data used to decompose the stock market returns based on different approaches, followed by the data of test asset portfolios

[102] The zero-beta rate is the expected returns of the zero-beta portfolio, which has its returns uncorrelated to the market portfolio's returns. This concept was invented by Black (1972) which explored the capital market equilibrium where risk-free asset does not exist in the markets and riskless borrowing or lending is not possible.

used to test the four-beta model. The descriptive statistics of data is presented at the end of this section.

5.5.1 VAR (and TV-VAR) data

To ensure our result is comparable to CV (2004), four state variables, which are excess market returns (r_M^e), the term yield spread (*TMS*), the price-earnings ratio (*PE*) and the small-stock value spread (*VS*), employed in their study are used in our VAR model to decompose the excess market returns into N_{CF} and N_{DR} for the period 1969:12 – 2014:12[103]. These four state variables are also employed in the literature (see Celiker, Kayacetin, Kumar and Sonaer, 2016; Chen and Zhao, 2009; CPV, 2010; Campbell, Giglio and Polk, 2013, CGP hereafter). The detailed construction of each variable is discussed as follows.

The excess market return (r_M^e) is computed as the monthly log stock market return minus the log risk-free rate. The stock market return is the value-weighted S&P 500 index returns (inclusive of dividends) retrieved from the Center for Research in Security Press (CRSP). The risk-free rate is 3-month Treasury-bill rate. As in Welch and Goyal (2008), the second state variable, *TMS*, is computed as the difference between the yield on U.S. long-term government bond and the yield on U.S. Treasury-bills. This measure is included in the VAR framework since it captures the business cycle variation (Fama and French, 1989), where the *TMS* is low (high) at the peaks (troughs) of the business cycle. Since expected stock market return is countercyclical, low term yield spread hence predicts low expected returns during the expansion period and vice versa. The risk-free rate together with both series used in the *TMS* computation are retrieved from Amit Goyal's website[104].

Next, the price-earnings ratio (*PE*) is defined as the log-smoothed *PE* ratio. Following CV (2004), it is constructed as ratio of the price of the S&P 500 index to a ten-year trailing moving average of the earnings of S&P 500 index, which aims to smooth out the cyclical variation in earnings. In their online appendix, CV (2004) advocate the use of data available

[103] The news series are computed from December 1969 in order to account for the effect of investor sentiment, which has its first data point in December 1968, from the previous twelve months on the news series. Hence, the sample from December 1968 to November 1969 are excluded in the VAR estimation in order to exclude the possibility that the unexpected returns during this period is affected by investor sentiment from the past twelve months, of which is not available prior to December 1968.

[104] http://www.hec.unil.ch/agoyal/

only up to time t to avoid any look-ahead bias. This ratio is log transformed. The S&P 500 index and market's earnings series are retrieved from the website of Robert J. Shiller[105].

The last state variable, the small-stock value spread (*VS*), is computed using the book-to-market ratio of small value and small growth portfolios obtained from the website of Kenneth R. French[106]. As stated on his website, "[t]he portfolios, which are constructed at the end of each June, are the intersections of 2 portfolios formed on size (market equity, *ME*) and 3 portfolios formed on the ratio of book equity to market equity (*BE/ME*). The size breakpoint for year t is the median NYSE market equity at the end of June of year t." This study employs the value-weighted average of *BE/ME* computed for June of year t to the June of year t+1. The value-weighted average of *BE/ME* is calculated as $\sum_{i=1}^{12}\left[ME_i \times \left(BE_{t-1} / ME_t\right)\right] / \sum_{i=1}^{12} ME_i$, where i represents a month from June of t to June of t + 1. BE_{t-1} is the book equity for the last fiscal year end in t – 1 and ME_t is market equity for June of year t[107]. The *BE/ME* breakpoints are the 30th and 70th NYSE percentiles. The monthly small-stock value spread is computed by subtracting the log *BE/ME* of small growth stocks from the log *BE/ME* of small value stocks.

5.5.2 Analysts' forecasts data

The calculation of the analyst forecast of returns on equity (*FROE*) requires the forecast of earnings per share (*FEPS*) and the book value (*BV*). The data and the construction of the numerator of *FROE,* which is the *FEPS,* is first discussed. The mean of one- and two-year-ahead *FEPS* can be obtained from the Bloomberg Estimates (BEst)[108]. In line with the literature, the forecast fiscal period value associated with a fiscal year is adopted in this study.

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[105] http://www.econ.yale.edu/~shiller/data.htm

[106] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[107] The *BE/*ME constructed from the *ME* for June of year t instead of the *ME* for December of t – 1, such as that used in the test asset portfolios in Section 5.5.3, is used here. The rationale being that VS computed using the *BE/ME* where the *ME* for June of year t is used has a higher correlation with the VS data provided by CV (2004) than the VS computed using the *BE/ME* where the *ME* for December of year t – 1 is used (i.e. 0.935 vs. 0.898).

[108] Although most studies employed the analysts' earnings forecasts retrieved from the Institute of Broker Estimates System (IBES), this study retrieves those forecasts from BEst as the access to the IBES is limited.

These forecasts are available from January 1990. The two-year-ahead *FEPS* from January to March of 2005 are missing[109]. These missing values are filled by using linear interpolation.

Although three-year-ahead *FEPS* does provided by BEst, many missing values (about 22% of the series) have been found in the series. Hence, the three-year-ahead forecast is computed based on the available one- and two-year-ahead forecasts and long-term earnings per share (*EPS*) growth rate (*LTG*) following Gebhardt et al. (2001) and Khimich (2017). *LTG* from BEst is the estimated Compounded Annual Growth Rate (CAGR) of the operating *EPS* over the company's next full business cycle, which is typically three to five years. The *LTG* series from BEst is only available from July 2005, the missing values prior to this month is filled by computing the composite growth rate underlying in the one- and two-year-ahead *FEPS* as in Gebhardt et al. (2001). The *FROE* beyond year 3 is interpolated linearly up to year 12, of which the *FROE* is the median of *ROE* computed as the 5-year moving median of past *ROE*s[110].

The denominator of *FROE* – *BV* – is computed using the *FEPS*, forecasted dividend per share (*FDPS*) and historical *BV*, which is used to construct the one-year-ahead *BV*. The historical dividends and earnings used to obtain the *FDPS* as well as the historical *BV* are retrieved from the Bloomberg terminal in order to ensure the forecast value is congruent to the realized value. For the historical dividend, this study opts for the most recently announced gross dividend in order to truly reflect the dividends received by investors. Meanwhile, the basic EPS is employed in this study.

There is a caveat using the analysts' earnings forecasts from BEst. As described in the footnotes 109, the aggregate value of forecast is provided by BEst as long as more than 50% of the securities have their *FEPS* reported by brokers. Nevertheless, it is uncertain what is the actual percentage of securities that have the brokers' estimates in each month, i.e. the actual coverage percentage could vary in between 51% to 100%. Apart from the issue of the coverage factor at the index level, the coverage at the individual securities also have the same issue, where the minimum number of brokers' estimates required for each security is one. Hence, the consistency of the earnings forecasts for the S&P 500 index across months could

[109] The missing values could be due to the lower coverage factor, where less than 50% of the securities have their *FEPS* reported from brokers for these few months. Hence, BEst is unable to aggregate the forecasts of the underlying constituent stocks to the index level forecast.

[110] This procedure follows closely to that of Gebhardt et al. (2001) and Khimich (2017), whose study focuses on the firm level. Instead of using the median industry *ROE*, this study uses the median value of aggregate *ROE*.

be a question. Besides that, the earnings forecasts available on the BEst has a much shorter sample period as compared to the earnings forecasts provided by IBES, which can be traced back to the year 1983. Hence, the results of the four-beta model computed based on the analysts' forecasts approach could be affected and may not fully comparable to previous studies which employed the forecasts from IBES.

5.5.3 Test asset portfolios

With the market news series computed from different approaches, the four-beta model can be tested on the 25 portfolios formed based on firm size and book-to-market ratio. These portfolios are downloaded from Kenneth R. French's website. The portfolios are the intersection of five portfolios sorted based on *ME* and five portfolios sorted based on *BE/ME* ratio, constructed at the end of each June. *BE/ME* for June of year t is the book equity for the last fiscal year end in $t-1$ divided by ME for December of $t-1$. The breakpoints for size and *BE/ME* are the NYSE quintiles. To perform the regression (5.28), we compute monthly simple excess returns on the test asset portfolios.

5.5.4 Descriptive statistics of data

Table 5.1 reports the descriptive statistics for the data used to decompose excess market returns into different news series based on VAR-type and analysts' forecasts approach, in panel A and B, respectively. The correlations among the state variables of VAR model are presented at the bottom of panel A.

Overall, the descriptive statistics of VAR's state variables are in line with that of reported in CV (2004). The r_M^e has a mean of 0.4% and a median of 0.8%. The standard deviation of r_M^e is 4.5%. These statistics of r_M^e are in line with the literature (see CV, 2004; Huang et al., 2015; Neely, Rapach, Tu and Zhou, 2014). Among all the state variables, *PE* ratio has the highest mean value, whereas *TMS* varies the most around its mean according to the standard deviation measure. The first-order autocorrelation measure indicates that all state variables but r_M^e are highly persistent with autocorrelation statistics of greater than 0.9.

The contemporaneous correlations among VAR state variables, as shown in the bottom of panel A, are highly significant even though the magnitude of each correlation is relatively low. The highest correlation of 0.269 is reported for the relationship between *VS*

Table 5.1: Summary statistics of data

Panel A: VAR Approach

	Mean	*Median*	*SD*	*Min*	*Max*	*ρ*(1)
r_M^e	0.004	0.008	0.045	-0.248	0.149	0.057
TMS	2.059	2.230	1.493	-3.650	4.550	0.946
PE	3.070	3.092	0.367	2.298	3.891	0.994
VS	1.495	1.487	0.145	1.231	1.952	0.945

Correlations	r_M^e	*TMS*	*PE*	*VS*
r_M^e	1.000			
TMS	0.086**	1.000		
PE	0.031	0.083*	1.000	
VS	-0.106**	0.255***	0.269***	1.000

Panel B: Analysts' Forecasts Approach

	Mean	*Median*	*SD*	*Min*	*Max*
DPS	1.672	1.509	0.831	0.538	4.680
EPS	47.963	43.590	28.532	4.660	108.710
BV	375.824	334.500	172.111	165.570	739.050
ROE	0.131	0.144	0.046	0.027	0.193
LTG	0.133	0.133	0.056	-0.133	0.464
FROE1	0.167	0.168	0.019	0.117	0.204
FROE2	0.165	0.165	0.013	0.136	0.194
FROE3	0.152	0.152	0.013	0.107	0.204
FROE4	0.150	0.150	0.012	0.113	0.198
FROE5	0.148	0.147	0.012	0.118	0.192
FROE6	0.147	0.143	0.013	0.122	0.185
FROE7	0.145	0.139	0.014	0.119	0.179
FROE8	0.143	0.138	0.016	0.116	0.175
FROE9	0.141	0.138	0.018	0.112	0.175
FROE10	0.140	0.138	0.021	0.109	0.175
FROE11	0.138	0.137	0.023	0.106	0.175
FROE12	0.136	0.135	0.026	0.102	0.176

Notes: This table presents the descriptive statistics of the state variables used in the VAR (panel A) and analysts' forecasts (panel B) approaches. The sample period for the VAR approaches spans for the period 1969:12 – 2014:12 (*i.e.* 541 months); whereas the sample period for the analysts' forecasts approach covers from 1990:01 to 2014:12. For the VAR approaches, r_M^e is the excess market returns, *TMS* is the term yield spread, *PE* is the log smoothed *PE* ratio and *VS* is the small-stock value spread. For the analysts' forecasts approach, *DPS* is the dividend per share, *EPS* is the basic earnings per share, *BV* is the book value per share, *ROE* is the returns on common equity, *LTG* is the long-term EPS growth rate, and *FROE1* to *FROE12* denotes the one-year-ahead to twelve-year ahead ROE forecasts. *SD* denotes standard deviation, *Min* is the minimum value, *Max* is the maximum value and *ρ*(1) is the first-order autocorrelation. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

and *PE*. Although the sign of the correlation between r_M^e and *PE* is inconsistent with the correlation reported in CV (2004), it is consistent with CGP (2013), who include a relatively latest sample period as compared to CV (2004). The stock market return is positively associated with *PE* ratio since the current high (low) price inflates (deflates) the contemporaneous stock return.

Panel B shows that the average of historical ROE over the sample period of 1990:01 – 2014:12 is 0.131, a value lower than the average forecasts of ROE across different forecast horizons, which range from 0.136 at twelve-year-ahead forecast to 0.167 at one-year-ahead forecast. This reflects that analysts generally produce optimistic forecasts, which is consistent with the literature (e.g. Chen, Da and Zhao, 2013; Hribar and McInnis, 2012). Nevertheless, the median forecast of ROE is not higher than the median historical ROE beyond six-year-ahead forecasts, reflecting pessimistic forecasts to a certain extent. Also, the difference between the mean historical ROE and the mean forecasts of ROE (i.e. approximation of forecast errors) decreases with the forecast horizon. This could probably indicate that the forecasts of ROE are not entirely optimistic across different forecast horizons, instead the initial optimistic bias could be offset by the pessimistic bias (or a reduction in the optimistic bias) in the long-horizons forecasts. Therefore, a neutral tone (i.e. no bias) in the news series could be obtained when we add up the revision in analysts' forecasts over time to form the news series as shown in equation (5.11).

5.6 Empirical results

5.6.1 The estimation of the TV-VAR model

Table 5.2 presents the average parameter estimates of the first-order TV-VAR model retrieved across 470 windows. The values in the square brackets underneath the parameter estimates are their heteroscedasticity and autocorrelation consistent (HAC) standard errors. Each regression regresses a state variable on five independent variables, which are a constant and the lagged terms of four state variables, in each window. The table also reports the average of time-series adjusted *R*-squared obtained from the OLS estimation across different windows in the last column.

As shown in the table, the coefficient sign of each state variable in the first row is consistent with the literature. First, the term yield spread, although statistically insignificant, predicts positively the excess market returns, consistent with Campbell and Thomson (2008), Fama and French (1989), Keim and Stambaugh (1986), Rapach, Ringgenberg and Zhou (2016). Second, both price-earnings ratio and value spread predict negatively and significantly the excess market returns, with the coefficient of -0.107 and -0.040, respectively[111]. Finally, the excess market return has a negative but statistically insignificant coefficient of -0.033, displaying a moderate price reversal, which is consistent with Campbell, Giglio and Polk (2013)[112].

Table 5.2: TV-VAR parameter estimates for aggregate stock market returns

	Constant	$r^e_{M,t}$	TMS_t	PE_t	VS_t	$Adj\text{-}R^2$ (%)
$r^e_{M,t+1}$	0.394***	-0.033	0.001	-0.107***	-0.040**	7.90
	[0.041]	[0.023]	[0.001]	[0.013]	[0.020]	
TMS_{t+1}	0.989**	0.657***	0.901***	-0.564***	0.547***	88.00
	[0.501]	[0.131]	[0.008]	[0.168]	[0.110]	
PE_{t+1}	0.302***	0.435***	0.000	0.915***	-0.027*	94.90
	[0.039]	[0.012]	[0.001]	[0.010]	[0.014]	
VS_{t+1}	-0.006	0.056***	0.000	0.057***	0.881***	84.80
	[0.051]	[0.018]	[0.001]	[0.018]	[0.013]	

Notes: This table reports the OLS parameter estimates for the first-order TV-VAR average across different estimation windows for the period 1969:12 – 2014:12. The associated Newey-West standard errors (with 12 lag) are reported in the square bracket. The state variables used in the TV-VAR model include the excess market returns (r^e_M), the term yield spread (*TMS*), the 10-year smoothed *PE* ratio (*PE*), and small-stock value spread (*VS*). The dependent variable of each regression is presented in the first column and the coefficients of explanatory variables are shown from the second through the sixth columns. The average of time-series adjusted-R^2 (in percentage term) is reported in the last column. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

The regressions of other state variables, from rows two to four, depict that most explanatory variables are highly autocorrelated with the coefficients on their lagged terms being greater than 0.90 in all cases, except that of *VS*. Their autocorrelation coefficients are highly significant at 1% level. These results are consistent with the autocorrelation statistics reported in Table 5.1. For the *TMS*, the table shows that other state variables also significantly predict future *TMS* at 1% significance level. In contrast to CV (2004), this study finds that not only the excess market returns, but *VS* also predicts significantly the next month's *PE* ratio. The coefficient of excess market returns, 0.435, is highly significant at 1% level; the

[111] Campbell and Thompson (2008), Neely et al. (2014), Rapach et al. (2016) find that earnings-price ratio predict aggregate stock returns positively. The negative relation between value spread and future excess market returns can be interpreted as lower future stock market returns is a result of the overvaluation of current small-growth stocks, which creates a larger value spread. Brennan, Wang and Xia (2002) report this negative relationship between *VS* and future excess market returns.

[112] The full sample estimation, however, shows that stock market returns exhibit a momentum with the lagged excess market returns has an insignificant coefficient of 0.053, in line with CV (2004).

coefficient of VS, -0.027, is statistically significant at 10% level. The negative association between *VS* and future *PE* is similar to that of *VS* and excess market returns. Increase in the value spread denotes that small growth stocks are currently overvalued, which forecast a lower expected stock market return and *PE* ratio. As for the value spread, it is also highly predictable by the lagged one month of other state variables, which are excess market returns and *PE* ratio, apart from its own lagged term.

Since *TMS*, *PE* and *VS* are highly persistent, the regression model for these state variables have higher explanatory power, in terms of the average of time-series adjusted R^2 statistics, as compared to the return predictive regression. One important thing to note is that a higher adjusted R^2 (7.90%) is obtained when the expected returns is estimated on a rolling window basis. Contrarily, the constant VAR approach produces an adjusted R^2 of 1.62%, close to 2% as reported in CV (2004) and Maio (2013a, 2013b) who estimate the VAR over the full sample period as well. This indicates that allowing the coefficients to pick up the dynamics of the state variables over time improves the predictive power of the return regression.

Table 5.3 reports the attributes of the two components of unexpected returns – N_{CF} and N_{DR}. Both news series are the values of the news series average across different estimation windows at each time *t*. The top panel of the table presents the variance-covariance matrix of N_{CF} and N_{DR}, and the values in bracket are correlation of the new series. It shows that the variance of N_{DR} is slightly higher than that of N_{CF}, which are 0.52% and 0.43%, respectively. This finding suggests that N_{DR} has a slightly more important role in the stock market returns, in line with most literature (*e.g.* Botshekan et al., 2012; Campbell, 1991; CV, 2004; CPV, 2010; Campbell et al., 2018). Furthermore, the discount rate news and cash flow news have a correlation of 0.8268, indicating that a good (bad) cash flow news is associated with an increase (a drop) in the discount rate. This relationship could be attributable to the mispricing, where investors extrapolate the favourable (unfavourable) stock prices movement resulted from good (bad) cash flow news in forming their expected return as discussed in Section 5.2, or could be due to the risk-based explanations as discussed in Cohen et al. (2002, p. 442).

The bottom panel depicts the time-series average of the linear function coefficients that connect the VAR shocks to the news series. $e1'+e1'\lambda$ is the cash flow news function and $e1'\lambda$ is the discount rate news function. Based on equations (5.8) and (5.9), only the innovation in r_M^e will be mapped differently into both news series. The additional term of

$\mathbf{e1'u_{t+1}}$ in the $N_{CF,t+1}$, where **e1'** has a unity value for only the first element in the vector, adds the value of r_M^e shocks (zero) to the $N_{CF,t+1}$ when the innovation of r_M^e (other state variables) is mapped into the $N_{CF,t+1}$. As such, shocks in *TMS*, *PE* and *VS* have the same contributions to both news series.

Table 5.3: The attributes of cash flow and discount rate news

News Cov / Corr	N_{CF}	N_{DR}
N_{CF}	0.0043	0.0039
	(1.0000)	(0.8268)
N_{DR}	0.0039	0.0052
	(0.8268)	(1.0000)
News Functions	$e1'+e1'\lambda$	$e1'\lambda$
r_M^e shocks	0.6188	-0.3812
TMS shocks	-0.0465	-0.0465
PE shocks	-0.6636	-0.6636
VS shocks	0.4298	0.4298

Notes: This table reports the attributes of the cash flow news (N_{CF}) and discount rate news (N_{DR}) estimated from the TV-VAR model for the period 1969:12 – 2014:12. The top panel shows the variance-covariance of both news series. The values in the bracket are the correlation matrix of news series. The bottom panel shows the time-series average of the linear function coefficients of N_{CF} ($e1'+e1'\lambda$) and N_{DR} ($e1'\lambda$), where $\lambda = \rho\Gamma(I-\rho\Gamma)^{-1}$, Γ is the point estimates of the VAR matrix and ρ = $0.95^{1/12}$. r_M^e is the excess market returns, *TMS* is the term yield spread, *PE* is the log smoothed *PE* ratio and *VS* is the small-stock value spread.

The coefficients of the linear functions capture the long-run effect of the shock in each state variable to the N_{CF} and N_{DR}. Therefore, the shocks of a state variable have a greater contribution to the discount rate news when that variable's coefficient is higher in the return predictive regression (CPV, 2010). Consistent with the coefficients shown in the first row of Table 5.2, *TMS*, which has the least impact on the expected excess market returns, also contributes the least (in absolute value) to both news series. On the other hand, shocks in *PE* receive the greatest weight (in absolute value) in the computation of both news series. The innovation of r_M^e have a positive long-run effect on the N_{CF} (0.6188), but a negative long-run effect on the N_{DR} (0.3812). This suggests that an increase in the r_M^e shocks is associated with an increase in the CF expectations and a decrease in the DR expectation. Whilst the shocks in *TMS* and *PE* are negatively correlated to the news series, *VS* shocks are mapped positively to the news series[113].

[113] The coefficients of the *TMS* and the *VS* shocks produced by constant VAR have a positive and negative effect, respectively, to the new series, consistent with CV (2004), CPV (2010), and Campbell et al. (2018). Therefore, the time-series average of the coefficients of these two shocks having an opposite sign under the TV-VAR framework could be due to the outliers in a few windows.

5.6.2 *The cash flow and discount rate beta*

Prior to the discussion of the two-beta model, Table 5.4 depicts the mean difference of portfolio returns. Panel A shows the difference in returns between value and growth stock portfolios across different firm sizes. The difference between extreme size portfolios' returns is shown in panel B. Panel A confirms that value stocks have attained significantly higher average returns than growth stocks despite the significance of return spread decreases with size. However, the higher returns of value stocks relative to growth stocks are not justifiable by their lower CAPM betas, which are the summation of $\beta_{i,CF}$ and $\beta_{i,DR}$, which will be shown in Table 5.5. On the other hand, the returns of large stocks exceed that of small stocks by a small amount for the lower *BE/ME* portfolios as shown in panel B. Specifically, a positive mean difference of returns between large and small stocks is seen for the growth stocks and the second *BE/ME* quintile portfolios. However, this pattern is reversed in the higher *BE/ME* portfolios, in which large stocks deliver lower average returns than small stocks.

Table 5.4: Mean difference of portfolio returns

	Diff	*S.E*	*t*-statistics
	Panel A: V – G		
Small	1.10×10^{-2}	1.79×10^{-3}	6.126
2	6.18×10^{-3}	1.80×10^{-3}	3.439
3	6.38×10^{-3}	1.92×10^{-3}	3.320
4	2.57×10^{-3}	1.83×10^{-3}	1.403
Large	2.22×10^{-3}	1.83×10^{-3}	1.214
	Panel B: L – S		
Growth	5.81×10^{-3}	2.49×10^{-5}	2.333
2	1.35×10^{-4}	2.21×10^{-5}	0.061
3	-6.74×10^{-4}	1.96×10^{-5}	-0.344
4	-4.22×10^{-3}	1.94×10^{-5}	-2.181
Value	-2.96×10^{-3}	2.00×10^{-5}	-1.476

Notes: This table illustrates the mean difference in return for extreme portfolios from December 1969 to December 2014. Panel A reports the return differences between value and growth stocks across various firm sizes and panel B shows the return difference between large and small stocks across different *BE/ME* portfolios. "Diff" is the mean difference of returns, "*S.E*" denotes the standard errors and the *t*-statistics are reported in the final column.

Table 5.5 reports the estimated cash flow beta ($\beta_{i,CF}$) and discount rate beta ($\beta_{i,DR}$) based on the stock market's cash flow and discount rate news retrieved from Table 5.3 for 25 portfolios sorted based on firm size (*ME*) and book-to-market (*BE/ME*) ratio. The top panel depicts the cash flow beta of 25 portfolios; the bottom panel shows the discount rate beta of 25 portfolios. These two betas sum up to the CAPM market beta. The betas are the slope coefficients obtained from the OLS estimation for the period 1969:12 – 2014:12. This sub-section investigates whether the beta patterns, i.e. value (growth) stocks have higher $\beta_{i,CF}$ ($\beta_{i,DR}$), as documented in CV (2004) is supported by the data of this study.

Consistent with the literature (e.g. CV, 2004; Garrett and Priestley, 2012), all portfolios have higher $\beta_{i,DR}$ than $\beta_{i,CF}$, indicating that most portfolios are more sensitive to the changes in discount rate expectations. The top panel shows that the cash flow beta decreases with the *BE/ME* ratio, regardless of the firm size. This reflects that growth stocks tend to have higher $\beta_{i,CF}$ than value stocks. This spread in $\beta_{i,CF}$, however, lose its significance in higher *ME* portfolios as shown in the last column. The finding that value stocks have lower $\beta_{i,CF}$ is in contrast to that of in the CV (2004) for their post-1963 findings[114]. Nevertheless, Chen and Zhao (2009) obtain similar finding as in this study when they re-estimated the stock market news terms and betas for the post-1952 period. Comparing the $\beta_{i,CF}$ between small and large stocks, large stocks have significantly higher cash flow beta across different *BE/ME* sorted portfolios, with the greatest spread concentrates in the growth and value portfolios, which are 0.19 and 0.20, respectively. Again, this finding is different from CV (2004), who find that the small stocks have greater $\beta_{i,CF}$. The results are closer to Garrett and Priestley (2012) who find that the $\beta_{i,CF}$ spreads of size portfolios across different *BE/ME* sorted portfolios are inconsistent, where the large stocks have higher $\beta_{i,CF}$ than small stocks in three out of five cases.

The estimated $\beta_{i,DR}$, as depicted in the bottom panel, show that growth stocks consistently have higher $\beta_{i,DR}$ than value stocks. Although the absolute term of the spread in $\beta_{i,DR}$ is greater than that in the $\beta_{i,CF}$ in three out of five portfolios of different size quintiles, only the small-growth stocks have significantly higher $\beta_{i,DR}$ than the small-value stocks with a spread of 0.22. The rest of the *BE/ME* sorted portfolios across different size quintiles show marginal and insignificant spread in $\beta_{i,DR}$. An exception to this can be seen from the large-value stocks, which have higher $\beta_{i,DR}$. However, the $\beta_{i,DR}$ spread between large-value and large-growth stocks is less than 0.05 and is insignificant. Contrarily to the top panel, the small stocks generally have higher $\beta_{i,DR}$ than the large stocks. The largest beta spread of large and small stocks is reported at -0.48 in the growth stocks category; the smallest spread is reported for the 4th quintile of the *BE/ME* sorted portfolio, which is -0.20. All discount rate beta spreads between large and small stocks are highly significant. Generally, the beta spreads in $\beta_{i,DR}$ across different size portfolios are consistent with the patterns documented in CV (2004).

[114] CV (2004) estimate the cash flow and discount rate news over the full sample period of 1929:1 – 2001:12, and subsequently compute the cash flow and discount rate betas for pre- and post-1963 periods.

Table 5.5: The reaction of portfolio returns in relation to the cash flow and discount rate news computed from TV-VAR

	Growth	2	3	4	Value	V - G
$\beta_{i,CF}$						
Small	0.06	0.05	0.03	0.02	0.00	-0.06
	[0.38]	[0.35]	[0.23]	[0.14]	[-0.02]	[-1.89]
2	0.13	0.07	0.05	0.07	0.04	-0.08
	[0.83]	[0.52]	[0.40]	[0.50]	[0.26]	[-1.69]
3	0.17	0.10	0.10	0.09	0.08	-0.09
	[1.14]	[0.70]	[0.74]	[0.62]	[0.47]	[-1.91]
4	0.17	0.14	0.13	0.11	0.12	-0.05
	[1.20]	[1.00]	[0.93]	[0.75]	[0.67]	[-0.82]
Large	0.25	0.17	0.18	0.18	0.20	-0.05
	[2.02]	[1.24]	[1.21]	[1.16]	[1.31]	[-0.77]
L - S	0.19	0.13	0.15	0.17	0.20	
	[3.76]	[2.72]	[2.58]	[2.63]	[3.08]	
$\beta_{i,DR}$						
Small	1.10	0.94	0.87	0.81	0.88	-0.22
	[3.48]	[3.45]	[3.55]	[3.42]	[3.43]	[-2.31]
2	1.03	0.91	0.83	0.78	0.92	-0.12
	[3.39]	[3.21]	[3.31]	[3.23]	[3.31]	[-1.29]
3	0.94	0.86	0.77	0.72	0.84	-0.10
	[3.05]	[3.30]	[3.18]	[3.10]	[3.29]	[-0.99]
4	0.88	0.82	0.76	0.71	0.84	-0.04
	[2.98]	[3.09]	[3.00]	[2.98]	[3.07]	[-0.44]
Large	0.62	0.68	0.60	0.61	0.66	0.03
	[2.33]	[2.86]	[2.80]	[2.74]	[2.77]	[0.35]
L - S	-0.48	-0.25	-0.27	-0.20	-0.23	
	[-4.91]	[-3.21]	[-3.26]	[-2.54]	[-2.93]	

Notes: This table presents the cash flow beta ($\beta_{i,CF}$) and the discount rate beta ($\beta_{i,DR}$) for size (*ME*) and book-to-market (*BE/ME*) ratio sorted portfolios for the period 1969:12 – 2014:12. The estimation is based on the following regression:

$$r_{i,t} = \alpha + \beta SN_{j,t} + \varepsilon_t \ , \qquad SN_{j,t} = \{SN_{CF,t}, SN_{DR,t}\}$$

where $r_{i,t}$ represents the portfolio returns and $SN_{j,t}$ denotes either the scaled cash flow news ($SN_{CF,t}$) or the scaled discount rate news ($SN_{DR,t}$) computed as $N_{j,t} \times Var(r_M^e)/Var(N_j)$. The beta coefficient, β, is cash flow or discount rate beta depending on which scaled news series is used to perform the above regression. Portfolios are sorted based on *BE/ME* ratio from left to right and based on *ME* from top to bottom in each panel. "Growth" portfolio has the lowest *BE/ME* ratio, "value" portfolio has the highest *BE/ME* ratio, "small" portfolio has the lowest *ME*, and "large" portfolio has the highest *ME*. "V – G" denotes the beta difference between value and growth portfolios. "L – S" denotes the beta difference between large and small portfolios. HAC standard errors are used and the values shown in square bracket are Newey-West *t*-statistics.

Overall, adding $\beta_{i,CF}$ and $\beta_{i,DR}$ shows that growth and small stocks have higher market betas (i.e. CAPM betas), implying that these portfolios are riskier than value and large stocks. Furthermore, the patterns of beta spread found in CV (2004), where value stocks have significantly higher $\beta_{i,CF}$, and growth stocks have significantly higher $\beta_{i,DR}$, are not seen in our sample. Since value stocks do not consistently have higher cash flow beta (i.e. bad beta) and vice versa for the growth stocks, the assumptions of CPV (2010) that are made based on the systematic risk patterns found in CV (2004) could be inappropriate[115].

5.6.3 The four news terms

Table 5.6 presents the correlations among the four scaled new series, which are irrational cash flow news (SN_{CF}^{IR}), rational cash flow news (SN_{CF}^{R}), irrational discount rate news (SN_{DR}^{IR}), and rational discount rate news (SN_{DR}^{R}). By construction, irrational news series and rational news series are uncorrelated. Besides that, in line with Table 5.3, the cash flow and discount rate are positively correlated in both rational and irrational channels. The irrational news series have a correlation of 0.896; whereas the rational news series have a correlation of 0.825.

Table 5.6: Correlations among the four news series

	SN_{CF}^{IR}	SN_{CF}^{R}	SN_{DR}^{IR}	SN_{DR}^{R}
SN_{CF}^{IR}	1			
SN_{CF}^{R}	0	1		
SN_{DR}^{IR}	0.896	0	1	
SN_{DR}^{R}	0	0.825	0	1

Notes: This table reports the correlations of the four scaled news series: irrational cash flow news (SN_{CF}^{IR}), rational cash flow news (SN_{CF}^{R}), irrational discount rate news (SN_{DR}^{IR}), and rational discount rate news (SN_{DR}^{R}).

Figure 5.2 plots the four smoothed news series[116] estimated based on the equations (5.17) to (5.20) with the N_{CF} and N_{DR} retrieved from the TV-VAR specification. Each row corresponds to one news series, where the first row presents the irrational cash flow news series (SN_{CF}^{IR}), the second row depicts the rational cash flow news series (SN_{CF}^{R}) followed by the irrational discount rate news series (SN_{DR}^{IR}), and the rational discount rate news series (SN_{DR}^{R}) is in the last row. The shaded bars denote the NBER-dated recessions.

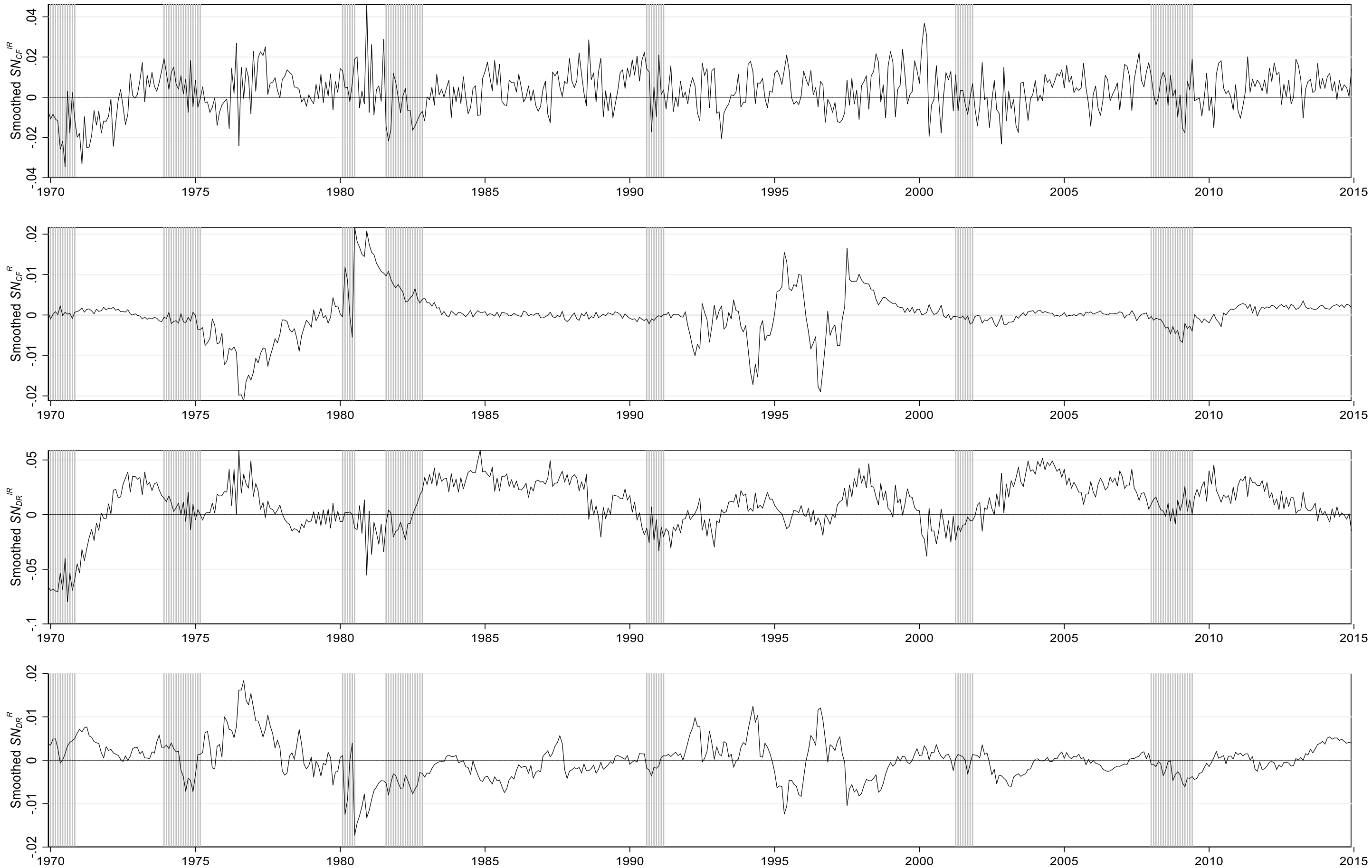
The illustration is consistent with the correlation reported in Table 5.6, where the rational and irrational news series in both cash flow and discount rate channels appear to not have any relationship. The variation in the N_{CF} seem to be mainly picked up by the variation

[115] In CV's two-beta model, the systematic risk of the value (growth) stocks is cash flow (discount rate) beta.

[116] The smoothed news series is used for the plot only. All empirical results reported in this study are based on unsmoothed news series.

Figure 5.2: Four scaled news series of the four-beta model

This figure depicts the four scaled news series estimated from equations (5.17) to (5.20) based on the TV-VAR specification for the sample period of 1969:12 – 2014:12. These news series are irrational cash flow news (SN_{CF}^{IR}), rational cash flow news (SN_{CF}^{R}), irrational discount rate news (SN_{DR}^{IR}), and rational discount rate news (SN_{DR}^{R}), presented in each row of the figure. These news terms are smoothed under the specification of an exponentially weighted moving average: $MA_t(SN_j^E) = 0.08SN_{j,t}^E + (1-0.08)MA_{t-1}(SN_j^E)$, where SN_j^E is the respective news series. The shaded bars represent the recession period as dated by NBER.



in SN_{CF}^{IR} since the SN_{CF}^{R} wavering around the zero value (i.e. no apparent shocks), except a few periods where the SN_{CF}^{R} has noticeable variation. Unlike the cash flow channel, both irrational and rational discount rate news vary considerably over time, justifying the greater role of discount rate news (i.e. greater variance) in the stock market as shown in Table 5.3.

In the early 1970s, both irrational cash flow and irrational discount rate news exhibit greater fluctuations during the oil shock, especially the huge increase of SN_{DR}^{IR} moving from negative news to positive news, which reflects the deterioration of investor sentiment that penalizes the expected returns heavily. During this period, the SN_{CF}^{R} drops from positive values to negative values, indicating a downward revision in the expectations of future fundamental cash flows.

The recession in the early 1980s can be explained by the declining rational and irrational cash flows given that both SN_{CF}^{IR} and SN_{CF}^{R} experience a sharp decline during this period. Also, there is an increase in both SN_{DR}^{IR} and SN_{DR}^{R}. Together, all forces push down the stock market price during this period. The expansion state after this period can be described by the negative rational discount rate news and an improvement in the irrational expectations of future cash flows. Turning to the recession in 1991, CV (2004) claim that it is a profitability recession caused by unfavourable move in the expectations about future cash flows. As shown in Figure 5.2, the bad cash flow news in 1991 is mainly ensued from the declining irrational expectations of future cash flows since changes in the rationally expected cash flows are near zero.

The technology boom in the late 1990s can be justified by not only the decrease in both irrational and rational discount rates, but also an increase in the irrational expectations of future cash flows, in line with Ofek and Richardson (2002) findings. The decrease in both rational and irrational discount rates also shows that lower discount rates during this period is not merely due to the improving sentiment as claimed by Campbell, Giglio and Polk (2013), but the risk-based explanation of discount rates also plays a role here. As for the SN_{CF}^{R}, the revision in the rational cash flow expectations remains positive even though the magnitude of the news is reducing. Similar causes but in the opposite direction are accountable for the burst of the dot-com bubble, where investors increased both discount rates and the high irrational expectations of future cash flows is now reversed. Prior to the recession in late 2000s, investors irrationally expected a high future payoff, which can be seen from the positive SN_{CF}^{IR}. Later, the recession in 2007 – 2009 could be ascribed to the negative SN_{CF}^{R}, supported by the declining irrational expectations of future cash flows as well as the positive SN_{DR}^{IR}. Overall, the four news terms align with the fluctuations in the US stock market.

5.6.4 The four-beta model

This section examines the sensitivity of portfolio returns to changes of both irrational and rational expectations in CF and DR channels. The investigation starts by evaluating the assumptions of CPV (2010). If their assumptions that cash flow news is driven by fundamentals and discount rate news is driven by sentiment are correct, then stock returns are not expected to react to the changes in irrationally expected cash flows and rational discount rate. Hence, this study tests the null hypothesis that the irrational cash flow betas and rational discount rate betas are not significantly different from zero, *i.e.* $H_0 : \beta_{CF}^{IR} = 0$ and $H_0 : \beta_{DR}^{R} = 0$. Later, this study answers to the research question of whether the predictive ability of investor sentiment is going through cash flow or discount rate channel by comparing the beta estimates of irrational cash flow and irrational discount rate betas.

(I) Time-varying VAR (TV-VAR) approach

The baseline results of TV-VAR model are reported in Table 5.7. Each panel in Table 5.7 corresponds to the four betas, which are irrational cash flow beta ($\beta_{i,CF}^{IR}$), rational cash flow beta ($\beta_{i,CF}^{R}$), irrational discount rate beta ($\beta_{i,\mathrm{DR}}^{IR}$), and rational discount rate beta ($\beta_{i,\mathrm{DR}}^{R}$), by regressing the portfolio returns on each of the scaled news series as shown in equations (5.17) to (5.20) for 25 size- and *BE/ME*-sorted portfolios. Those news series are retrieved under TV-VAR framework as described in Section 5.4.1[117]. The summation of $\beta_{i,CF}^{IR}$ and $\beta_{i,CF}^{R}$ equals to the $\beta_{i,CF}$; whereas $\beta_{i,\mathrm{DR}}^{IR}$ and $\beta_{i,\mathrm{DR}}^{R}$ add up to the $\beta_{i,DR}$. The betas are the slope coefficients obtained via OLS regression for the period of 1969:12 – 2014:12 and the Newey-

[117] The beta estimation of the TV-VAR approach addresses only one issue – constant parameter estimates – in the constant VAR model, where the assumption that the parameter estimates of the VAR model is static is relaxed in constructing the news series. However, as mentioned in Section 5.4.1, the news series are averaged across different windows at a particular month. Besides that, the four betas are computed over the entire sample (*i.e.* betas are not varying over time). Therefore, this procedure does not address look-ahead bias that exists in the constant VAR approach. To further address the look-ahead bias whilst allowing the parameter estimates in the VAR framework to vary over time, this study conducts an out-of-sample analysis on the asset pricing test which is presented in Section 5.6.6.

Table 5.7: The stock price movements in respond to four news series computed from TV-VAR

	Growth	2	3	4	Value
			Panel A: Irrational cash flow beta		
Small	0.035	0.029	0.023	0.026*	0.020
	[1.408]	[1.498]	[1.516]	[1.726]	[1.460]
2	0.040**	0.026*	0.020	0.023*	0.017
	[1.994]	[1.692]	[1.542]	[1.871]	[1.194]
3	0.034*	0.035**	0.021**	0.016	0.021*
	[1.955]	[2.584]	[2.011]	[1.429]	[1.860]
4	0.037*	0.024**	0.018*	0.016	0.019
	[1.836]	[2.223]	[1.872]	[1.477]	[1.430]
Large	0.024	0.010	0.008	0.012	0.011
	[1.616]	[0.859]	[0.914]	[1.250]	[0.902]
			Panel B: Rational cash flow beta		
Small	0.023	0.018	0.007	-0.009	-0.023
	[0.152]	[0.137]	[0.057]	[-0.078]	[-0.170]
2	0.085	0.045	0.032	0.046	0.024
	[0.593]	[0.337]	[0.251]	[0.339]	[0.156]
3	0.131	0.063	0.075	0.071	0.054
	[0.941]	[0.470]	[0.591]	[0.524]	[0.341]
4	0.130	0.111	0.111	0.097	0.099
	[0.995]	[0.852]	[0.816]	[0.663]	[0.572]
Large	0.229*	0.163	0.174	0.171	0.190
	[1.955]	[1.192]	[1.172]	[1.102]	[1.290]
			Panel C: Irrational discount rate beta		
Small	-0.003	-0.008	-0.003	-0.007	0.000
	[-0.145]	[-0.479]	[-0.206]	[-0.525]	[0.038]
2	-0.009	-0.004	0.000	-0.006	0.000
	[-0.498]	[-0.345]	[0.007]	[-0.527]	[-0.037]
3	-0.005	-0.012	-0.005	0.000	-0.006
	[-0.299]	[-0.983]	[-0.497]	[-0.030]	[-0.609]
4	-0.011	-0.001	-0.001	-0.001	0.003
	[-0.688]	[-0.139]	[-0.133]	[-0.135]	[0.244]
Large	0.000	0.009	0.011	0.006	0.008
	[-0.012]	[0.909]	[1.303]	[0.686]	[0.792]
			Panel D: Rational discount rate beta		
Small	1.104***	0.944***	0.869***	0.820***	0.882***
	[3.477]	[3.457]	[3.568]	[3.421]	[3.468]
2	1.043***	0.916***	0.827***	0.789***	0.916***
	[3.323]	[3.292]	[3.346]	[3.291]	[3.365]
3	0.944***	0.870***	0.770***	0.725***	0.850***
	[3.088]	[3.338]	[3.279]	[3.160]	[3.382]
4	0.891***	0.818***	0.759***	0.709***	0.839***
	[3.036]	[3.181]	[3.081]	[3.058]	[3.141]
Large	0.624**	0.673***	0.588***	0.608***	0.649***
	[2.397]	[2.931]	[2.847]	[2.801]	[2.801]

Notes: This table presents the four betas computed based on the news series retrieved from the time-varying VAR (TV-VAR) approach for portfolios sorted based on size (*ME*) and book-to-market (*BE/ME*) ratio from December 1969 to December 2014 in four panels. Panel A and B report the irrational cash flow beta ($\beta_{i,CF}^{IR}$) and the rational cash flow beta ($\beta_{i,CF}^{R}$), respectively. Panel C and D show the irrational discount rate beta ($\beta_{i,\mathrm{DR}}^{IR}$) and the rational discount rate beta ($\beta_{i,\mathrm{DR}}^{R}$), respectively. The estimation is based on the following regression:

$$r_{i,t} = \alpha + \beta SN_{\mathrm{j},t}^{k} + \varepsilon_t \ , \qquad SN_{j,t}^{k} = \left\{ SN_{\mathrm{CF},t}^{IR}, SN_{\mathrm{CF},t}^{R}, SN_{\mathrm{DR},t}^{IR}, SN_{\mathrm{DR},t}^{R} \right\}$$

where $r_{i,t}$ represents the portfolio returns and $SN_{j,t}^{k}$ denotes one of the four scaled news series computed in equations (5.17) – (5.20). The β is the beta estimate corresponds to one of the four scaled new series applied in the above regression. Portfolios are sorted based on *BE/ME* ratio from left to right and based on firm size (*ME*) from top to bottom in each panel. "Growth" portfolio has the lowest *BE/ME* ratio, "value" portfolio has the highest *BE/ME* ratio, "small" portfolio has the lowest *ME*, and "large" portfolio has the highest *ME*. HAC standard errors are used and the values shown in square bracket are Newey-West *t*-statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

West *t*-statistics (automatic bandwidth selection) are reported underneath the beta estimates in the square brackets.

Panel A of Table 5.7 shows that the $\beta^{IR}_{i,CF}$ of all portfolios but one have a value of greater than 0.010. Furthermore, about half of the portfolios considered here are significantly affected by the changes in the irrationally expected cash flows at a significance level of at least 5%. Looking at the magnitude of $\beta^{IR}_{i,CF}$, the results show that growth stocks respond stronger to the fluctuations in irrational cash flow expectations, as do small stocks as compared to large stocks. On the other hand, variations in rational expectations of future cash flows, in general, do not significantly affect the stock price movements, as shown in panel B, even though the rational cash flow beta estimates (in absolute term) are higher than the irrational cash flow beta estimates for most portfolios, except for the small stocks. As for the discount rate channel, panel D depicts that all assets considered in this study react significantly (1% significance level) to the rational discount rate news but are not significantly affected by the shocks in irrational discount rates as shown in panel C. While none of the $\beta^{IR}_{i,DR}$ has an estimate of greater than 0.10, the $\beta^{R}_{i,DR}$ estimates range from the value of 0.588 to 1.104, which is more than five times of the $\beta^{IR}_{i,DR}$.

In general, these results show that the covariances for most asset's returns with the irrational cash flow news and the rational discount rate news are significantly different from zero, which does not support the claims made by CPV (2010) that cash flow news is driven by fundamentals whereas sentiment affects only the discount rate news. Besides that, the results presented in Table 5.7 also support the findings of Huang et al. (2015) who find that the predictive power of investor sentiment on the future stock market returns is going through the cash flow channel instead of the discount rate channel.

To provide further comparison on the relative importance of $\beta^{IR}_{i,\mathrm{CF}}$ and $\beta^{IR}_{i,\mathrm{DR}}$, the proportion (in absolute term) of the irrational news to the rational news in each cash flow and discount rate channel is computed in Table 5.8. Panel A reports the results for the proportion of the irrational beta to the rational beta in the cash flow channel (i.e. $\beta^{IR}_{i,CF} / \beta^{R}_{i,CF}$); panel B shows the proportion of the irrational beta to the rational beta in the discount rate channel (i.e. $\beta^{IR}_{i,\mathrm{DR}} / \beta^{R}_{i,\mathrm{DR}}$). Apparently, the proportion of the irrational cash flow beta to the rational cash flow beta (i.e. $\beta^{IR}_{i,CF} / \beta^{R}_{i,CF}$ in panel A) is higher than the proportion of the irrational discount rate beta to the rational discount rate beta (i.e. $\beta^{IR}_{i,\mathrm{DR}} / \beta^{R}_{i,\mathrm{DR}}$ in panel B) across all portfolios. For instance, the small-growth stocks have a $\beta^{IR}_{i,CF} / \beta^{R}_{i,CF}$ of 0.607 but a $\beta^{IR}_{i,\mathrm{DR}} / \beta^{R}_{i,\mathrm{DR}}$ of only

0.003. This shows that the irrational component constitutes a higher proportion in the cash flow risk than in the discount rate risk. Indeed, a considerable source of cash flow risk is originated from the irrational cash flow beta when $\beta^{IR}_{i,CF} / \beta^{R}_{i,CF}$ exceeds 0.50. These findings again suggest that the return predictability by investor sentiment is channelled through the cash flow.

Table 5.8: The proportion of the irrational beta relative to the rational beta in CF and DR channels under the TV-VAR approach

	Growth	2	3	4	Value
	Panel A: Proportion of irrational cash flow beta				
Small	0.608	0.616	0.757	1.547	6.075
2	0.323	0.366	0.386	0.331	0.406
3	0.208	0.355	0.214	0.181	0.280
4	0.221	0.176	0.143	0.142	0.161
Large	0.095	0.059	0.044	0.065	0.056
	Panel B: Proportion of irrational discount rate beta				
Small	0.003	0.008	0.003	0.008	0.000
2	0.009	0.005	0.000	0.007	0.001
3	0.005	0.014	0.007	0.000	0.007
4	0.013	0.002	0.002	0.002	0.003
Large	0.000	0.013	0.018	0.009	0.013

Notes: This table presents the proportion of irrational cash flow beta over the rational cash flow beta $\beta^{IR}_{i,CF} / \beta^{R}_{i,CF}$ in Panel A, and the proportion of irrational discount rate beta over the rational discount rate beta $\beta^{IR}_{i,\mathrm{DR}} / \beta^{R}_{i,\mathrm{DR}}$ in Panel B for 25 portfolios sorted based on size (*ME*) and book-to-market (*BE/ME*) ratio. The cash flow and discount rate news are estimated under the TV-VAR specification. The estimation covers the period from December 1969 to December 2014.

The comparison in Table 5.8 also further strengthen the previous findings that the CPV's assumption is not appropriate. If the claims from previous literature that cash flow news is linked to fundamentals and discount rate news is sentiment driven are true, we would expect that $\beta^{IR}_{i,\mathrm{DR}} / \beta^{R}_{i,\mathrm{DR}} = \infty$ and $\beta^{IR}_{i,CF} / \beta^{R}_{i,CF} = 0$, or $\beta^{IR}_{i,\mathrm{DR}} / \beta^{R}_{i,\mathrm{DR}}$ is higher than $\beta^{IR}_{i,CF} / \beta^{R}_{i,CF}$ if irrationality has a greater influence in the discount rate channel than in the cash flow channel. However, the results shown here reveal the opposite findings. Therefore, the findings from this comparison suggest that the cash flow (discount rate) news and hence the cash flow (discount rate) risk are not solely links to fundamentals (sentiment).

As mentioned in the introduction, although the expected returns could be more accurately characterized by the TV-VAR approach, this approach does introduce small sample bias that could possibly affect the conclusions. In view of this, the results retrieved from the constant VAR approach are presented next. The conclusion could be strengthened if both approaches with the trade-off between precision and bias lead to identical conclusions.

(II) Constant VAR approach

The sensitivity of portfolio returns to the changes in the four news series retrieved from the constant VAR approach is presented in Table 5.9. The four betas are arranged in the similar order as in Table 5.7. It is apparent from panel A that all portfolio returns, regardless of the firm size and the *BE/ME* ratio, are sensitive to the variations in the irrationally expected cash flows. The value of $\beta_{i,CF}^{IR}$ ranges from 0.012 to 0.023. Despite the responsiveness of stock prices to irrational cash flow news is not of great amount, irrational cash flow beta estimates are significant at 5% level in 22 out of 25 portfolios, and the beta estimates of the other three portfolios are significant at 10% level. Thus, this result again shows that the variations in the irrational expectations of cash flows should not be ignored and $H_0 : \beta_{CF}^{IR} = 0$ is rejected. Meanwhile, panel B shows that $\beta_{i,CF}^{R}$ of all portfolios sorted based on size and *BE/ME* ratio are highly significant at 1% level, with the magnitude of beta estimates higher than 0.40 across the board.

Turning to the discount rate betas, panel D shows that discount rate betas in the rational channel are highly significant at 1% level, consistent with the results shown in Table 5.7. Similar to $\beta_{i,CF}^{R}$, $\beta_{i,\mathrm{DR}}^{R}$ of each portfolio is greater than 0.40. As for the irrational discount rate betas in the panel C, all portfolios' returns are significantly affected by the fluctuations in irrationally expected returns with the *t*-statistics of $\beta_{i,\mathrm{DR}}^{IR}$ are greater than 1.96 in half of the portfolios considered. This finding shows that stocks' exposure to the systematic variations in discount rates is attributable to both rational and behavioural explanations and hence $H_0 : \beta_{DR}^{R} = 0$ is not appropriate.

Comparing $\beta_{i,CF}^{IR}$ against $\beta_{i,\mathrm{DR}}^{IR}$ as shown in Table 5.9, it appears that the irrational cash flow beta estimates are greater than the irrational discount rate beta across 25 portfolios. Besides that, the null hypothesis that stock price is not sensitive to the variations in the irrationally expected cash flows can be rejected at a more stringent significance threshold as compared to the irrational discount rate beta. To provide further comparison, the ratio of

Table 5.9: The stock price movements in respond to four news series computed from VAR

	Growth	2	3	4	Value
	Panel A: Irrational cash flow beta				
Small	0.023**	0.016**	0.017**	0.017**	0.018**
	[2.079]	[1.990]	[2.167]	[2.277]	[2.373]
2	0.021**	0.017**	0.017**	0.015**	0.014*
	[2.287]	[2.181]	[2.424]	[2.118]	[1.721]
3	0.023***	0.019***	0.014*	0.014**	0.013*
	[2.667]	[2.654]	[1.944]	[1.984]	[1.795]
4	0.019**	0.021***	0.015**	0.013**	0.016**
	[2.485]	[3.009]	[2.158]	[1.980]	[2.053]
Large	0.021***	0.017***	0.015**	0.012**	0.016**
	[3.220]	[3.029]	[2.601]	[1.988]	[2.193]
	Panel B: Rational cash flow beta				
Small	0.638***	0.551***	0.506***	0.470***	0.490***
	[11.899]	[11.251]	[9.520]	[8.826]	[8.298]
2	0.655***	0.562***	0.501***	0.492***	0.545***
	[12.367]	[11.563]	[10.497]	[10.668]	[8.605]
3	0.641***	0.553***	0.502***	0.478***	0.514***
	[13.757]	[12.236]	[12.939]	[10.896]	[10.617]
4	0.604***	0.550***	0.521***	0.481***	0.567***
	[13.665]	[15.174]	[11.116]	[12.048]	[13.274]
Large	0.504***	0.498***	0.452***	0.469***	0.520***
	[11.846]	[15.094]	[11.789]	[9.701]	[11.887]
	Panel C: Irrational discount rate beta				
Small	0.016**	0.010*	0.010*	0.009*	0.009*
	[2.328]	[1.731]	[1.798]	[1.948]	[1.827]
2	0.015**	0.011**	0.010**	0.008*	0.009*
	[2.453]	[2.117]	[2.047]	[1.932]	[1.729]
3	0.013**	0.009**	0.008*	0.007**	0.008*
	[2.399]	[1.955]	[1.771]	[2.030]	[1.715]
4	0.011**	0.008*	0.008*	0.008*	0.011**
	[2.317]	[1.708]	[1.930]	[1.875]	[2.271]
Large	0.009**	0.008*	0.007**	0.009**	0.008**
	[2.102]	[1.852]	[1.978]	[2.447]	[2.028]
	Panel D: Rational discount rate beta				
Small	0.623***	0.520***	0.466***	0.423***	0.455***
	[17.906]	[14.796]	[12.956]	[10.579]	[9.671]
2	0.604***	0.513***	0.453***	0.430***	0.490***
	[17.603]	[12.287]	[12.038]	[11.430]	[9.723]
3	0.568***	0.485***	0.438***	0.414***	0.479***
	[16.422]	[13.302]	[12.983]	[10.673]	[11.023]
4	0.544***	0.490***	0.457***	0.427***	0.476***
	[17.427]	[14.577]	[12.647]	[11.704]	[10.739]
Large	0.464***	0.437***	0.400***	0.419***	0.420***
	[14.246]	[13.891]	[12.833]	[8.998]	[8.329]

Notes: This table presents the four betas computed based on the news series retrieved from the constant VAR approach for portfolio sorted based on size and book-to-market (*BE/ME*) ratio from December 1969 to December 2014 in four panels. Panel A and B report the irrational cash flow beta ($\beta^{IR}_{i,CF}$) and the rational cash flow beta ($\beta^{R}_{i,CF}$), respectively. Panel C and D show the irrational discount rate beta ($\beta^{IR}_{i,\mathrm{DR}}$) and the rational discount rate beta ($\beta^{R}_{i,\mathrm{DR}}$), respectively. The estimation is based on the following regression:

$$r_{i,t} = \alpha + \beta SN^{k}_{\mathrm{j},t} + \varepsilon_t \ , \qquad SN^{k}_{j,t} = \left\{ SN^{IR}_{\mathrm{CF},t}, SN^{R}_{\mathrm{CF},t}, SN^{IR}_{\mathrm{DR},t}, SN^{R}_{\mathrm{DR},t} \right\}$$

where $r_{i,t}$ represents the portfolio returns and $SN^{k}_{j,t}$ denotes one of the four scaled news series computed in equations (5.17) – (5.20). The β is the beta estimate corresponds to one of the four new series applied in the above regression. Portfolios are sorted based on *BE/ME* ratio from left to right and based on firm size (*ME*) from top to bottom in each panel. “Growth” portfolio has the lowest *BE/ME* ratio, “value” portfolio has the highest *BE/ME* ratio, “small” portfolio has the lowest *ME*, and “large” portfolio has the highest *ME*. HAC standard errors are used and the values shown in square bracket are Newey-West *t*-statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 5.10: The proportion of irrational beta relative to rational beta in CF and DR channels under the VAR approach

	Growth	2	3	4	Value
	Panel A: Proportion of irrational cash flow beta				
Small	0.035	0.029	0.033	0.034	0.036
2	0.032	0.030	0.033	0.029	0.024
3	0.035	0.033	0.026	0.028	0.024
4	0.030	0.037	0.027	0.026	0.028
Large	0.040	0.034	0.033	0.025	0.030
	Panel B: Proportion of irrational discount rate beta				
Small	0.025	0.020	0.020	0.021	0.020
2	0.025	0.021	0.021	0.019	0.017
3	0.022	0.019	0.018	0.017	0.016
4	0.020	0.016	0.017	0.018	0.022
Large	0.018	0.017	0.018	0.021	0.019

Notes: This table presents the proportion of irrational cash flow beta over the rational cash flow beta $\beta_{i,CF}^{IR} / \beta_{i,CF}^{R}$ in Panel A, and the proportion of irrational discount rate beta over the rational discount rate beta $\beta_{i,\mathrm{DR}}^{IR} / \beta_{i,\mathrm{DR}}^{R}$ in Panel B for 25 portfolios sorted based on size (*ME*) and book-to-market (*BE/ME*) ratio. The cash flow and discount rate news are estimated under the VAR specification. The estimation covers the period from December 1969 to December 2014.

the irrational cash flow beta to the rational cash flow beta (*i.e.* $\beta_{i,CF}^{IR} / \beta_{i,CF}^{R}$ in panel A) and the ratio of the irrational discount rate beta to the rational discount rate beta (*i.e.* $\beta_{i,\mathrm{DR}}^{IR} / \beta_{i,\mathrm{DR}}^{R}$ in panel B) are shown in Table 5.10. The findings are in line with that of in Table 5.8. The irrational beta has a higher proportion in the cash flow channel than in the discount rate channel. Even though the magnitude of $\beta_{i,CF}^{IR} / \beta_{i,CF}^{R}$ has seen a drop across the board, this does not affect the conclusion that a relatively greater irrational component is embedded in the cash flow risk than in the discount rate risk. The relatively important irrational cash flow beta again renders support to the findings of Huang et al. (2015) that the predictive ability of investor sentiment is stemmed from the cash flow channel.

(III) TV-VAR vs. VAR

Comparing the beta estimates constructed from both approaches, this study confirms that cash flow channel is the underlying source of the sentiment-return relationship. Moreover, the assets' returns are not immune to the changes in irrationally expected cash flows and rational discount rates since $\beta_{i,CF}^{IR}$ and $\beta_{i,\mathrm{DR}}^{R}$ are the two beta estimates that remain significant under both approaches; whereas $\beta_{i,CF}^{R}$ and $\beta_{i,\mathrm{DR}}^{IR}$ lose their significance under the TV-VAR approach. Hence, the findings do not support the claims that cash flow news is driven by fundamentals and discount rate news merely reflects the changes in investor sentiment[118]. CV (2004) find that the cash flow and discount rate beta estimates are biased downward when there is a small sample bias. Looking at both Table 5.7 (TV-VAR) and Table 5.9 (constant VAR), we notice that the downward bias in the beta estimates could be due to $\beta_{i,CF}^{R}$ and $\beta_{i,DR}^{IR}$, where both estimates are substantially lower when the news series are retrieved from the TV-VAR.

(IV) Analysts' forecasts (AF) approach

The beta estimates produced under the analysts' forecasts approach is reported in Table 5.11. As shown in panel B and D, stock returns are sensitive to the movements in the rational expectations, regardless of the cash flow or discount rate channel. However, panel C shows that only a few portfolios are affected by the changes in irrational discount rates. The result of insignificant irrational cash flow beta across 25 portfolios as in panel A is inconsistent with our intuition that the variations in irrationally expected cash flows computed from AF approach will significantly affect the stock prices, since previous studies found that analysts' earnings forecasts contain systematic errors (La Porta, 1996) and could be overoptimistic (Abarbanell and Bernard, 1992; De Bondt and Thaler, 1990; Hribar and Mclnnis, 2012). This could be due that the sample period used for this approach is limited, where the data starts from January 1990, and the analysts' forecasts in this study is sourced from the Bloomberg Earnings Estimates (BEst), which has a few issues as discussed in the Section 5.5.2. Nevertheless, the findings from three approaches agree that the discount rate news is not merely affected by sentiment, rather risk-based explanations seem to play a more important role. Meanwhile, both $\beta_{i,CF}^{IR}$ and $\beta_{i,\mathrm{DR}}^{IR}$ are, on average, insignificant, and hence the relative importance of either channel on the predictive power of investor sentiment is indeterminate based on this approach.

[118] As a robustness check, the TV-VAR is estimated on a longer rolling window size – 180 months (consistent with Section 4.4). The results are robust to the change in the rolling window size of the TV-VAR framework. $\beta_{CF}^{IR} / \beta_{CF}^{R}$ is greater than $\beta_{DR}^{IR} / \beta_{DR}^{R}$, confirming that cash flow channel is an important medium through which the sentiment affects the stock prices. The number of portfolios that are sensitive to the irrational cash flow and rational discount rate betas has also seen an increase. Furthermore, the degree of significance of the rational discount rate beta increases across the board. In general, the results tend towards the findings obtained from the constant VAR model.

Table 5.11: The stock price movements in respond to four news series computed from AF

	Growth	2	3	4	Value
	Panel A: Irrational cash flow beta				
Small	-0.007	-0.003	-0.026	-0.023	-0.041
	[-0.152]	[-0.084]	[-0.844]	[-0.703]	[-1.192]
2	0.014	-0.003	-0.024	-0.014	-0.009
	[0.393]	[-0.094]	[-0.845]	[-0.487]	[-0.241]
3	0.007	-0.009	-0.016	-0.023	-0.007
	[0.227]	[-0.303]	[-0.617]	[-0.769]	[-0.197]
4	0.029	-0.017	-0.016	-0.009	0.004
	[0.849]	[-0.672]	[-0.548]	[-0.318]	[0.102]
Large	0.012	-0.004	-0.019	0.005	0.002
	[0.588]	[-0.174]	[-0.772]	[0.143]	[0.061]
	Panel B: Rational cash flow beta				
Small	0.242*	0.206***	0.210***	0.188**	0.209***
	[1.944]	[2.707]	[3.390]	[2.583]	[2.726]
2	0.238**	0.183***	0.176***	0.241***	0.278***
	[2.376]	[2.638]	[2.974]	[3.681]	[2.860]
3	0.223***	0.200***	0.191***	0.158**	0.146*
	[2.764]	[2.916]	[3.251]	[2.275]	[1.820]
4	0.182**	0.157**	0.190***	0.173**	0.280***
	[2.034]	[2.446]	[2.649]	[2.202]	[2.681]
Large	0.199*	0.193***	0.212***	0.275***	0.332**
	[1.924]	[2.669]	[3.436]	[3.352]	[2.601]
	Panel C: Irrational discount rate beta				
Small	0.063	0.044	0.064**	0.059*	0.087***
	[1.409]	[1.164]	[2.136]	[1.894]	[2.622]
2	0.038	0.046	0.061**	0.048	0.05
	[1.023]	[1.312]	[2.071]	[1.594]	[1.228]
3	0.048	0.049	0.05	0.058	0.049
	[1.386]	[1.468]	[1.495]	[1.640]	[1.381]
4	0.017	0.056*	0.054	0.042	0.042
	[0.560]	[1.946]	[1.645]	[1.224]	[1.120]
Large	0.02	0.034	0.037	0.026	0.041
	[0.772]	[1.227]	[1.258]	[0.739]	[0.951]
	Panel D: Rational discount rate beta				
Small	0.967***	0.804***	0.706***	0.653***	0.696***
	[4.577]	[4.488]	[3.953]	[4.089]	[3.940]
2	0.937***	0.805***	0.708***	0.654***	0.767***
	[4.743]	[4.299]	[4.106]	[4.158]	[4.147]
3	0.906***	0.796***	0.718***	0.734***	0.855***
	[4.773]	[4.254]	[4.279]	[4.548]	[4.983]
4	0.913***	0.807***	0.784***	0.740***	0.779***
	[4.796]	[4.682]	[4.682]	[4.741]	[4.138]
Large	0.729***	0.687***	0.613***	0.681***	0.729***
	[5.247]	[5.467]	[4.457]	[3.988]	[3.791]

Notes: This table presents the four betas computed based on the news series retrieved from the constant analysts' forecasts (AF) approach for portfolio sorted based on size and book-to-market (*BE/ME*) ratio from January 1990 to December 2014 in four panels. Panel A and B report the irrational cash flow beta ($\beta^{IR}_{i,CF}$) and the rational cash flow beta ($\beta^{R}_{i,CF}$), respectively. Panel C and D show the irrational discount rate beta ($\beta^{IR}_{i,\mathrm{DR}}$) and the rational discount rate beta ($\beta^{R}_{i,\mathrm{DR}}$), respectively. The estimation is based on the following regression:

$$r_{i,t} = \alpha + \beta SN^{E}_{\mathrm{j},t} + \varepsilon_t \ , \qquad SN^{E}_{j,t} = \left\{ SN^{IR}_{\mathrm{CF},t}, SN^{R}_{\mathrm{CF},t}, SN^{IR}_{\mathrm{DR},t}, SN^{R}_{\mathrm{DR},t} \right\}$$

where $r_{i,t}$ represents the portfolio returns and $SN^{E}_{j,t}$ denotes one of the four scaled news series computed in equations (5.17) – (5.20). The β is the beta estimate corresponds to one of the four new series applied in the above regression. Portfolios are sorted based on *BE/ME* ratio from left to right and based on firm size (*ME*) from top to bottom in each panel. "Growth" portfolio has the lowest *BE/ME* ratio, "value" portfolio has the highest *BE/ME* ratio, "small" portfolio has the lowest *ME*, and "large" portfolio has the highest *ME*. HAC standard errors are used and the values shown in square bracket are Newey-West *t*-statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

(V) Direct proxy approach

Unreported results of the two-beta model constructed using the direct proxy approach show that all portfolios are sensitive to the discount rate news but none of them react to the changes in the cash flow expectations across all examining horizons, *k*, contradicting the theory that stock prices are affected by the cash flow expectations (*e.g.* Cohen et al., 2002; Hong and Sraer, 2016; Hou et al., 2015). Furthermore, the cash flow betas of value and growth stocks are not significantly different across various size quintiles, likewise for the small and large stocks across different *BE/ME* portfolios. These results are inconsistent with CV (2004) and Da and Warachka (2009).

As for the four-beta model, unreported results also show that all portfolios react significantly only to the rational discount rate news and the effects of other news series – N_{CF}^{IR}, N_{CF}^{R} and N_{DR}^{IR} – are muted across all examining horizons, except the 48-month horizon. The results show that portfolios are generally sensitive to all news series in the four-beta model at 48-month horizon, with the exception of the rational cash flow news. Nevertheless, the irrational cash flow betas of the portfolios have a negative sign. Considering that the results contradict to the literature and are inconsistent across different examining horizons, conclusive finding is unable to be drawn from this approach. Hence, this approach will not be used for analyses conducted beyond this section.

(VI) Summary

In general, the results confirm that the predictive ability of investor sentiment, which is captured by S^{TV}, is due to its influence on the cash flow expectations since irrational cash flow news consistently have significant effects on stock returns as compared to the irrational discount rate news. This finding implies that overly optimistic (pessimistic) expectations of future cash flows formed by naïve investors during high (low) sentiment period push the stock prices beyond and above (below) the fundamental values, leading to a price reversal in the future when fundamental cash flow information is unveiled.

The results also confirm that CPV's assumptions of cash flow news is driven by fundamentals and discount rate news is driven by sentiment are less appropriate seeing that the stock prices consistently move in response to the changes in SN_{CF}^{IR} and SN_{DR}^{R} according to TV-VAR and VAR approaches, and that $\beta_{i,CF}^{IR}$ is a relatively more important systematic risk component as compared to $\beta_{i,\mathrm{DR}}^{IR}$. Apart from validating the assumptions, the results do provide support to the findings of previous literature that stock prices are affected by the irrational expectations of future cash flows (*e.g.* Engelberg et al., 2018; Kim, Ryu and Seo, 2014; LSV, 1994; Park, 2005), and the rationally expected future returns (*e.g.* Bansal et al., 2012; Campbell and Cochrane, 1999; Lettau and Ludvigson, 2001b; Gabaix, 2012).

Previous studies claimed that the cash flows of value stocks are fundamentally riskier than that of growth stocks since value stocks consistently have poor earnings (Fama and French, 1993; 1995), and hence the higher expected returns of value stocks are compensation for the high fundamental cash flow risk (see Campbell, Polk and Vuolteenaho, 2010; Campbell and Vuolteenaho, 2004). If their claim is correct, we would expect value stocks to have higher rational cash flow betas, which reflect the fundamental cash flow risk, than growth stocks. Yet, the results based on TV-VAR and VAR approaches show that values stocks are not fundamentally riskier since the rational cash flow betas of value stocks are lower than that of growth stocks across different size quintiles. Hence, the results do not support the risk-based explanation to a certain extent.

5.6.5 The prices of four betas

The results from previous section show that stocks are sensitive not only to the rational movement in the news series, but also to the irrational fluctuation in the news series. Therefore, the standard asset pricing test is employed to investigate how the four betas are being priced cross-sectionally by performing the FMB as shown in equation (5.28). The FMB estimates also allow us to examine the relative importance of the premium investors allocate to each component of the four-beta model. Furthermore, we compare the performance of the four-beta model against the Capital Asset Pricing Model (CAPM) and the two-beta model in pricing the risks. The CV's two-beta model from this section onwards is constructed based on the news series retrieved from the TV-VAR approach[119].

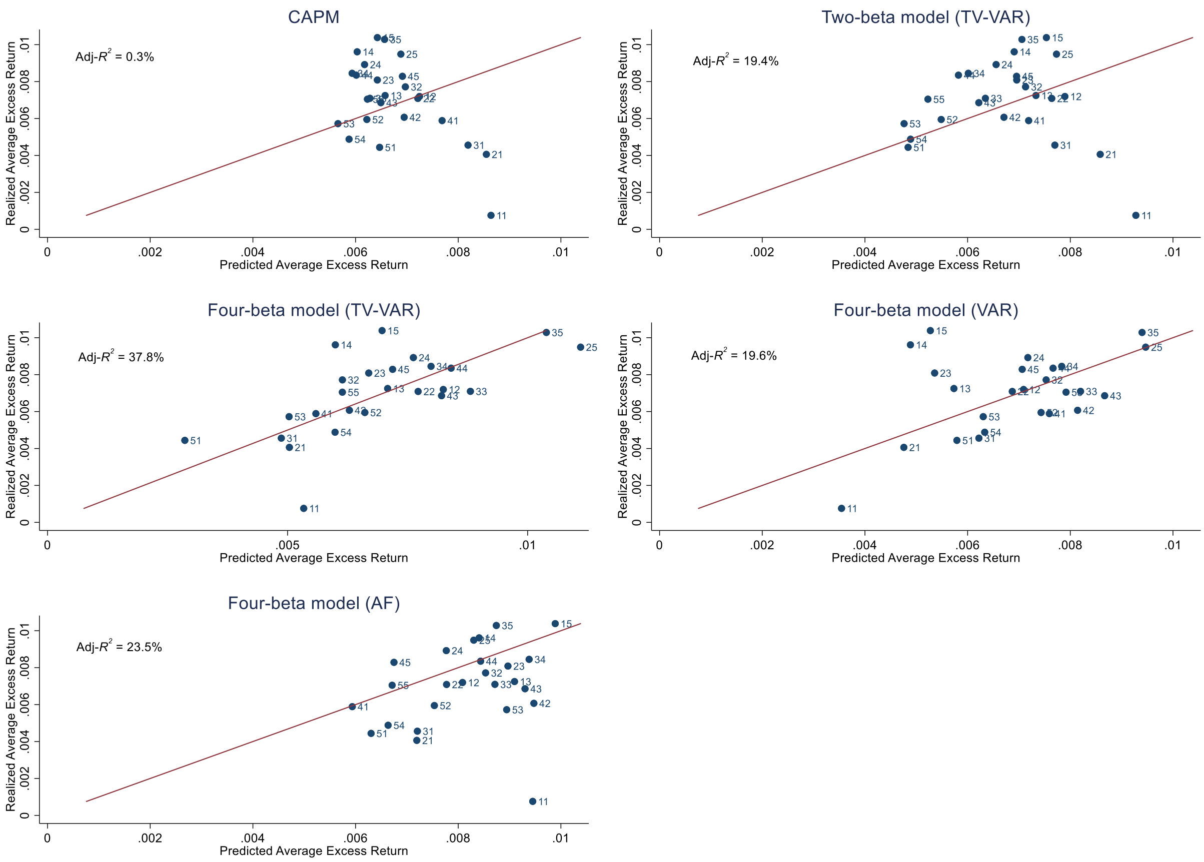
Figure 5.3 provides a visual examination on the model fit of different asset pricing models. The figure plots the average realized returns in excess of risk-free rate (vertical axis)

[119] The TV-VAR approach is used in the construction of CV's two-beta model to ensure a fair comparison with the four-beta model in the asset pricing test and since the TV-VAR estimates produce a higher adjusted-R^2 statistic for the return regression as in Table 5.2. In fact, the asset pricing tests reveal that the adjusted cross-sectional R^2 of the two-beta model constructed under the TV-VAR framework is higher than that of constructed under the constant VAR framework.

against the average fitted excess returns (horizontal axis). The average fitted excess returns is the fitted value of equation (5.28) estimated from December 1969 to December 2014, except the four-beta model (AF) where the sample period covers from January 1990 to December 2014 due to the data availability. The dots in each graph are 25 portfolios sorted based on *ME* and *ME/BE*, represented by the two-digit number labelled next to each data point. The first digit denotes the size quintile (*ME*) and the second digit represents the book-to-market quintile (*BE/ME*)[120]. If a model explains 100% of the variation in the cross section of average stock returns, all data points would lie exactly on the 45-degree line.

Figure 5.3: Realized vs. fitted average excess returns

This figure plots the realized average excess return against the fitted (or predicted) average excess returns on 25 portfolios sorted based on firm size (*ME*) and book-to-market (*ME/BE*) ratio (represented as dots in the figure) for different asset pricing models: Capital Asset Pricing Model (CAPM), CV's two-beta model, four-beta models computed with the news series retrieved from the time-varying VAR (TV-VAR), the constant VAR and the analysts' forecasts (AF) approach. The predicted average excess returns are estimated from equation (5.28) for the period of 1969:12 – 2014:12, except the four-beta model (AF), which has the sample period spans from 1990:01 – 2014:12. The number labelled next to each data point represents the portfolios sorted according to *ME* and *BE/ME* ratio (*e.g.* double-digit 15 denotes small-value portfolio).



[120] For instance, the double-digit 11 denotes the small-growth portfolio, *i.e.* ME1BM1 portfolio.

The CAPM and CV's two-beta models are plotted on the top of Figure 5.3, and the other three graphs are the four-beta models constructed under different approaches, which are the time-varying VAR (TV-VAR), the Vector Autoregressive Model (VAR) and the analysts' forecasts (AF). Of all the five models, CAPM apparently performs the worst as the model seems to predict average excess returns of different portfolios far too away from the 45-degree reference line. Although the model fit is improved in the two-beta model, we notice that the data points produced by the four-beta model generally have much smaller spread from the reference line, regardless of the approach used to compute the four-beta model. A noticeable exception can be seen from the small-growth portfolio (labelled as 11), where it has the greatest distance from the 45-degree line not only in the four-beta models, but also in the CAPM and two-beta models.

To confirm the visual evidence, the cross-sectional regression result of each model is presented in Table 5.12. The result of each asset pricing model is presented in column (1) to (5). Each row is presented with the point estimate of a particular risk component (i.e. risk premium) associated with its heteroscedasticity and autocorrelation consistent *t*-statistics (shown in the square bracket). If a risk factor is an important factor, we would expect that risk factor to be priced significantly across different stocks. Hence, the null hypothesis of interest is that $H_0 : \lambda_{j,t} = 0$. The tests statistics of adjusted cross-sectional R^2 (*Adj*-R^2) and pricing errors, measured as root-mean-squared-pricing-errors (*RMSPE*) and the mean-pricing-errors (*MPE* (%)), are used to evaluate the performance of each asset pricing model as presented in the last three rows. A better asset pricing model is expected to deliver a higher *Adj*-R^2 whilst producing a lower pricing error.

The first column shows that the explanatory power of CAPM, i.e. *Adj*-R^2, on the cross-sectional stock returns is only 0.3% although the model produces a positive risk price for the market beta (i.e. 7.2% per annum for λ_M [121]) that is highly significant at 1% level. This result suggests that the CAPM model is unable to price the cross-sectional stock returns and produces the largest average pricing error (e.g. 0.024 *RMSPE*), consistent with the visual representation as shown in Figure 5.3. When the market beta is disentangled into cash flow and discount rate beta, the *Adj*-R^2 statistic even though does improved tremendously to 19.4%, as shown in column (2), the *RMSPE* improved by less than 0.005 to 0.021. Besides

[121] The point estimates reported in Table 5.12 are monthly risk premium estimates. To obtain the annual risk premium in the percentage term, simply multiply the point estimates by 1200.

Table 5.12: Prices of risks

	CAPM	Two-beta model	Four-beta model		
			TV-VAR	VAR	AF
	(1)	(2)	(3)	(4)	(5)
λ_M	0.006***				
	[2.823]				
λ_{CF}		-0.002			
		[-0.272]			
λ_{DR}		0.009***			
		[2.715]			
λ_{CF}^{IR}			-0.622***	-0.282**	-0.183
			[-3.672]	[-2.037]	[-1.438]
λ_{CF}^{R}			0.015*	0.037*	0.002
			[1.859]	[1.807]	[0.197]
λ_{DR}^{IR}			-0.554***	-1.017***	-0.086
			[-4.176]	[-3.833]	[-0.745]
λ_{DR}^{R}			0.023***	0.004	0.013***
			[4.723]	[0.203]	[3.123]
Adj-R^2	0.003	0.194	0.378	0.196	0.235
RMSPE	0.024	0.021	0.016	0.019	0.021
MPE (%)	0.023	0.023	0.009	0.009	0.007

Notes: This table presents the results of the Fama-Macbeth regression for the Capital Asset Pricing Model (CAPM), the CV's two-beta model with the news series retrieved from the time-varying VAR (TV-VAR) approach, and the four-beta models computed with the news series retrieved from the time-varying VAR (TV-VAR), the constant VAR and the analysts' forecasts (AF) approach. The test assets are 25 portfolios sorted based on size (*ME*) and book-to-market (*BE/ME*) ratio. The risk premium estimates are the time-series average of the cross-sectional parameter estimates for the period of 1969:12 – 2014:12, except the four-beta model (AF), which has the sample period of 1990:1 – 2014:12. λ_M is the price of market risk, λ_{CF} is the price of cash flow risk, λ_{DR} is the price of discount rate risk, λ_{CF}^{IR} is the price of irrational cash flow risk, λ_{CF}^{R} is the price of rational cash flow risk, λ_{DR}^{IR} is the price of irrational discount rate risk, and λ_{DR}^{R} is the price of rational discount rate risk. The heteroskedastic and autocorrelation consistent *t*-statistics are presented within the square brackets. The adjusted cross-sectional R^2 statistic (*Adj-R^2*), the root-mean-squared-pricing-errors (*RMSPE*), the mean-pricing-errors (*MPE*) are presented in the last three rows. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

that, only the discount rate beta carries a positive risk premium (i.e. 10.8% per annum for λ_{DR}^{IR}) that is significant at 1% level. Although CV (2004) and Garrett and Priestley (2012) report a higher cross-sectional R^2 statistic (i.e. more than 40%) for the two-beta model, Botshekan et al.

(2012) who included a more recent sample period present a much lower cross-sectional R^2 statistic, which is less than 10%[122].

Columns (3) to (5) show the results of pricing tests for the four-beta models constructed using news series retrieved from TV-VAR, VAR, AF approach, respectively. The four-beta models perform better than the CAPM and CV's two-beta models in terms of the *Adj-*R^2 statistic. The higher *Adj-*R^2 statistics together with much lower average pricing errors suggest that the four-beta models are able to explain the variation in average stock returns at the cross-sectional level better than the other two asset pricing models, reassuring the visual evidence shown in Figure 5.3. This improvement is purely the result of decomposing the cash flow and discount rate betas into irrational and rational components that yield a richer description of the risk components faced by different stocks since the news series used in both two-beta and four-beta models are retrieved from the TV-VAR approach.

Of the three four-beta models, the TV-VAR approach performs best with the highest *Adj-*R^2 (i.e. 37.8%), and all risk components but the rational cash flow risk (β_{CF}^{R}) are priced at 1% significance level. Also, it produces the least *RMSPE* of 0.016. On the risk premia estimates, irrational beta risks are consistently and significantly priced in the cross-section of stock returns under the VAR frameworks. In particular, the irrational factors constructed based on the TV-VAR approach carry negative risk premia of about 60% with the *t*-statistics lie beyond three standard deviations from the mean. The exposure to the rational factors, on the other hand, demand positive risk premia, where the β_{CF}^{R} is consistently priced under both VAR approaches at 10% significance level.

It is also worth noting that the irrational betas are relatively important components in describing the cross-sectional stock returns given that irrational cash flow and irrational discount rate betas consistently carry a larger risk premium (in the absolute terms) as compared to their rational counterparts across all four-beta models, *i.e.* $\lambda_{CF}^{IR} > \lambda_{CF}^{R}$ and $\lambda_{DR}^{IR} > \lambda_{DR}^{R}$. Given the relative importance of irrational risk premia, and since expected returns are the product of beta estimates and the corresponding risk prices, investors should pay

[122] The modern sample period of CV (2004) is from July 1963 to December 2001 and Garrett and Priestley (2012) employ the annual data from 1928 to 2001; whereas Botshekan et al (2012) extend the sample period of CV (2004) to December 2008.

attention to the assets that are more sensitive to the variations in the irrational news, despite the magnitude of irrational betas is smaller than that of rational betas.

In accord with our expectation and previous literature, irrational cash flow and irrational discount rate risks (*i.e.* β_{CF}^{IR} and β_{DR}^{IR}) consistently carry a negative risk premium across three different approaches used in retrieving the news terms. A few potential rational and behavioural explanations to the negative risk premium are discussed below.

The pricing of irrational beta risks could be well reflected by the pricing of lottery-like stocks' characteristics. Investors who trade on sentiment tend to invest in lottery-like stocks, and hence, the returns of lottery-like stocks tend to be driven by investor sentiment (Carpentier, Romon and Suret, 2018; Fong, 2013; Fong and Toh, 2014). At the same time, Kumar (2009) define the lottery-like stocks as stocks typically with high idiosyncratic volatility (IVOL) and positive idiosyncratic skewness (SKEW)[123]. As IVOL is highly correlated with market volatility, Barinov (2018) shows that IVOL carries a negative risk premium, an insurance investors pay to shield from an unfavourable move in market volatility – consistent with the rational explanation. Hence, lottery-like stocks with high IVOL beta tend to earn lower expected returns since it hedges against market volatility risk.

As for the positive SKEW, Barberis and Huang (2008) claim that cumulative prospect theory investors overweight the small probability of huge gains of lottery-like stocks[124], and hence investors are willing to pay a price for the lottery-like stocks, hoping for a potentially huge payoff, and accept a lower average excess returns – consistent with the behavioural explanation[125]. Therefore, the positive SKEW is priced negatively in the cross-section of expected returns (Bali, Cakici, and Whitelaw, 2011; Boyer, Mitton and Vorkink, 2010; Lin and Liu, 2018). Given that lottery-like stocks are affected by investor sentiment, and that the characteristics of lottery-like stocks are negatively priced, the negative risk premia of

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[123] Fong (2013) also mention that other characteristics of lottery stocks are similar to that of the sentiment-driven stocks, such as small, young, unprofitable, distressed and high growth stocks.

[124] Apart from overweighting the tail probability, investors face limited downside risk with asymmetric payoff structure of lottery stocks. Pessimistic investors will stand on the side line when investment opportunities deteriorate and stock prices will not be punished severely, but they might be greatly rewarded when optimistic investors actively purchase the lottery-like stocks.

[125] In fact, investors prefer any securities that exhibit positive skewness in the return distribution, such as, premium bond (Lobe and Hölzl, 2008; Pfiffelmann; 2013) and lottery-linked deposit account (Guillén and Tschoegl, 2002).

sentiment-induced irrational betas could be a manifestation of the negative risk premia associated with those characteristics – IVOL and SKEW.

As a whole, stocks with high irrational betas would command a negative risk premium. The pricing of irrational beta risks in the four-beta model is consistent with return differences and beta estimates reported in Table 5.4 and Table 5.7, respectively. As shown in Table 5.4, growth stocks consistently have lower average returns after controlling for the size effect. The lower average returns of growth stocks can be seen corresponding to higher irrational cash flow betas as compared to value stocks in Table 5.7. Meanwhile, Table 5.9 shows that the beta estimates constructed under the VAR approach have both irrational cash flow and irrational discount rate betas of growth stocks higher than that of value stocks. Therefore, growth stocks that are more sensitive to the changes in irrational expectations earn lower average excess returns. In sum, giving credit to irrational risk factors explicitly captures well the different risks faced by different stocks and hence the four-beta model describes average stock returns at the cross-sectional level better than the CAPM and the two-beta model.

5.6.6 The price of four betas in the future returns

The previous section shows that all four betas constructed based on the TV-VAR approach are significantly priced at the cross-sectional level when the contemporaneous relationship between average stock returns and different risk factors is considered. For a more stringent test on the pricing of four-beta model, this study considers the risk premia components of future returns. If a particular beta is an important factor that captures well certain risk, the risk premium estimate of that beta corresponds to future returns should be significantly different from zero.

Following Botshekan et al. (2012), future information is not utilised in the beta construction. Hence, unlike the TV-VAR approach where N_{CF} and N_{DR} of a month are obtained by averaging out the news series computed across different windows where future information are utilized in some windows, this exercise uses the news series retrieved in a window of up to month t in estimating the beta, avoiding the potential look-ahead bias. In particular, the VAR parameters and news series are estimated on a rolling window basis with a window size of 72 months. The four betas are then estimated by regressing the portfolio returns on the news series over the same window. This process is repeated when the window is rolled over by one month and a series of updated beta estimates are obtained. For instance, the VAR parameters, the four new series and the four betas are estimated using the data available from 1969:12 until 1975:11 in the first window. This fixed window-size estimation period is then rolled to estimate the betas over the period of 1970:01 to 1975:12. Finally, this study performs the FMB regression by regressing expected portfolio returns of different forecast horizons on four betas estimated up to time *t*. Consistent with previous chapters, the forecast horizons, *h*, from 1-month up to 60-month are considered in this sub-section. This presents another way of examining the economic source underlying the predictive ability of investor sentiment on future stock returns as documented in Section 5.6.4.

Table 5.13: Future risk premia estimates of the four-beta model

	h = 1	*h = 3*	*h = 6*	*h = 9*	*h = 12*	*h = 24*	*h = 36*	*h = 60*
λ_{CF}^{IR}	-0.093*	-0.071	-0.077*	-0.086*	-0.088**	-0.051*	0.016	0.069
	[-1.708]	[-1.510]	[-1.666]	[-1.939]	[-2.054]	[-1.677]	[0.652]	[2.833]
λ_{CF}^{R}	0.017	0.012	0.015	0.012	0.012	0.008	0.004	-0.005
	[1.218]	[0.926]	[1.236]	[1.084]	[1.162]	[0.960]	[0.533]	[-0.585]
λ_{DR}^{IR}	-0.021	-0.019	-0.021	-0.021	-0.018	-0.008	-0.013	0.001
	[-0.905]	[-0.961]	[-1.226]	[-1.301]	[-1.275]	[-0.709]	[-1.194]	[0.135]
λ_{DR}^{R}	0.014**	0.012**	0.014***	0.016***	0.017***	0.016***	0.016***	0.013***
	[2.170]	[2.069]	[2.687]	[3.038]	[3.290]	[3.912]	[4.623]	[4.985]

Notes: This table reports the risk premia estimates associated with the irrational cash flow risk (λ_{CF}^{IR}), rational cash flow risk (λ_{CF}^{R}), irrational discount rate risk (λ_{DR}^{IR}), rational discount rate risk (λ_{DR}^{R}) for the future expected returns across different forecast horizons retrieved from the following Fama-Macbeth (FMB) regression:

$$R_{i,t+h}^{e} = \lambda_{CF,t}^{IR}.\hat{\beta}_{i,CF}^{IR} + \lambda_{CF,t}^{R}.\hat{\beta}_{i,CF}^{R} + \lambda_{DR,t}^{IR}.\hat{\beta}_{i,DR}^{IR} + \lambda_{DR,t}^{R}.\hat{\beta}_{i,DR}^{R} + e_{i,t}$$

The values in the square brackets are Newey-West *t*-statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

The risk premium estimate of future stock returns associated with each of the four betas are presented in Table 5.13. The irrational cash flow risk is significantly and consistently priced in the cross-sectional of future stock returns from the next-month forecast up to the 24-month forecast horizons, except the 3-month forecast horizon. The negative risk premium estimate of β_{CF}^{IR} is also consistent with the results shown in Table 5.12, confirming that investors are willing to pay a price for stocks that are sensitive to the changes in irrationally expected future cash flows. Despite the risk premium of β_{CF}^{IR} in the out-of-sample is lower than that of in the in-sample analysis (i.e. Table 5.12), the monthly λ_{CF}^{IR} ranging between 5% and 9% for different forecast horizons are still sizeable. Contrarily, the irrational discount rate risk is not significantly priced in future stock returns across different forecast horizons even though this beta risk also commands a negative risk premium. These results again demonstrate that the predictability of sentiment on future stock returns is going through the cash flow channel given that the irrational cash flow risk has its negative premium sustained even in the out-of-sample context.

As for the rational component, only the rational discount rate risk is significantly priced in the cross-sectional of future stock returns at 5% significance level across all forecast horizons. Similar to λ_{CF}^{IR}, the monthly λ_{DR}^{R} also experiences a drop, where the risk premium associated with the β_{DR}^{R} decreases slightly from more than 2% in the in-sample analysis (Table 5.12) to less than 2% a month in the out-of-sample analysis (Table 5.13). On the other hand, the rational cash flow beta does not carry a significant risk premium in future stock returns regardless of the forecast horizon.

In summary, only the risks originated from irrational cash flow beta and rational discount rate beta survive in both in-sample and out-of-sample asset pricing tests. Given that these two risk components are significantly priced in the cross-sectional of stock returns, the changes in irrational expectations of cash flows and rational discount rates should not be neglected. The results here provide further support to the findings that the cash flow news is not merely driven by fundamental and discount rate new is not merely sentiment induced. Indeed, the irrational cash flow expectations and rational discount rate expectations are two important risk components in pricing the stocks at cross-sectional level.

5.6.7 Sub-sample analysis

Recognizing the fact that beta is not constant across time, this section conducts a sub-sample analysis to investigate if the beta estimates and their associated risk premia produced under the TV-VAR approach change across different sub-sample periods. The sub-sample analysis is performed under a structural break framework to identify the period when there is a breakdown in the return-beta relationship.

This study employs the single break with unknown break point test of Andrew (1993) in locating the single break point. Specifically, the break point is identified separately on cash flow and discount rate news instead of each of the four news terms in order to avoid having different break points for all four series. Hence, both rational and irrational news series are combined in each channel when performing the test for structural break date. To avoid having different break points for each portfolio, this study treats 25 test asset portfolios as the representative of stock market and the break point identified on the stock market return-beta relationship is applied to all test asset portfolios considered in this study. Although the multiple break test could have been used to identify multiple break points, the multiple break test complicates the analysis as the test produces multiple yet different break points for cash flow and discount rate news. Since a consistent break date for both cash flow and discount rate betas is required for further analysis of risk pricing, the single break test that identifies major structural change in the return-beta relationship is opted. The break date identified for the cash flow and discount rate beta are September 1997 and February 1998, respectively. In view of the need of having a consistent break point for both betas, the sample period from September 1997 to January 1998 is excluded. Therefore, the first sub-sample period covers from December 1969 to August 1997, and the second sub-sample period spans from February 1998 to December 2014.

(I) The effect of structural break on four beta estimates

As usual, Table 5.14 and Table 5.15 report the four beta estimates in four panels for 25 portfolios sorted based on *ME* and *BE/ME* ratio: the irrational cash flow beta, $\beta_{i,CF}^{IR}$ (panel A), the rational cash flow beta, $\beta_{i,CF}^{R}$ (panel B), the irrational discount rate beta, $\beta_{i,\mathrm{DR}}^{IR}$ (panel C), and the rational discount rate beta, $\beta_{i,\mathrm{DR}}^{R}$ (panel D) in the first and second sub-sample period, respectively. Each row provides the beta estimates together with the Newey-West *t*-statistics reported in square brackets. Similar to Section 5.6.4, this sub-section is interested at: (1) whether the predictive ability of investor sentiment is coming from discount rate or cash flow channel, (2) whether $H_0:\beta_{CF}^{IR}=0$ and $H_0:\beta_{DR}^{R}=0$ can be rejected in each sub-sample period.

Panel A of Table 5.14 shows that all portfolios but one are insensitive to the fluctuations in irrationally expected cash flows in the first sub-sample period given that $\beta_{i,CF}^{IR}$ are insignificant. Nonetheless, the results of panel A in Table 5.15 resemblance to that of panel A in Table 5.7, where some assets respond significantly to irrational cash flow news in the second sub-sample period. The responsiveness of each portfolio towards the variations in irrational expectations of cash flows, in terms of the magnitude of $\beta_{i,CF}^{IR}$, has seen a substantial increase from the first sub-sample period to the second sub-sample period for most of the portfolios. For instance, the estimate of $\beta_{i,CF}^{IR}$ for small-growth stocks increases from 0.009 in the first sub-sample period to 0.079 in the second sub-sample period.

Table 5.14: Four betas estimated for the first sub-sample period

	Growth	2	3	4	Value
			Panel A: Irrational cash flow beta		
Small	0.009	0.012	0.011	0.01	0.008
	[0.440]	[0.846]	[0.765]	[0.878]	[0.631]
2	0.025	0.012	0.01	0.012	0.001
	[1.079]	[0.813]	[0.756]	[0.932]	[0.102]
3	0.024	0.022*	0.015	0.005	0.01
	[1.226]	[1.663]	[1.148]	[0.405]	[0.649]
4	0.018	0.017	0.013	0.004	0.001
	[1.068]	[1.283]	[1.087]	[0.261]	[0.061]
Large	0.017	0.006	0.016	0.01	-0.007
	[0.943]	[0.397]	[1.293]	[0.792]	[-0.548]
			Panel B: Rational cash flow beta		
Small	-0.037	-0.044	-0.06	-0.069	-0.095
	[-0.257]	[-0.349]	[-0.485]	[-0.619]	[-0.731]
2	0.015	-0.012	-0.04	-0.032	-0.067
	[0.112]	[-0.093]	[-0.336]	[-0.258]	[-0.466]
3	0.058	-0.011	-0.002	-0.006	-0.026
	[0.445]	[-0.093]	[-0.019]	[-0.052]	[-0.176]
4	0.062	0.034	0.028	0.021	0.012
	[0.503]	[0.284]	[0.228]	[0.156]	[0.076]
Large	0.161	0.084	0.085	0.08	0.093
	[1.464]	[0.673]	[0.637]	[0.575]	[0.718]
			Panel C: Irrational discount rate beta		
Small	0.014	0.004	0.004	0.005	0.006
	[0.759]	[0.232]	[0.370]	[0.455]	[0.569]
2	0.002	0.005	0.006	0	0.006
	[0.096]	[0.383]	[0.535]	[0.013]	[0.597]
3	0.001	-0.003	-0.002	0.009	-0.003
	[0.053]	[-0.325]	[-0.142]	[0.889]	[-0.252]
4	0.003	0.004	0.002	0.007	0.014
	[0.198]	[0.351]	[0.187]	[0.699]	[1.116]
Large	0.004	0.012	0.006	0.006	0.020*
	[0.251]	[0.906]	[0.549]	[0.615]	[1.947]
			Panel D: Rational discount rate beta		
Small	0.795***	0.702***	0.664***	0.624***	0.680***
	[2.995]	[2.923]	[3.013]	[2.960]	[2.985]
2	0.768***	0.685***	0.633***	0.588***	0.686***
	[2.771]	[2.766]	[2.836]	[2.791]	[2.894]
3	0.686**	0.647***	0.569***	0.532***	0.621***
	[2.569]	[2.800]	[2.759]	[2.623]	[2.857]
4	0.629**	0.614***	0.559**	0.515**	0.599**
	[2.529]	[2.648]	[2.567]	[2.522]	[2.594]
Large	0.428*	0.498**	0.432**	0.413**	0.415**
	[1.809]	[2.357]	[2.224]	[2.212]	[2.202]

Notes: This table presents the four betas computed based on the news series retrieved from the TV-VAR approach for portfolio sorted based on size and book-to-market (*BE/ME*) ratio from December 1969 to August 1997 in four panels. Panel A and B report the irrational cash flow beta ($\beta^{IR}_{i,CF}$) and the rational cash flow beta ($\beta^{R}_{i,CF}$), respectively. Panel C and D show the irrational discount rate beta ($\beta^{IR}_{i,\mathrm{DR}}$) and the rational discount rate beta ($\beta^{R}_{i,\mathrm{DR}}$), respectively. The estimation is based on the following regression:

$$r_{i,t} = \alpha + \beta SN^{k}_{\mathrm{j},t} + \varepsilon_t \ , \qquad SN^{k}_{j,t} = \left\{ SN^{IR}_{\mathrm{CF},t}, SN^{R}_{\mathrm{CF},t}, SN^{IR}_{\mathrm{DR},t}, SN^{R}_{\mathrm{DR},t} \right\}$$

where $r_{i,t}$ represents the portfolio returns and $SN^{k}_{j,t}$ denotes one of the four scaled news series computed in equations (5.17) – (5.20). The β is the beta estimate corresponds to one of the four new series applied in the above regression. Portfolios are sorted based on *BE/ME* ratio from left to right and based on firm size (*ME*) from top to bottom in each panel. “Growth” portfolio has the lowest *BE/ME* ratio, “value” portfolio has the highest *BE/ME* ratio, “small” portfolio has the lowest *ME*, and “large” portfolio has the highest *ME*. HAC standard errors are used and the values shown in square bracket are Newey-West *t*-statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 5.15: Four betas estimated for the second sub-sample period

	Growth	2	3	4	Value
	Panel A: Irrational cash flow beta				
Small	0.079	0.056	0.043	0.056	0.043
	[1.363]	[1.296]	[1.299]	[1.577]	[1.374]
2	0.067	0.05	0.038	0.043*	0.046*
	[1.628]	[1.604]	[1.394]	[1.687]	[1.662]
3	0.051	0.058**	0.029	0.038*	0.039*
	[1.425]	[2.267]	[1.620]	[1.842]	[1.822]
4	0.070**	0.034*	0.028	0.040**	0.051**
	[2.013]	[1.938]	[1.507]	[1.989]	[2.544]
Large	0.034	0.015	-0.007	0.013	0.046**
	[1.581]	[0.968]	[-0.504]	[0.676]	[2.397]
	Panel B: Rational cash flow beta				
Small	1.108**	1.101**	1.154**	0.998**	1.174**
	[2.130]	[2.152]	[2.567]	[2.082]	[2.511]
2	1.281***	1.048**	1.239***	1.326***	1.542**
	[3.001]	[2.364]	[3.300]	[3.539]	[2.602]
3	1.372***	1.321***	1.351***	1.318***	1.389***
	[3.584]	[3.518]	[4.297]	[3.743]	[2.976]
4	1.298***	1.406***	1.457***	1.310***	1.563***
	[4.095]	[4.516]	[4.840]	[4.230]	[4.374]
Large	1.361***	1.489***	1.627***	1.661***	1.771***
	[7.381]	[7.895]	[7.521]	[5.286]	[8.434]
	Panel C: Irrational discount rate beta				
Small	-0.033	-0.028	-0.014	-0.031	-0.009
	[-0.668]	[-0.629]	[-0.451]	[-0.896]	[-0.304]
2	-0.029	-0.022	-0.012	-0.017	-0.013
	[-0.792]	[-0.748]	[-0.457]	[-0.677]	[-0.439]
3	-0.014	-0.03	-0.011	-0.021	-0.010
	[-0.366]	[-1.126]	[-0.431]	[-0.981]	[-0.413]
4	-0.037	-0.01	-0.007	-0.018	-0.016
	[-1.022]	[-0.531]	[-0.353]	[-0.762]	[-0.67]
Large	-0.006	0.006	0.024	0.008	-0.016
	[-0.295]	[0.381]	[1.417]	[0.483]	[-0.639]
	Panel D: Rational discount rate beta				
Small	3.735***	3.006***	2.627***	2.521***	2.648***
	[16.000]	[20.479]	[10.363]	[9.248]	[10.080]
2	3.412***	2.886***	2.505***	2.551***	2.921***
	[16.852]	[11.180]	[11.795]	[13.342]	[11.196]
3	3.170***	2.795***	2.519***	2.419***	2.838***
	[13.802]	[14.377]	[14.296]	[10.916]	[13.140]
4	3.126***	2.575***	2.507***	2.41***	2.898***
	[13.035]	[15.346]	[9.404]	[13.228]	[11.401]
Large	2.328***	2.182***	1.943***	2.317***	2.698***
	[17.370]	[13.312]	[8.735]	[6.584]	[8.891]

Notes: This table presents the four betas computed based on the news series retrieved from the TV-VAR approach for portfolio sorted based on size and book-to-market (*BE/ME*) ratio from February 1998 to December 2014 in four panels. Panel A and B report the irrational cash flow beta ($\beta^{IR}_{i,CF}$) and the rational cash flow beta ($\beta^{R}_{i,CF}$), respectively. Panel C and D show the irrational discount rate beta ($\beta^{IR}_{i,\mathrm{DR}}$) and the rational discount rate beta ($\beta^{R}_{i,\mathrm{DR}}$), respectively. The estimation is based on the following regression:

$$r_{i,t} = \alpha + \beta SN^{k}_{\mathrm{j},t} + \varepsilon_t \ , \qquad SN^{k}_{j,t} = \left\{ SN^{IR}_{\mathrm{CF},t}, SN^{R}_{\mathrm{CF},t}, SN^{IR}_{\mathrm{DR},t}, SN^{R}_{\mathrm{DR},t} \right\}$$

where $r_{i,t}$ represents the portfolio returns and $SN^{k}_{j,t}$ denotes one of the four scaled news series computed in equations (5.17) – (5.20). The β is the beta estimate corresponds to one of the four new series applied in the above regression. Portfolios are sorted based on *BE/ME* ratio from left to right and based on firm size (*ME*) from top to bottom in each panel. "Growth" portfolio has the lowest *BE/ME* ratio, "value" portfolio has the highest *BE/ME* ratio, "small" portfolio has the lowest *ME*, and "large" portfolio has the highest *ME*. HAC standard errors are used and the values shown in square bracket are Newey-West *t*-statistics. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Comparing panel B of Table 5.14 and Table 5.15, a change in the $\beta^{R}_{i,CF}$ moving from the first sub-sample period to the second sub-sample period is observed. In the first sub-sample period, the negative $\beta^{R}_{i,CF}$ reported in Table 5.14 indicates that the relationship between assets' returns and rational cash flow news could possibly go in the wrong way since an increase in the rational cash flow expectations signifies a stronger fundamentals in the future and, hence, asset prices should move in the favourable direction. Nevertheless, these estimates are statistically insignificant and of smaller magnitude than the estimates of $\beta^{R}_{i,CF}$ in the second sub-sample period, as shown in Table 5.15. Panel B of Table 5.15 depicts that all assets' returns have a positive covariance with the variations in rationally expected future cash flows and the beta estimates are mostly greater than 1. Furthermore, $\beta^{R}_{i,CF}$ for most of the portfolios are highly significant at 1% level, except the $\beta^{R}_{i,CF}$ of small stocks which have a slightly lower statistical significance (i.e. at 5% level). Based on this comparison, it seems that the negative beta estimates in the first sub-sample period together with the positive beta estimates in the second sub-sample period could potentially contribute to the insignificant estimates of $\beta^{R}_{i,CF}$ shown in Table 5.7.

The statistically insignificance of $\beta^{IR}_{i,DR}$ in the full sample period could also be well justified from the sub-sample analysis. Panel C in Table 5.14 and Table 5.15 illustrate that the estimates of $\beta^{IR}_{i,DR}$ are small and statistically insignificant across the board in both sub-sample periods, with the exception of the large-value stocks which have a weak yet statistically significant (i.e. 10% significance level) $\beta^{IR}_{i,DR}$ in the first sub-sample period. Contrarily to the $\beta^{R}_{i,CF}$, $\beta^{IR}_{i,DR}$ are generally positive in the first sub-sample period, but are negative in the second sub-sample period.

Finally, panel D of both tables depict that the estimates of $\beta^{R}_{i,DR}$ are highly significant at 1% level for most assets, especially in the second sub-sample period, indicating that all stock prices are affected by the fluctuations in rational expectations of future returns (i.e. discount rates). The variations in rational discount rates do not only affect stock prices, but also become more influential across the board with the passage of time considering that the estimates of $\beta^{R}_{i,DR}$ in the second sub-sample are about four times or more of the $\beta^{R}_{i,DR}$ estimates in the first sub-sample period.

Overall, the findings in this sub-section is consistent with the findings documented in the Section 5.6.4. First, the significant β_{CF}^{IR} and insignificant β_{DR}^{IR} reinforce the finding that the predictive power of investor sentiment on future stock returns is going through the cash flow channel: investor sentiment affects the formation of cash flow expectations, which then drives stock prices to deviate from fundamental values. Second, findings on the beta estimates in this sub-sample analysis again do not support the claim made by CPV (2010). As shown in the tables, the effect of the variations in rational discount rates on stock prices is robust across different sub-sample periods. Besides that, some stocks are sensitive to the variations in irrational cash flow expectations as well in the second sub-sample period. Thereby, the findings suggest that $Cov(r_{i,t}, SN_{CF,t}^{IR}) \neq 0$ and $Cov(r_{i,t}, SN_{DR,t}^{R}) \neq 0$, rejecting both $H_0 : \beta_{CF}^{IR} = 0$ and $H_0 : \beta_{DR}^{R} = 0$ with confidence.

Cochrane (2011), whose analysis spans from 1947 to 2009, argues that the variations in stock prices is entirely due to the variations in expected returns, leaving no role for the expected cash flows. Based on the sub-sample analysis in this study, the results from the first sub-sample period support his argument that only the variations in expected returns (*i.e.* discount rate news) is accountable for the variations in assets' prices. The results also provide further details that within the discount rate channel, only shocks in the rational discount rate matter. The second sub-sample period analysis shows that, although rational discount rate news being the most important contributor to the variations in stock prices (in terms of the magnitude), the cash flow news, both irrational and rational channels, also play an important role in explaining the variations in stock prices.

(II) The pricing of risks across different sample periods

Table 5.16 reports the risk premia estimates associated with each risk factor for the CAPM, CV's two-beta model, and the four-beta model across different sample periods. Panel A presents the prices of risks for the first sub-sample period; whereas the prices of risks for the second sub-sample period are reported in panel B. The null hypothesis that the risk premium associated with a particular risk factor is not significantly different from zero ($H_0 : \lambda_{j,t} = 0$) is examined in both sub-sample periods. Besides that, this section investigates whether the explanatory power of the model represented by adjusted cross-sectional R^2 has changed across sub-sample periods and whether the superiority of the four-beta model in pricing the risks continue to hold in the sub-sample analysis.

Panel A shows that the CAPM model, although has a significant risk premium for the market beta, delivers the lowest adjusted cross-sectional R^2 of 1.80%, in the first sub-sample period. As for the CV's two-beta model, it has a better explanatory power over the stock returns at cross-sectional level as compared to the CAPM given that its adjusted cross-sectional R^2 statistic is 20.4%. This is evident in the graphical depiction in panel A of Figure 5.4, illustrating that all data points in the two-beta model spread more closely around the 45-degree line relative to the CAPM model. Consistent with the full sample results, only discount rate risk factor is positively and significantly priced at 5% level with a risk premium of 1.10% per month, and the cash flow beta delivers a negative and insignificant risk price. The results from both full sample and sub-sample analysis are different from the findings of CV (2004) who emphasize on the higher risk premium of cash flow beta being the root cause to the higher average returns of value stocks which have a higher cash flow beta.

The last column in panel A of Table 5.16 shows that the model fit has greatly improved in the four-beta model, where the adjusted cross-sectional R^2 increases to 33.8% and it has the least *RMSPE* (i.e. 0.015) among three models in the first sub-sample period. This suggests that the four-beta model fits well the data in the cross-section, supported by the visual representation in panel A of Figure 5.4. The figure shows that the dispersion of each data point from the diagonal line is much smaller for the four-beta model than the other two models. All beta risks are precisely priced at 1% significance level, except the rational cash flow beta which is priced at 5% significance level. In line with the results obtained from the full sample analysis, rational beta risks carry a positive premium but the irrational beta risks carry a negative premium. Both irrational betas risks have a price of more than 50% per month (in absolute value), whereas the prices of risks for the rational betas are just slightly more than zero, *i.e.* about 3% per month.

Panel B of Table 5.16 shows that the adjusted cross-sectional R^2 statistics of all three asset pricing models have decreased in the second sub-sample period. FF (2015, p.10) mention that "we want to identify the model that is best (but imperfect) story for average returns on portfolios formed in different ways". Similarly, this study is interested at the model that performs best in the second sub-sample period even though all pricing models have a weaker explanatory power.

Across three models, the four-beta model again stands out to be the best model, delivering the highest *Adj-*R^2 statistic of 21% with the lowest *RMSPE* (i.e. 0.020). This

Table 5.16: Prices of risks across different sample periods

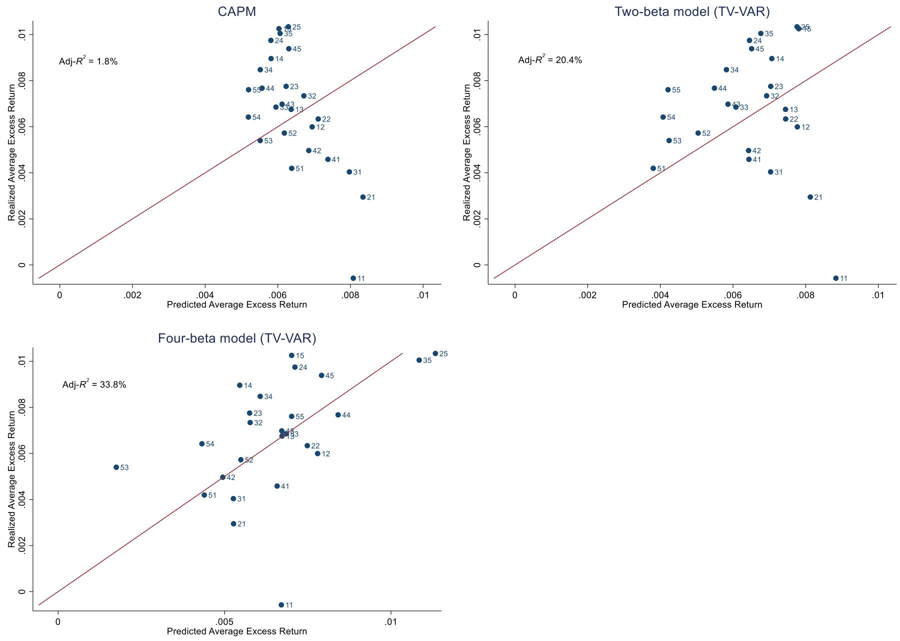
	CAPM	Two-beta model	Four-beta model (TV-VAR)
	Panel A: First sub-sample period (December 1969 - August 1997)		
λ_M	0.006**		
	[2.113]		
λ_{CF}		-0.005	
		[-0.524]	
λ_{DR}		0.011**	
		[2.144]	
λ_{CF}^{IR}			-0.577***
			[-3.752]
λ_{CF}^{R}			0.033**
			[2.469]
λ_{DR}^{IR}			-0.549***
			[-3.998]
λ_{DR}^{R}			0.026***
			[4.902]
Adj-R^2	0.018	0.204	0.338
RMSPE	0.021	0.018	0.015
MPE (%)	0.033	0.031	0.021
	Panel B: Second sub-sample period (February 1998 - December 2014)		
λ_M	0.007*		
	[1.820]		
λ_{CF}		0.001	
		[0.251]	
λ_{DR}		0.002	
		[0.637]	
λ_{CF}^{IR}			-0.242*
			[-1.785]
λ_{CF}^{R}			0.001
			[0.257]
λ_{DR}^{IR}			-0.285**
			[-2.211]
λ_{DR}^{R}			0.004
			[1.522]
Adj-R^2	-0.011	0.186	0.210
RMSPE	0.029	0.022	0.020
MPE (%)	0.016	0.013	0.010

Notes: This table presents the results of the Fama-Macbeth regression for the Capital Asset Pricing Model (CAPM), the CV's two-beta model, and the four-beta model computed with the news series retrieved from the time-varying VAR (TV-VAR) approach. Panel A reports the risk premium estimated from 1969:12 to 1997:08; Panel B provides the risk premium estimates for the period of 1998:02 to 2014:12.The test assets are 25 portfolios sorted based on size (*ME*) and book-to-market (*BE/ME*) ratio. The risk premium estimates are the time-series average of the cross-sectional parameter estimates. λ_M is the price of market risk, λ_{CF} is the price of cash flow risk, λ_{DR} is the price of discount rate risk, λ_{CF}^{IR} is the price of irrational cash flow risk, λ_{CF}^{R} is the price of rational cash flow risk, λ_{DR}^{IR} is the price of irrational discount rate risk, and λ_{DR}^{R} is the price of rational discount rate risk. The heteroskedastic and autocorrelation consistent *t*-statistics are presented in the square bracket. The adjusted cross-sectional R^2 statistic (*Adj-R^2*), the root-mean-squared-pricing-errors (*RMSPE*), the mean-pricing-errors (*MPE*) are presented in the last three rows. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

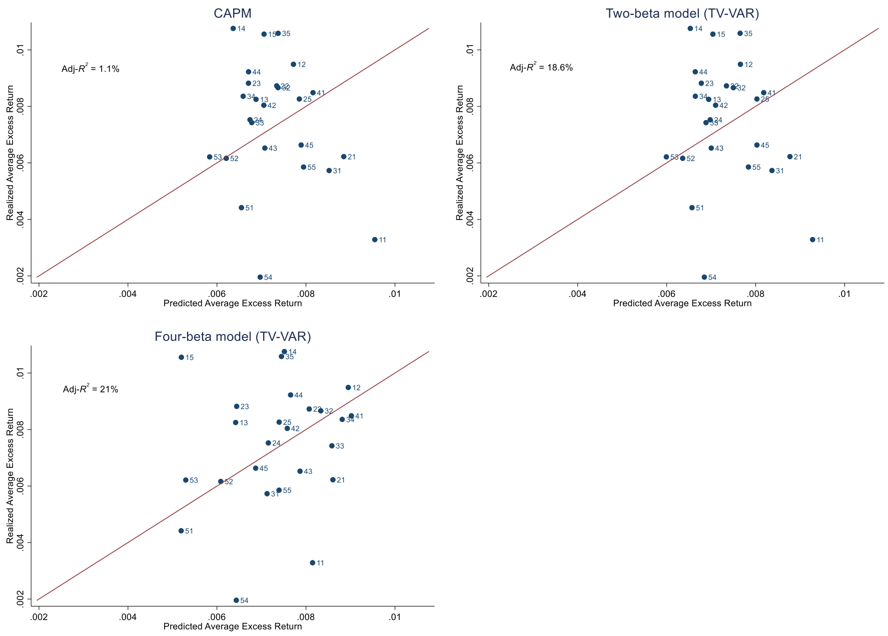
Figure 5.4: Realized vs. fitted average excess returns across different sample periods

This figure plots the realized average excess return against the predicted average excess returns on 25 portfolios sorted based on firm size and book-to-market ratio (represented as dots in the figure) for different asset pricing models: Capital Asset Pricing Model (CAPM), CV's two-beta model, four-beta model computed with the news series retrieved from the time-varying VAR (TV-VAR). The predicted average excess returns are estimated from the equation (27) for the first sub-sample period (panel A) and the second sub-sample period (panel B). The number labelled next to each dot represents the portfolio sorted according to *ME* and *BE/ME* ratio (*e.g.* double-digit 15 denotes small-value portfolio).

Panel A: First Sub-sample Period (December 1969 - August 1997)



Panel B: Second Sub-sample Period (February 1998 – December 2014)



shows that the superiority of the four-beta model in describing the cross section of average stock returns persist in the second sub-sample period. The two-beta model has a slightly lower adjusted cross-sectional R^2 statistic (i.e. 18.6%) even though disentangling $\beta_{i,M}$ into $\beta_{i,CF}$ and $\beta_{i,DR}$ does improve the model fit of the CAPM. The CAPM delivers the worst adjusted cross-sectional R^2 statistic, which is -1.10%. The failure of the CAPM model in explaining the cross-section of stock returns is clearly shown in panel B of Figure 5.4, where the pairings of the realized and predicted average excess returns for most portfolios lying far above and below the diagonal line.

The better ability of the four-beta model in explaining the cross-section of stock returns is seen in panel B of Figure 5.4, where most of the data points are lying closer to the reference line. A few portfolios are hard to be priced by all asset pricing models considered in this study, especially the small stocks, such as portfolios denoted with the two- digit numbers of 11, 14, 15 and 54. The failure to price these few assets could be the source that reduces the adjusted cross-sectional R^2 statistic of the four-beta model in the second sub-sample period.

As for the risk price of each risk factor, both $\beta_{i,CF}$ and $\beta_{i,DR}$ of the two-beta model are not significantly priced with risk premia estimates of 10 and 20 basis points, respectively. For the four-beta model, $\beta^R_{i,CF}$ and $\beta^R_{i,DR}$ have lost their influence in the cross-sectional asset pricing since the risk premia estimates of 10 basis points per month for $\beta^R_{i,CF}$ and 40 basis points per month for $\beta^R_{i,DR}$ are statistically insignificant. Contrarily, irrational beta risks remain significantly priced in the cross-section of stock returns. Both irrational betas have almost similar risk premia (20% to 30% per month in the absolute term). The findings suggest that significant risk premia for irrational beta risks are robust across different sub-sample periods. This observation is consistent with the results reported in the full sample period. Therefore, structural break in the beta estimates does not greatly affect the pricing of risk for the four-beta model despite the explanatory power reducing in the second sub-sample period.

5.7 Robustness checks on asset pricing test

This section performs some robustness checks to ensure that the performance of asset pricing test is robust to the inclusion of other portfolios and to the well-known control variables.

5.7.1 *Adding extra test asset portfolios*

The asset pricing performance obtained thus far are performed on the standard 25 size and *BE/ME* sorted portfolios – the baseline results. As the 25 size and *BE/*ME sorted portfolios (FF25) possess a factor structure that explains well the variation of average stock returns at the cross-sectional level, Lewellen et al. (2010) mention that high cross-sectional R^2 can be easily obtained from any asset pricing model as long as the risk factor considered in a model is weakly correlates to the size and value effects. To address the concern of the potential inflated risk premium and cross-sectional R^2 in the four-beta model, this section follows the suggestion of Lewellen et al. (2010) by including other test asset portfolios sorted either by other characteristics or by industry as a robustness check. They claimed that using industry portfolios provide a fairer test as compared to the use of momentum portfolios, of which the returns are hard to be explained by any asset pricing model. Hence, it would be interesting to examine also whether the results are robust to the inclusion of momentum portfolios as a test asset.

Table 5.17 presents the risk premia estimates of different asset pricing models computed based on 35 test asset portfolios for the full sample period. The analysis begins by investigating the robustness of asset pricing test results to the inclusion of additional 10 momentum sorted portfolios (10MOM) as in panel A, followed by the inclusion of additional 10 industry sorted portfolios (10IND) as in panel B. The risk premium of each factor for different asset pricing models are presented in column (1) to (5) with the values in square brackets are the Newey-West *t*-statistics. As usual, the null hypothesis of interest is $H_0 : \lambda_{j,t} = 0$ and the performance of the four-beta model is evaluated against the CAPM and CV's two-beta model.

The pricing performance of the CAPM and the two-beta model in Table 5.17 are consistent with that in Table 5.12. The CAPM consistently be the inferior model in explaining the cross section of stock returns given its lowest adjusted-R^2 statistics despite having a highly significant market risk premium estimate of 0.6% per month in both panels. As for the two-beta model, β_{DR} continue to be significantly priced when extra portfolios are included as test assets, whereas λ_{CF} remains negative and insignificant. In general, the risk premia estimates of these two models are similar regardless of the test asset portfolios being employed.

Table 5.17: Prices of risks estimated based on 35 test asset portfolios

	CAPM	Two-beta model	Four-beta model		
			TV-VAR	VAR	AF
	(1)	(2)	(3)	(4)	(5)
			Panel A: FF25 + 10MOM		
λ_M	0.006***				
	[2.631]				
λ_{CF}		-0.008			
		[-1.177]			
λ_{DR}		0.009***			
		[2.935]			
λ_{CF}^{IR}			-0.657***	-0.579***	-0.112
			[-4.973]	[-4.788]	[-0.917]
λ_{CF}^{R}			0.016**	0.016	0.026**
			[2.142]	[0.823]	[2.409]
λ_{DR}^{IR}			-0.685***	-0.782***	-0.128
			[-6.057]	[-3.021]	[-1.203]
λ_{DR}^{R}			0.023***	0.032	0.010**
			[5.710]	[1.582]	[2.233]
Adj-R^2	0.012	0.184	0.310	0.185	0.167
RMSPE	0.026	0.022	0.019	0.021	0.023
MPE (%)	0.029	0.030	0.013	0.015	0.026
			Panel B: FF25 + 10IND		
λ_M	0.006***				
	[2.835]				
λ_{CF}		-0.001			
		[-0.158]			
λ_{DR}		0.008***			
		[2.754]			
λ_{CF}^{IR}			-0.361***	-0.244**	-0.179
			[-3.620]	[-2.205]	[-1.470]
λ_{CF}^{R}			0.007	0.038**	0.017**
			[1.078]	[2.270]	[2.069]
λ_{DR}^{IR}			-0.288***	-0.470**	-0.136
			[-3.142]	[-2.069]	[-1.359]
λ_{DR}^{R}			0.017***	-0.011	0.012***
			[4.453]	[-0.605]	[2.897]
Adj-R^2	0.026	0.169	0.292	0.200	0.189
RMSPE	0.027	0.024	0.021	0.023	0.025
MPE (%)	0.025	0.026	0.010	0.011	0.015

Notes: This table presents the results of the Fama-Macbeth regression for the Capital Asset Pricing Model (CAPM), the CV's two-beta model with the news series retrieved from the time-varying VAR (TV-VAR) approach, and the four-beta models computed with the news series retrieved from the TV-VAR, the constant VAR and the analysts' forecasts (AF) approach. The test assets are 25 portfolios sorted based on size and book-to-market ratio (FF25) plus the additional ten portfolios sorted based on either momentum portfolios (10MOM) in panel A or industry (10IND) in panel B. The risk premium estimates are the time-series average of the cross-sectional parameter estimates for the period of 1969:12 – 2014:12, except the four-beta model (AF), which has the sample period of 1990:1 – 2014:12. λ_M is the price of market risk, λ_{CF} is the price of cash flow risk, λ_{DR} is the price of discount rate risk, λ_{CF}^{IR} is the price of irrational cash flow risk, λ_{CF}^{R} is the price of rational cash flow risk, λ_{DR}^{IR} is the price of irrational discount rate risk, and λ_{DR}^{R} is the price of rational discount rate risk. The heteroskedastic and autocorrelation consistent *t*-statistics are presented in the square bracket. The adjusted cross-sectional R^2 statistic (*Adj-R^2*), the root-mean-squared-pricing-errors (*RMSPE*), the mean-pricing-errors (*MPE (%)*) are presented in the last three rows. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Looking at panel A in Table 5.17, a slight drop in *Adj-*R^2 statistics is observed across the board, except the CAPM. Nevertheless, the four-beta model constructed based on the TV-VAR approach delivers the highest *Adj-*R^2 value of 31% as compared to the 18.4% of the two-beta model and 1.2% of the CAPM. Thus, this does not affect the finding that the four-beta model improves the explanatory power of CAPM and two-beta model in explaining the difference in average stock returns at the cross-sectional level.

Column (3) to (5) in panel A also show that the risk premia estimates of irrational betas are consistent with the baseline results, where the negative risk premia of these factors are highly significant at 1% level. Indeed, there is an upward shift in the risk premia (in absolute term) of irrational betas constructed under the TV-VAR framework. Similar to the baseline results, rational betas are seen to deliver positive risk premia even though they lose their significance when the news are constructed using the VAR approach.

Panel B confirms the superior performance of the four-beta model in pricing a different set of portfolios, which include FF25 and 10IND. The four-beta model constructed under the TV-VAR framework again delivers the highest adjusted cross-sectional R^2 statistic (29.2%) with the lowest pricing errors (*RMSPE* is 2.1%). The positive and negative risk premia associated with the rational and irrational risk premia, respectively, are in line with the baseline results. Most importantly, irrational beta risks have a strong presence in the pricing test across different portfolios, where these factors are significantly and negatively priced in different portfolios under the VAR frameworks.

Overall, the baseline results of the four-beta model are robust to the inclusion of additional test asset portfolios. The four-beta model is not only able to price the 25 size and *BE/ME* sorted portfolios, but also able to describe the average stock returns of momentum portfolios, which are known to be anomalous to other models, and of industry-sorted portfolios better than the other two asset pricing models.

5.7.2 Control for well-known risk factors

Since the introduction of CAPM, different risk factors have been proposed in the literature to explain the cross section of average stock returns[126]. To arrive at a firm conclusion regarding the pricing performance of the four-beta model, a set of Fama-French

[126] Review of different systematic risks proposed in the literature can be found in Campbell (2000) and Goyal (2012).

factors is incorporated as control variables in the FMB regression (5.28). Specifically, this section considers the Fama and French (1993) three factors (FF-3), Carhart (1997) four factors (FFC-4)[127], and Fama and French (2015) five factors (FF-5) as control variables in separate regressions. Incorporating FF-3 in the regression controls for the size (SMB) and value (HML) effects[128], and the FFC-4 extended from the FF-3 accounts for the additional momentum effect (UMD). Finally, including FF-5 controls for the profitability (RMW) and the investment (CMA) effects apart from the size and value effects. Grounded on the robustness test results shown in Table 5.17, where the $Adj\text{-}R^2$ statistics of the two-beta and four-beta models constructed under the TV-VAR framework are higher in panel A than that in panel B, the 35 portfolios that include FF25 and 10MOM is employed as the test assets in this sub-section.

The risk premia estimates of the CAPM, the two-beta and the four-beta models after controlling for Fame-French factors are presented in Table 5.18. Each of the three columns in every asset pricing model corresponds to the FMB regression controlling for FF-3, FFC-4 and FF-5, respectively. The results of the four-beta model show that control for size, value and momentum variables have negligible effects on the four-beta model, as reported in the columns (7) and (8). Despite a downward shift in the risk premium is observed for the irrational betas (e.g. the absolute value of λ_{CF}^{IR} drops from 0.657 in the panel A of Table 5.17 to 0.384 in the specification (7) of Table 5.18) and an upward shift in the λ_{DR}^{R} (*i.e.* risk premium estimate of 0.023 increases slightly to 0.025), all changes are immaterial. The only risk factor that is more sensitive to the control of other systematic risks is β_{CF}^{R}, where it has a negative risk premium when the FF-3 are used as control variables and loses its significance when we control for momentum effect as shown in the specification (8).

If the RMW and CMA are added to the list of control variables as in the specification (9), the signs of all risk premia estimates are in line with the baseline results although β_{CF}^{IR} has lost its significance. Since the HML factor is consistently and significantly priced in stock returns at the cross-sectional level as in columns (8) and (9), the decrease in the marginal

[127] Since Carhart (1997) four-factor model is built on the Fama and French (1993) three-factor model, this study terms it as Fama-French-Carhart four factors (FFC-4).

[128] The market risk effect in the Fama-French factor model is accounted for by the risk associated with the news series decomposed from stock market returns. Therefore, the excess market return is omitted as a risk factor in the control variable list.

Table 5.18: Prices of risks after controlling for Fama-French factors

	CAPM			Two-beta model			Four-beta model		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
λ_{M}	0.004**	0.005**	0.017***						
	[2.12]	[2.412]	[5.152]						
λ_{CF}				-0.052***	0.006	0.024***			
				[-3.665]	[0.637]	[2.807]			
λ_{DR}				0.020***	0.006*	0.018***			
				[5.166]	[1.764]	[4.120]			
λ_{CF}^{IR}							-0.384***	-0.220***	-0.037
							[-5.387]	[-3.176]	[-0.623]
λ_{CF}^{R}							-0.024**	0.012	0.030***
							[-2.088]	[1.331]	[3.512]
λ_{DR}^{IR}							-0.466***	-0.270***	-0.207***
							[-6.045]	[-3.582]	[-3.224]
λ_{DR}^{R}							0.025***	0.012***	0.019***
							[5.680]	[2.940]	[4.354]
λ_{SMB}	0.001	0.0004	0.0002	-0.009***	0.0004	0.001	-0.007***	-0.0001	0.000
	[0.683]	[0.281]	[0.148]	[-3.542]	[0.220]	[0.425]	[-3.019]	-0.053	[0.040]
λ_{HML}	0.005***	0.005***	0.006***	0.002	0.005***	0.005***	0.001	0.004***	0.006***
	[3.008]	[3.458]	[3.463]	[0.985]	[3.576]	[3.390]	[0.728]	[2.674]	[3.529]
λ_{UMD}		0.008***			0.007***			0.006***	
		[3.619]			[3.440]			[2.718]	
λ_{RMW}			0.002			0.001			0.001
			[0.705]			[0.470]			[0.378]
λ_{CMA}			0.013***			0.013***			0.013***
			[4.086]			[4.718]			[4.106]
Adj-R^2	0.332	0.478	0.467	0.416	0.486	0.473	0.442	0.511	0.493
RMSPE	0.019	0.015	0.015	0.017	0.015	0.015	0.016	0.014	0.014
MPE (%)	0.019	0.005	0.003	0.010	0.005	0.002	0.008	0.004	0.003

Notes: This table presents the results of the Fama-Macbeth regression for the Capital Asset Pricing Model (CAPM), the CV's two-beta model, and the four-beta models computed with the news series retrieved from the time-varying VAR (TV-VAR) approach. The test assets are 25 portfolios sorted based on size and book-to-market ratio (FF25) plus the additional ten portfolios sorted based on momentum (10MOM). The risk premium estimates are the time-series average of the cross-sectional parameter estimates for the period of 1969:12 – 2014:12. λ_{M} is the price of market risk, λ_{CF} is the price of cash flow risk, λ_{DR} is the price of discount rate risk, λ_{CF}^{IR} is the price of irrational cash flow risk, λ_{CF}^{R} is the price of rational cash flow risk, λ_{DR}^{IR} is the price of irrational discount rate risk, λ_{DR}^{R} is the price of rational discount rate risk, λ_{SMB} is the price for size factor, λ_{HML} is the price for value factor, λ_{UMD} is the price for momentum factor, λ_{RMW} is the price for profitability factor, and λ_{CMA} is the price for investment factor. The heteroskedastic and autocorrelation consistent *t*-statistics are presented within the square bracket. The adjusted cross-sectional R^2 (*Adj-R^2*) statistic, the root-mean-squared-pricing-errors (*RMSPE*), the mean-pricing-errors (*MPE*) are presented in the last three rows. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

effect of β_{CF}^{IR} in specification (9) could be view as a result of controlling for investment effect which has its slope coefficient statistically significant at 1% level.

Models (1) to (6) show that the risk premia estimates of the CAPM and two-beta model are generally robust to Fama-French factors. The CAPM consistently delivers a positive and significant risk premium for the market beta regardless of which control variables are being used. As for the two-beta model, the negative premium of β_{CF} becomes significant after controlling for FF-3 factors. This cash flow risk, however, commands a positive risk premium that is falling beyond two standard errors from the mean when FF-5 factors are added to the regression. This indicates that the investment effect has strengthened the power of cash flow risk in explaining average returns of different stocks.

The *Adj*-R^2 and pricing errors statistics in three different specifications, i.e. the regressions controlling for FF-3, FFC-4 and FF-5 factors, for each asset pricing model clearly depict that the cross-sectional regression controlling for FFC-4 explains better the cross-sectional variation of average stock returns. Furthermore, Table 5.18 does not only show that the pricing of the four betas generally stands firm even after controlling for the Fama-French factors, but also demonstrates the superiority of the four-beta model in explaining the difference in stock returns at the cross-sectional level given that the four-beta model consistently delivers the highest *Adj*-R^2 statistic regardless of the regression specification considered as compared to its counterparts (e.g. the *Adj*-R^2 statistics of the CAPM, the two-beta and the four-beta models after controlling for FF-5 are 46.7%, 47.3% and 49.3%, respectively).

Therefore, the baseline results that (1) the four-beta model explains the cross-sectional variation of asset returns better than the CAPM and the two-beta model, (2) the irrational beta risks are consistently priced at the cross-sectional level and carry negative premia, and (3) the rational beta risks demand a positive premium, are robust to different settings as discussed in this section.

5.8 Anomalies tests

Given the usefulness of the four-beta model in explaining the cross-sectional variation of average stock returns, it would be interesting to know whether the model can explain various equity anomalies documented in the literature. Following Campbell et al. (2018), this section considers eight anomaly portfolios and five zero-cost portfolios, which will be discussed in detailed in the following. Data are retrieved from the website of Professor Kenneth French.

5.8.1 Anomaly portfolios

Market (RMRF). The RMRF represents the market returns in excess of risk-free returns, i.e. $R_m - R_f$. The difference in stock market returns and risk-free returns is called as equity risk premium, since, on average, stocks earn higher returns than risk-free assets such as Treasury bills given their higher risk level. Nevertheless, the substantial equity risk premium is hardly justified by the standard economic theory, resulting in an anomaly termed as the equity premium puzzle. Mehra and Prescott (1985) is the first paper that documented this anomaly, where they reported an average equity risk premium of about 6% per year for the US stock market from 1889-1978 and claimed that the large return dispersion between stocks and risk-free assets can only be realized if investors are extremely averse to risk, which is implausible. Mehra (2006) and Siegel and Thaler (1997) provide a detailed review on the risk-based and behavioural models employed in the literature to explain this anomaly. Generally, the risk-based explanations built either on the utility of consumption of representative agents in a complete market or on models that focus on the idiosyncratic income shocks. On the other hand, Benartzi and Thaler (1995) propose a behavioural explanation to this puzzle, which is myopic loss aversion. Specifically, investors require a high equity premium since they are averse to losses and constantly evaluate the stock performance. Experimental tests are conducted by researchers to provide support to this possible explanation (see the review of experimental studies in Duxbury, 2015a).

Size (SMB) and Value (HML). Banz (1981) find that the risk-adjusted returns of small stocks are higher than that of large stocks. This phenomenon is termed as the size effect anomaly. Van Dijk (2011) points out that the size effect re-emerged in 2000s even though empirical studies documented its disappearance after 1980s, and this anomaly should not be ignored. Another popular anomaly – value anomaly (or effect) – discovered by Rosenberg, Reid and Lanstein (1985) is a phenomenon where stocks with high book-to-market (*BE/ME*) ratio (i.e. value stocks) outperform stocks with low *BE/ME* ratio (*i.e.* growth stocks).

These effects are then incorporated into the popular 3-factor model of Fama and French (1992; 1993) with the SMB factor refers to the return dispersion between small stocks and big stocks and the HML factor denotes the returns dispersion between high *BE/ME* stocks and low *BE/ME* stocks. On the one hand, Fama and French (1995) explain the size and value effects from the risk perspective in that the return dispersion reflects the differences in the financial distress risk, where small and value stocks consistently have poor earnings and profits and hence require higher average returns. On the other hand, Lakonishok et al. (1994) explain the value effect from the behavioural perspective. They claimed that investors naively formed the expected future cash flow growth of value and growth stocks by extrapolating the past growth. Baker and Wurgler (2006) find that investor sentiment predicts negatively the returns of small stocks, consistent with the mispricing theory[129].

Profitability (RMW) and Investment (CMA). Fama and French (2006) and Novy-Marx (2013) reveal that more profitable firms have significantly higher expected returns than less profitable firms. Meanwhile, Fama and French (2006), Titman, Wei and Xie (2004) and Xing (2008) discover that the expected returns of high-investment stocks are significantly lower than that of low-investment stocks. Therefore, Fama and French (2015) construct two factors mimicking portfolios correspond to the profitability and investment anomalous returns, which are RMW and CMA, respectively. RMW denotes the return difference between robust profitability firms and weak profitability firms; whereas CMA refers to the return spread between firms invest conservatively and firms invest aggressively. Detailed review on the explanations of these two anomalies based on both rational and behavioural perspectives are given in Section 5.2.

Momentum (UMD). Momentum effect is one of the most well-known anomalies discovered by Jegadeesh and Titman (1993). They found that stocks with high past returns continue to perform well and outperform stocks with falling prices in the past medium-term period (i.e. 3 to 12 months)[130]. Hence, UMD refers to the returns of past winners minus the returns of past losers, and is included in the Carhart (1997) 4-factor model, which is extended from the Fama and French 3-factor model. From the behavioural point of view, investors underreact or overreact to the new information (Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999), especially during high sentiment periods (Antoniou, Doukas and Subrahmanyam, 2013). Duxbury (2015b) reviews a set of experimental studies that provide confirmation to the investors' underreaction and overreaction. Conrad and Kaul (1998), on the

[129] A review on the size effect is provided by Van Dijk (2011). Different explanations on the value effect are discussed in Piotroski and So (2012).

[130] Momentum portfolio provided on the Professor Kenneth French's website is constructed using the returns from prior two months to prior 12 months.

other hand, argue that cross-sectional variation in the mean returns instead of the return patterns at the time series level is accountable for the momentum profits.

Short-term reversal (STR) and Long-term reversal (LTRVS). Jegadeesh (1990) shows that monthly stock returns exhibit a negative serial correlation and this phenomenon is termed as STR; whereas LTRVS, as documented in De Bondt and Thaler (1985), is a phenomenon where the losers outperform winners over the horizon of 3 to 5 years. Both phenomena suggest that buying losers and selling winners[131] over either the short-term or the long-term, but not over the medium term, will generate profits, presenting an anomalous return.

STR can be attributable to the (1) microstructure effects, where the profits associated with the contrarian strategy fall in the bid-ask bounce (Conrad, Gultekin and Kaul, 1997; Mech, 1993) or disappear in the presence of transaction cost (Avramov et al., 2006), (2) liquidity effect, where the profits from short-run contrarian strategy represent the compensation to liquidity providers who hold illiquid stocks (Avramov, et al., 2006; Da, et al., 2014), (3) overvaluation stemmed from biased belief (Da et al., 2014; Subrahmanyam, 2005).

As for the LTRVS, the underpinning psychological models of Barberis et al. (1998) and Daniel et al. (1998) that explain the momentum effect also contribute to the long-term price reversal, which occurs as a result of stock price reverting to fundamental value[132]. Besides that, McLean (2010) reports that idiosyncratic risk, which limits the arbitrage activities, explains the long-term reversal. Contrarily, Ball and Kothari (1989) argue that the returns spread between past winners and past losers in the long run is attributable to the difference in risk.

5.8.2 Zero-cost portfolios

Market β (BETA). It is widely known that the beta-return relationship as proposed in the CAPM does not hold (e.g. Baker, Bradley and Wurgler, 2011; Black, Jensen and Scholes, 1972, Fama and French, 1992). Accordingly, buying low-beta stocks and shorting high-beta stocks yield excess returns as mentioned in Frazzini and Pedersen (2014). Different rationales,

[131] This is called as contrarian strategy.

[132] Other studies discuss about the price reversal as a consequence of investor overreaction to the news include Chopra, Lakonishok and Ritter (1992), De Bondt and Thaler (1985) and Shiller, Fischer and Friedman (1984).

both fundamentals and behavioural, have been suggested to explain this beta anomaly, such as, time-varying risk (Jagannathan and Wang, 1996), market friction (Baker et al., 2011), and sentiment-induced mispricing (Antoniou, Doukas, Subrahmanyam, 2016; Hong and Sraer, 2016; Liu, Stambaugh and Yuan, 2018).

Accruals (ACC). Sloan (1996) show that there is a negative relationship between accruals and stock returns in the subsequent period. Therefore, one could exploit this anomaly by buying low-accruals stocks and selling high-accruals stocks. He claimed that the source of this anomaly can be explained based on the earnings fixation hypothesis, where investors fail to distinguish the persistence of accruals and cash flow components of earnings when predicting future earnings. Investors who overestimate the persistence of accruals may be too optimistic about the future prospect of the earnings of high-accruals stocks, leading to the overvaluation, which is subsequently corrected. Literature discussing on the mispricing and the risk-based explanations of accruals anomaly can be found in Detzel, Schaberl and Strauss (2018).

Net issuance (NI). The negative association between net stock issuance and expected returns has been put forward by Loughran and Ritter (1995). Subsequently, Fama and French (2008) and Pontiff and Woodgate (2008) report that NI predicts negatively and significantly the cross-sectional of average stock returns. This implies that abnormal returns can be realized from buying low-issuance stocks and selling high-issuance stocks. Baker and Wurgler (2000), Loughran and Ritter (1995) and Pontiff and Woodgate (2008) argue that more stocks are issued during the period when stocks are overvalued, leading to a price reversal in the subsequent period. Another stream of studies provides rational explanations, such as, cash-flow proxy (Fama and French, 2008) and risk-based explanation (Carlson, Fisher and Giammarino, 2006; Greenwood and Hanson, 2012).

Idiosyncratic volatility (IVOL). The notable study by Ang, Hodrick, Xing and Zhang (2006) find that stocks with higher idiosyncratic volatility earn lower average returns, attracting a bunch of studies to explain the underlying sources of this anomaly. The idiosyncratic volatility puzzle could be attributable to the risk (Chen, Chollete and Ray, 2010; Chen and Petkova, 2012), the risk-seeking attitude (Bhootra and Hur, 2015), and the arbitrage asymmetry (Stambaugh, Yu and Yuan, 2015). Other potential explanations, such as lottery preference, market frictions and other fundamental factors, are discussed in Hou and Loh

(2016). Following Fama and French (2015), this study considers two measures of IVOL – **variance of returns (VARR)**, and **variance of risk-adjusted returns (RESVAR)**[133].

As discussed above, fundamental explanation is not the only branch of the underlying sources of the anomalies discussed here. Behavioural explanation also contributes to the understanding of those anomalies. Therefore, this study conjectures that the four-beta model, which incorporates both rational and irrational risks, could explain the anomalies better than the CAPM and CV's two-beta model that do not give a role to the irrational risk factors.

5.8.3 Test results

Following Campbell et al. (2018), this study measures the ability of an asset pricing model in explaining the anomalies by comparing the abnormal returns, α, produced by different models. A model is claimed to have a superior ability in explaining the anomalies whenever it produces lower α. The abnormal returns of an anomaly portfolio is calculated as $\alpha_i = \bar{R}_i^e - E(R_i^e)$, where $\bar{R}_i^e$ is the sample mean excess return and $E(R_i^e)$ is the predicted excess returns, following Campbell et al. (2018).

The out-of-sample evaluation of anomalies is considered here. The risk premium estimate associated with each beta in the CAPM, the CV's two-beta and the four-beta models are not re-estimated. Instead, the risk premium estimates are retrieved from panel A of Table 5.17, where FF25+10MOM are used as the test asset portfolios[134]. We denote the risk premium corresponds to a particular beta as $\lambda_{35,\beta}$. The betas of each asset pricing model are re-computed to measure the sensitivity of anomaly portfolio returns to the (1) market returns in the CAPM model, (2) cash flow and discount rate news in the two-beta model, (3) rational and irrational news series of each cash flow and discount rate channel in the four-beta model. Each of these betas is denoted as $\hat{\beta}_{i,k}$, where *i* represents one of the anomaly portfolios and *k* corresponds to one of the news series (or market returns for the CAPM model). The predicted excess returns of an anomaly portfolio are then computed as $E(R_i^e) = \sum \hat{\lambda}_{35,\beta} \times \hat{\beta}_{i,k}$.

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[133] The risk-adjusted returns are the residual of FF-3 regression.

[134] The risk premia estimates computed based on FF25+10MOM are employed because this set of test asset portfolios addresses the issue of the strong factor structure of FF25 and delivers higher adjusted R^2 statistics for the two-beta and four-beta models constructed under TV-VAR framework. In fact, the general conclusion obtained in this section is unaffected by the use of FF25 or FF25+10IND as the test asset portfolios.

Table 5.19: Anomalies test performance

Strategy	μ	σ	β_{CF}^{IR}	β_{CF}^{R}	β_{DR}^{IR}	β_{DR}^{R}	α_{CAPM}	α_{2B}	α_{4B}
RMRF	0.521	4.597	0.020	0.154	0.003	0.702	-0.067	0.024	0.182
SMB	0.148	3.136	0.013	-0.128	-0.012	0.221	0.084	-0.139	-0.102
HML	0.389	2.928	-0.013	-0.053	0.004	-0.066	0.483	0.390	0.044
RMW	0.292	2.295	-0.002	0.002	0.002	-0.084	0.347	0.367	0.490
CMA	0.370	2.017	-0.018	-0.044	0.005	-0.078	0.468	0.384	-0.226
UMD	0.667	4.395	0.007	-0.053	-0.012	-0.056	0.756	0.690	0.535
STR	0.470	3.281	0.010	0.079	-0.006	0.096	0.348	0.463	0.321
LTRVS	0.291	2.577	-0.006	-0.045	-0.004	0.073	0.301	0.186	-0.467
BETA	0.008	6.699	-0.046	-0.053	0.020	-0.697	0.544	0.542	0.082
ACC	0.366	2.761	-0.003	-0.009	0.006	-0.056	0.410	0.402	0.775
NI	0.528	3.263	-0.017	0.007	0.009	-0.175	0.659	0.671	0.428
VARR	0.669	8.046	-0.057	0.044	0.020	-0.830	1.232	1.396	0.128
RESVAR	0.802	7.341	-0.048	0.130	0.018	-0.726	1.242	1.516	0.331

Notes: This table presents the performance of capital asset pricing model (CAPM), the two-beta model (2B), and the four-beta model (4B) in pricing the anomalies. Each of the anomaly strategies are discussed in Section 5.8.1 and 5.8.2. α denotes the abnormal returns of anomaly computed as the difference between the mean excess returns (μ) and the predicted excess returns computed using different asset pricing models. The test covers the period from 1969:12 to 2014:12. All data are expressed in percentage term except beta estimates.

The pricing performance of each model on the anomaly portfolios is shown in Table 5.19. The mean excess returns (μ) and the standard deviation (σ) of anomaly portfolios are reported in second and third column, respectively, followed by the four-beta estimates. The last three columns present the abnormal returns of anomalies (expressed in percentage term) computed based on the CAPM (α_{CAPM}), the two-beta model (α_{2B}), and the four-beta model (α_{4B}). The second column shows that all anomaly strategies have positive excess returns, which can be partially explained by the negative loadings associated with irrational risk components. As reported in Section 5.6 and 5.7, the irrational betas are robustly priced across assets and consistently command a negative risk premium. Therefore, assets that are highly sensitive to irrational risk components should earn lower returns and vice versa. The positive excess returns of anomaly portfolios, except the RMRF, are hence justifiable on the ground of their negative irrational betas in the cash flow and/ or discount rate channel.

The abnormal returns produced by CAPM, α_{CAPM}, are positive across all anomalies but RMRF, which has the abnormal return of slightly below zero. This implies that realized returns are generally greater than expected returns as predicted by the CAPM. As mentioned earlier, a model performs better than other models in explaining a particular anomaly when the estimated alpha has reduced. The results show that CV's two-beta model does not perform any better than the CAPM since the abnormal returns (in the absolute term) of about half of the anomalies are higher with the two-beta model. Contrarily, the four-beta model is seen to perform better than the CAPM and the two-beta model, where the model produces the lowest abnormal returns for more than half of the anomaly portfolios. The four-beta model performs exceptionally well for the anomaly strategies of idiosyncratic volatility (VARR and RESVAR), HML, and BETA with more than 80% reduction in α relative to the other two models is observed. Exceptions where the four-beta model does not perform as well as the other two models in explaining the anomalies include the returns on RMRF, SMB, RMW, LTRVS and ACC.

To get a clearer picture, the anomalies test results are summarized in Table 5.20. The mean absolute alphas, $\bar{\alpha}$, generated by different models across all anomaly strategies (All), the portfolios of Fama and French (1993) three-factor model (FF-3), the portfolios of Fama-French-Carhart (1997) four-factor model (FFC-4), and the portfolios of Fama and French (2015) five-factor model (FF-5) are presented. Both the raw and scaled mean absolute alphas are shown in the table. The scaled alpha is estimated by rescaling the mean absolute alpha of each anomaly to have the same variability as RMRF.

Table 5.20: Mean absolute alpha of asset pricing models

Strategy	$\bar{\alpha}_{CAPM}$ (%)	$\bar{\alpha}_{2B}$ (%)	$\bar{\alpha}_{4B}$ (%)
All (not scaled)	0.534	0.552	0.316
All (scaled)	0.134	0.132	0.100
FF-3 (not scaled)	0.211	0.185	0.109
FF-3 (scaled)	0.069	0.061	0.029
FFC-4 (not scaled)	0.347	0.311	0.216
FFC-4 (scaled)	0.095	0.085	0.052
FF-5 (not scaled)	0.289	0.261	0.209
FF-5 (scaled)	0.118	0.107	0.083

Notes: This table report the mean absolute alpha, $\bar{\alpha}$, of the capital asset pricing model (CAPM), the two-beta model (2B), and the four-beta model (4B) averaged across all anomaly strategies, three-factor, four-factor and five-factor anomalies. The scaled mean absolute alpha is computed as $\alpha_i \times \sigma_{RMRF} / \sigma_i$, where the alpha, α_i, and the volatility, σ_i, of anomaly portfolio are obtained from Table 5.19.

The last column clearly depicts that the four-beta model has the lowest mean absolute alpha, both scaled and unscaled, across all anomaly strategies. The anomaly returns left unattended by the four-beta model are about 0.30% and 0.10% for unscaled and scaled alpha, respectively. The two-beta model, on the other hand, have near zero reduction in the mean absolute alpha relative to the CAPM across all strategies. In fact, the unscaled mean absolute alpha of the two-beta model is slightly higher than that of the CAPM, which is 0.55% versus

0.53%. As for the Fama and French (1993) three-factor anomalies, the mean absolute abnormal returns of the four-beta model decrease from the CAPM's 0.21% to 0.11%. Similar results are observed when the Fama-French-Carhart (1997) four-factor anomalies and the Fama and French (2015) five-factor anomalies are considered, where the four-beta model has about 0.10 percentage point reduction in the unscaled alpha as compared to CAPM.

As emphasized in Lewellen et al. (2010), a model can be viewed as successful even if it explains only one or two anomalies as long as the factor structure issue is addressed by expanding the test asset portfolios. As such, the four-beta model not only can be viewed as a success, but also outperforms the other two models in describing the average returns of anomalies given the great shrink in anomaly returns averaged across all strategies. This result implies that the factors in the four-beta model capture well the risk exposures that describe the average stock returns.

5.9 Conclusion

This study decomposes the cash flow and discount rate betas of the CV's two-beta model into a four-beta model by taking into consideration the effects of irrational expectations on stock prices. Thereby, the four-beta model comprises four components, which are the rational and irrational components in each cash flow and discount rate beta. By using the four-beta model, this study investigates the channel (i.e. cash flow or discount rate) through which the investor sentiment transmits its impact on stock prices. A particular channel is claimed to be the main source of the sentiment-return relationship if irrational component in that channel is greater than in another channel. Besides that, the study also empirically evaluates the assumptions applied in previous studies, especially the claims made by CPV (2010), that the cash flow news is fundamentally driven and the discount rate news is mainly driven by investor sentiment. If these assumptions were correct, two null hypotheses should not be rejected: (1) covariances between stock returns and shocks in the irrational cash flow expectations (*i.e.* irrational cash flow beta) is zero, and (2) covariances between stock returns and shocks in the rational discount rate expectations (*i.e.* rational discount rate beta) is zero. Finally, the study also assesses whether each of the four components in the four-beta model is priced in the cross-section of average stock returns.

The baseline results are based on the cash flow and discount rate news series generated from the time-varying VAR (TV-VAR) approach on account of the fact that the predictability of each state variable on future stock market returns is varying over time. The baseline results are supported with the findings obtained from the constant VAR approach. Empirically, this study confirms that the predictive ability of investor sentiment is stemming from the cash flow channel since stock returns are relatively more sensitive to the variations in irrationally expected cash flows than in irrational discount rates.

The four-beta model also reveals that the covariances of stock returns with irrational cash flow news and rational discount rate news are indeed significantly different from zero. Thus, the null hypotheses as stated above are rejected with confidence. In fact, only the irrational cash flow beta and the rational discount rate beta are consistently having positive and significant estimates under both TV-VAR and constant VAR frameworks. Meanwhile, the structural break analysis reveals that the response of asset prices to the variations in rational discount rate expectations is robust across different sub-sample periods. Also, the significant effect of irrational cash flow news on stock prices is observed in the latest sub-sample period. All these findings reinforce the conclusion that the assumptions made in previous studies might not appropriate.

The asset pricing test of the four-beta model against the CAPM and the two-beta model shows that the four-beta model greatly improves the explanatory power, in terms of the adjusted cross-sectional R^2 statistic and the pricing errors, of the other two asset pricing models. The cross-sectional regression also shows that irrational beta risks (*i.e.* irrational cash flow and irrational discount rate betas) as well as the rational discount rate beta are priced in the cross section of stock returns. The sub-sample analysis also find that these three risk factors are consistently priced across different sub-sample periods even though the explanatory power of the four-beta model has been affected slightly in the second sub-sample period. Whilst irrational betas command negative risk premia, rational discount rate beta carries a positive risk premium across different stocks. These findings are robust to the inclusion of additional test asset portfolios as well as to the control of a set of Fama-French factors. Further empirical evaluation of the four-beta model shows that the model is useful in explaining a set of anomalies.

Overall, these findings imply that the negative sentiment-return relationship is a result of mispricing coming from the irrational expectations on future cash flows: investors might form overly optimistic forecasts on future cash flows, leading to the current stock overvaluation and the subsequent price reversal, and the reverse holds during the pessimistic period. Besides that, the variation in the cash flow expectations is not merely link to the fundamental factors, likewise, the variation in the discount rate should not be treated as mispricing news at all times. Therefore, the cash flow beta is not driven merely by fundamentals; the discount rate beta is not solely driven by sentiment. Furthermore, given that a better model fit in the cross section of stock returns is achieved by the four-beta model, the asset pricing model in the future should incorporate both irrational and rational elements into one model instead of studying their implication on the pricing of risk separately. The pricing of the four betas also suggests that investors are willing to pay a price for stocks that are sensitive to the irrational risk factors but require a risk premium for bearing the rational risks.

Chapter 6. Conclusion

6.1 Summary of findings

This thesis presents three empirical findings relating to investor sentiment and asset pricing. Given that the effect of investor sentiment in the stock market is well acknowledged and that academics have increasingly embraced the alternative explanations for the equity anomalies, this thesis concentrates on several issues: (1) how to accurately measure the investor sentiment over time (2) whether investor sentiment is more powerful in affecting the stock market as compared to the fundamental economic predictors (3) through which channel does the sentiment 'exports' its effect to the stock market (4) whether incorporating the sentiment-induced risks into the asset pricing model explains better the cross-sectional stock returns.

In the third chapter, extending the framework of Baker and Wurgler (2006), an enhanced investor sentiment index is constructed to address the weak predictive power of BW index in the time-series context. The constant loadings being assigned to each sentiment component in the index over time could be the culprit for the failure of BW index in predicting stock market returns, as this feature hinders the dynamic ability of each sentiment component to capture the latent investor sentiment across time. In view of this, Chapter 3 proposes a novel approach to accurately measure the investor sentiment by relaxing the constant contribution assumption applied to investor sentiment proxies in the BW index. Specifically, the new index is constructed by allowing the weights (i.e. contributions) of investor sentiment proxies to change through time, and hence the enhanced investor sentiment index is termed as the time-varying weighted investor sentiment index (S^{TV}). The construction of this index also avoids any look-ahead bias, another issue presented in the BW index. The validity of S^{TV} being a good proxy of investor sentiment (i.e. the sentiment values today predict negative future stock market returns) has been tested. The empirical findings confirm that S^{TV} does not only demonstrate the basic property of a good sentiment measure, but also demonstrates to be a superior investor sentiment index relative to its counterparts within the in-sample return predictive regression framework. Its superior in-sample predictive performance is not confined to the aggregate level, but is extended to the time-series of characteristics portfolio returns. In summary, Chapter 3 proposes a superior investor sentiment index that can be widely applied in future empirical studies.

The next chapter examines the main driving force behind the stock market movements after the superior predictive power of S^{TV} against its sentiment competitors, as reported in the Chapter 3, has been reaffirm within the out-of-sample framework. Although voluminous research exerts significant effort in searching for the variables that can be used to predict the stock market returns, fewer attempts are made to understand which type of predictor (i.e. sentiment or fundamentals) has overriding power in the stock market. Accordingly, Chapter 4 performs a series of out-of-sample evaluations on the forecasting performance of S^{TV} and economic predictors in predicting stock market returns. Empirically, the results demonstrate that S^{TV}-based forecasts contain unique information that are useful to forecasting stock market returns, and hence outperforms economic predictors. Although the predictive power of S^{TV} is weakened slightly under the restrictive regression framework (i.e. the forecasts reduced to HMM-based forecasts when the coefficient sign is inconsistent with the theory) as compared to the economic predictors, this result, however, shows that investor sentiment has a greater influence in the stock market. The poorer forecasting performance of S^{TV} under the restrictive regression framework reflects that stock market returns would be better predicted purely from S^{TV}. In contrast, the forecasts produced solely from economic predictors are less accurate than the mixed forecasts (i.e. the mix of fundamental-based forecasts and HMM-based forecasts in the restrictive regression). As such, economic predictors cannot be the main driving force of stock market movements. The return forecasts generated by S^{TV} are also economically more valuable than those of economic predictors based on the economic value analysis. Overall, empirical results in this study confirm that investor sentiment is relatively more important to the stock market movements given the predictive validity presented in this chapter. This could possibly explain why the economic predictors are found to have poor out-of-sample forecasting performances as documented in Welch and Goyal (2008), if investor sentiment is the main driving force of the swings in the stock market.

The last empirical study investigates the channel (i.e. cash flow or discount rate) through which the investor sentiment drives the stock market movements after having established its relatively vital role in the stock market. To this aim, inspired by the two-beta model of Campbell and Vuolteenaho (2004), Chapter 5 develops a four-beta model that consists of irrational cash flow beta, rational cash flow beta, irrational discount rate beta and rational discount rate beta. Each beta measures the comovements of 25 size- and value-sorted portfolio returns and a particular news series: irrational and rational news series in both cash flow and discount rate channel. The conclusion on the underlying source of the sentiment-return relationship is derived by comparing the beta loadings of the irrational cash flow betas to the irrational discount rate betas. The empirical results suggest that the sentiment effect on stock market returns is 'transmitted' through the cash flow channel since irrational cash flow betas are significant and are of greater magnitude than the insignificant irrational discount rate betas. Furthermore, this chapter empirically evaluates the assumptions of CPV (2010) that the fundamentals is the main element which changes the cash flow expectation; whereas investor sentiment affects the discount rates. The four beta estimates, however, do not support these assumptions, and indeed the opposites are revealed, i.e. cash flow (discount rate) news is mainly driven by investor sentiment (fundamentals). Further to the key research questions as discussed, this chapter also investigates the pricing of these four beta risks and compares the pricing performance of the four-beta model to the CAPM and the two-beta model. The results reveal that irrational (rational) beta risks command a negative (positive) risk premium, and the four-beta model has a stronger explanatory power than the other two asset pricing model on the cross-section of stock returns.

Generally, the implication emerging from this thesis is that the assumption of traditional finance theory, that only rational expectations matter and that the effect of sentiment (or noise) traders is trivial, is shown to be inappropriate. The strong predictive power of S^{TV} on the stock market returns, and indeed superior to the fundamental predictors, points out that the market is inefficient to a certain extent. This predictive ability of investor sentiment is ensued from the expectation errors in the forecasts of future cash flows, where investors might be overly optimistic or pessimistic in forming their forecasts, resulting in future price reversals when the facts unveil. However, to truly reflect the predictive power of investor sentiment on stock market returns, an accurate measure of investor sentiment is essential.

6.2 Policy and practical implications

Given the accurate measure of investor sentiment index constructed in this thesis together with an in-depth understanding on the transmission channel of the sentiment effect in the stock market, this thesis could have important implications for various parties: policy makers, practitioners and investors, and key parties participating in the corporate governance.

6.2.1 Government and policy makers

The findings from Chapter 4 that investor sentiment exerts a significantly stronger influence on stock markets than fundamental predictors in the stock market calls for policy makers' attention to closely monitor the time-varying market-wide investor sentiment. The enhanced investor sentiment index, S^{TV}, constructed in Chapter 3 allows policy makers to accurately measure investor sentiment at different times, which helps to have better return forecasts. With this information, policy makers would be able to take necessary action in a timely manner to prevent any damage to wealth, both at individual and at national level, caused by the time-varying investor sentiment.

Prior to the collapse of the Dotcom bubble, Internet stocks experienced unprecedented growth with much evidence highlighting the irrationality of investors. Ofek and Richardson (2002) show that Internet stocks are widely traded by investors[135] before the Dot-com bubble burst, with the trading volume for Internet stocks being threefold on average as compared to non-Internet stocks. They further documented that an excess return of 40.6% over a 10-year period is required to reach the excessively high implied price-earnings (PE) ratio of 605 for Internet stocks at the end of the year 1999[136]. Cooper, Dimitrov and Rau (2001) even find that an addition of ".com" to the company name generated an abnormal return of 74% accumulated for a 10-day period around the announcement day, despite little support in the literature for such a phenomenon. Furthermore, not only did the number of IPOs for Internet stocks increase tremendously during 1998-2000, but those IPOs recorded astronomically high first-day returns with an average of more than 95% (Ofek and Richardson, 2003). However, once the lockup agreements expired, the overwhelming selling pressure from pessimistic investors led the Dotcom bubble to burst, causing negative excess returns in Internet stocks (Ofek and Richardson, 2003). These phenomena support the view that investors are on aggregate overly optimistic, building up a bubble that eventually causes huge loses to investors when it bursts. Indeed, other studies also hold the same view that high investor sentiment led to the formation of various asset pricing bubbles and subsequently caused the financial crises (e.g. Brunnermeier and Nagel, 2004; Shiller, 2005; Pan, 2020; Temin and Voth, 2004; Zouaoui, Nouyrigat and Beer, 2011).

Recognizing investor sentiment as a source of fluctuations in the stock market implies that an accurate measure of market-wide investor sentiment is key to avoiding a financial crisis in the future and hence S^{TV} is important in this regard. Since Kurov (2010) and Lutz

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[135] Ofek and Richardson (2003) claim that retail investors constitute a greater proportion of participants in the Internet stocks.

[136] They employed industry's income margins in the computation of implied PE ratio for the Internet stock in a particular industry since the aggregate earnings for Internet stocks is negative.

(2015) find that investor sentiment is affected by monetary policy, policy makers could introduce appropriate monetary policy to stabilize investor sentiment given the knowledge regarding the trajectory of sentiment level produced by S^{TV} index. For instance, a tightening (expansionary) monetary policy could be introduced when investors are persistently optimistic (pessimistic) as reflect by S^{TV}, i.e. S^{TV} is above (below) its steady state value.

The findings of this thesis could also help to inform government policy on financial/ investor education. A negative relationship between investor sentiment and future stock returns indicates that investor sentiment will eventually fade away and stock prices will revert to fundamental values. Therefore, government could inform individual investors about sentiment trading and the risk of investing during periods characterised by excessive optimism. Government could also educate individual investors on how to efficiently allocate their portfolios based on their investment horizons. A passive investing strategy instead of an aggressive investing strategy could be promoted by government since investment performance is less likely to be affected by changes of investor sentiment in the long-run. This is especially beneficial to investors with long-term financial objectives. Moreover, government could advise retail investors to reduce their investment exposure in small, value and loser stocks since Chapter 3 demonstrates that these stocks are more sensitive to investor sentiment.

6.2.2 Practitioners and investors

The findings documented in Chapter 4 and Chapter 5 bring awareness to the practitioners in the finance industry that stock prices do not merely reflect the fundamental information or rational news. Instead, practitioners should pay additional attention to changes in the sentiment-induced expectations, and the enhanced investor sentiment index, S^{TV}, constructed in Chapter 3 could be useful to them in this regard. The economic values generated by the S^{TV} that captures well the sentiment risk, which are systematically priced across different stocks, indicate that portfolio managers could benefit from the use of S^{TV} in generating profits to their clients. Finally, investors could also utilise the new sentiment index to gauge the impact of investor sentiment, helping them to develop appropriate investment strategies over time.

6.2.3 Key parties participating in corporate governance

The findings that the sentiment-return relationship stem from the errors in the cash flow expectations is of relevance to the corporate governance. Since the sentiment effect has been found to be particularly strong during the expansion period and not during the recession period, any manipulation to the earnings could potentially magnify the sentiment effect when the market is in the good state and investors are optimistic. Brown, Christensen, Elliot and Mergenthaler (2011) reveal that the tendency for managers to disclose the pro forma earnings, which are usually higher than the GAAP earnings, is high when the investor sentiment is high. Their further analysis showed that managers attempt to mislead investors through favourable pro forma earnings metrics that are greatly emphasized in the earnings press releases. Similarly, Simpson (2013) finds that earnings are inflated by managers through accruals management during the high sentiment period, but rather conservative earnings are announced during low sentiment period, since sentiment traders could be 'blinded' by their optimistic expectations during high sentiment periods. Therefore, investors could potentially form an even more optimistic forecast about future cash flow due to the favourable pro forma earnings disclosure and earnings management during high sentiment periods.

To avoid the potential build-up of speculative bubbles due to the exceptionally optimistic forecasts of future cash flows, regulators might want to intervene in the disclosure of pro-forma earnings and increase inspections of financial statements that attempt to influence the investor expectations about the future cash flow especially during the high sentiment period. Boards of directors, who also tend to be shareholders, might want to be able to measure the investor sentiment using our enhanced investor sentiment index in order to gauge the tendency of managers manipulating the earnings at a particular time, and hence take the necessary precaution to ensure that managers act in shareholders' best interest. The findings of this thesis also bring awareness to the auditors. Given that stock prices are affected by irrationally expected cash flow and that managers have the motives to manipulate earnings in order to meet the expectations of sentiment traders, auditors might need to be more rigorous during the auditing process, especially when market-wide sentiment is high. Finally, standard-setters could introduce more stringent standards and guidelines to prevent managers from taking advantage of the loopholes in accounting standards, especially during the high sentiment period.

6.3 Limitations and extensions

As in any study, this thesis has its limitations as discussed below. Following the discussion of each limitation, extensions that could possibly address the limitations or future directions are also discussed in this section.

1) The arbitrary sign being assigned to principal components could be an issue in the construction of S^{TV}. Nonetheless, the PCA method has also been used in the estimation of S^{BW} and this issue has been addressed in the construction of S^{TV} by flipping the sign of first principal component (PC1) if RIPO has a negative loading. Whilst RIPO has been used as a benchmark to construct S^{TV} given the rationales discussed in Section 3.3.3, future research could consider using other sentiment proxy as a benchmark in constructing the time-varying weighted investor sentiment index.
2) Since S^{TV} is defined as the PC1 in each window, the index captures slightly less than 50% of the average proportion of variance across different windows. Nevertheless, PC1 is used to estimate S^{TV} in order to ensure that S^{TV} is comparable to S^{BW} since Baker and Wurgler (2006) also define S^{BW} as PC1. As our findings confirm that allowing the loadings of each sentiment to vary over time as in S^{TV} does enhance the accuracy of the return forecasts, future study could construct the time-varying weighted investor sentiment index by combining first and second principal components in each window that potentially explains a greater proportion of variance across different sentiment proxies, and examine whether constructing investor sentiment index in this way could further enhance the forecasts of stock market returns.
3) S^{TV} constructed in this thesis is a low-frequency sentiment measure (i.e. monthly sentiment index) that could be of practical use to long-term investors as they will not constantly and emotionally be affected by the fluctuations of investor sentiment measured at the high frequency level. Nevertheless, day traders might prefer to have a high-frequency sentiment measure (e.g. daily or intraday measure) if they would like to tap into the changes of investor sentiment on a daily basis. In view of this, future research could construct a high-frequency composite sentiment index (e.g. daily measure of sentiment) using market-based sentiment proxies. This would also produce a real-time measure of investor sentiment that might be useful to study the contemporaneous sentiment-return relationship and help to form profitable short-term trading strategies. Having a real-time sentiment measure would also help policy

makers to have a better understanding on investors' instantaneous reaction to monetary policy changes as mentioned in Sun et al. (2016).

4) Due to the data availability during which this research is conducted, the sample period of this thesis can only cover up to December 2014. Since Jeffrey Wurgler and Amit Goyal have updated their data recently, the analyses of this thesis can be extended to year 2018 in the future.

5) One limitation of the four-beta model is that irrational news series used to estimate irrational betas could have noise since they are retrieved as the predicted values of the regression of news series on investor sentiment index. Despite each sentiment proxy has been orthogonalized to fundamental factors, we might not be able to claim that fundamental information has been completely removed from sentiment proxies. Nevertheless, as mentioned in Brown and Cliff (2005, p.417), "we acknowledge that we might be missing some important rational factor, but we feel our set of control variables is a reasonable effort in mitigating this problem". Moreover, same macroeconomic variables as in Baker and Wurgler (2006) have been used in the orthogonalization process. Therefore, the approach employed in this thesis to extract information on investor sentiment is largely in line with the literature. To further confirm the results in Chapter 5, future study could possibly incorporate more macroeconomic variables in the orthogonalization process in order to remove as much fundamental information as possible. Besides that, different types of sentiment measures could also be used to retrieve irrational news series as to provide a robustness check to the findings.

6) Since the access to the Institute of Broker Estimates System (IBES) is not granted, using analysts' forecasts retrieved from Bloomberg Estimates (BEst) does not allow the results obtained in Chapter 5 to be directly comparable to the literature. Therefore, future study could consider the use of analysts' forecast obtained from IBES in the construction of the four-beta model and compare the results obtained to the results presented in this thesis.

7) Following the literature (e.g. Botshekan et al., 2012; Fama and French, 2008; Gregory, Tharyan and Christidis, 2013; Lettau and Ludvigson, 2001b), this thesis utilises the Fama-Macbeth (FMB) regression in the cross-sectional asset pricing test. Future research could consider estimating risk premia using Generalized Method of Moment (GMM) as Cochrane (2001) argues that GMM procedure accounts for the error-in-variable bias associated with the estimated regressors in the cross-sectional regression

of FMB approach. This thesis does not use the GMM approach in the asset pricing test since Jagannathan, Skoulakis and Wang (2010) mention that a long historical data on stock returns is required in the GMM procedure in order to ensure that the variance-covariance of stock returns can be estimated precisely. However, it is still worthwhile to apply the GMM approach to examine the pricing of different models, including the four-beta model, in the future.

8) Having constructed an enhanced investor sentiment index, S^{TV}, in the future, research focus on the application of this newly constructed sentiment index could be conducted. For instance, future research could investigate (1) whether S^{TV} can be used to enhanced the profitability of long-short portfolio strategies, (2) whether S^{TV} can explain the mean-variance puzzle, and (3) whether S^{TV} can accurately predict the stock market crisis.

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