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Understanding the impact of investor sentiment on the price formation process: A review of the conduct of American stock markets

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ABSTRACT

Applying both survey-based and market-based measures, we examined how investor sentiment affects the way with which prices reflect information and whether or not it manifests itself in the trading behavior of investors in the U.S. stock market. We also compared the effect of investor sentiment on several U.S. stock market indices. Our research improves our understanding of the price formation process when supporting the notion that sentiment-induced buying and selling is an important determinant of stock price variation. Our research design is novel as it suggests that sentiment-driven traders may not be as irrational as is presupposed in classical asset pricing and it provides more comprehensive statistical evidence on the impact of differing types of sentiment on the price formation process, especially in the various U.S. stock market indices. We consider that sentiment is linked to shifts in risk tolerance and this triggers contrarian-type behavior. Given this, using an EGARCH parameter estimation, we have shown the following concerning the behavior of sentiment driven investors; (i) They are more motivated to trade on survey-based indicators than market based indicators, (ii) They respond asymmetrically to shifts in sentiment and trade more aggressively during periods of declining sentiment, (iii) They respond asymmetrically to sentiment measures when incorporating the possible impact of market conditions and business cycles on trading behavior.

1. Introduction

Investor sentiment is an elusive concept which is difficult to define and ~~to~~ measure. Merton (1973, 1980) tried to study the linkages between stock price movements and intertemporal variation in relevant state factors in order to put in question traditional asset pricing models that usually leave no role for investor sentiment. Academics, practitioners and regulators expend significant resources to extract many measures of investor sentiment in order to evaluate levels of optimism and pessimism (Aggarwal, 2019; Zhou, 2018). Understanding investor sentiment is very important to practitioners for two reasons: On the one hand, sentiment indicates the general attitude or mood of investors toward a particular security or the market as a whole. Edelen et al. (2010), for instance, argued that this tone, mood or feeling can drive prices in ways which do not reflect fundamentals or changes in the investment opportunity set. Thus, it is logical that practitioners are required to monitor their portfolios for changes which can occur even in the absence of news related to underlying fundamentals. On the other hand, generally saying, investor psychology and sentiment can spread quickly through the market and this in turn impacts the risk aversion of investors and portfolio selection independently from cash flow prospects or measures of fundamental

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value. Based on the quick ability for sentiment to spread, the role sentiment plays by being involved in the prediction of some rare events such as crashes, manias, bubbles and black swans which undermine financial infrastructure and economic growth have directly interested regulators.[1] Investors are categorized as either rational and informed or irrational and sentiment-driven. Classical finance theory states that rational mean-variance optimizers are dominant in the long-term. Also, information diffusion is assumed to be shared between all market participants without restriction and therefore we can deduce that market participants act and compete equally and fairly on the basis of their merits. Consistently, Friedman (1953) noted that fair competition on competitive markets leads to equilibrium and to fairly priced securities which only reflect fundamental value whereby mispricing is proved to be a transitory phenomenon that would be quickly corrected by arbitrageurs at virtually zero cost or risk. This line of reasoning does not explicitly reject the existence of sentiment-driven investors because it leaves little room for a rigorous logical analysis concerning their role. Shleifer and Vishny (1997) have doubted that arbitrageurs can effortlessly eliminate mispricing since their resources may presumably be limited. Black (1986) said that they might be incapable of deciphering real information from noise, while De Long, Shleifer, Summers, and Waldmann (1990, 1991), and Shleifer and Summers (1990) supported the idea that they are hesitant to attack mispricing given the possibility for prices to further deviate from fundamentals. Ding et al. (2019) extended the noise trader risk model of Delong et al. (1990) to a model with multiple risky assets to demonstrate the effect of investor sentiment on the cross-section of stock returns. Their model formally demonstrates that market-wide sentiment leads to relatively higher contemporaneous returns and lower subsequent returns for stocks that are more prone to sentiment and difficult to arbitrage.According to Wurgler and Zhuravskaya (2002), stocks are considered imperfect substitutes, thus it is not possible to eliminate such potential risk. Abreu and Brunnermeier (2002, 2003) presented that arbitrageurs are not able to coordinate and synchronize their efforts in order to become a stronger driving force in the market capable of correcting mispricing.Rupande et al. (2019) hypothesized that there are movements in risk that are driven by volatility linked to sentiment-driven noise trader activity whose patterns are irreconcilable with changes in fundamental factors. Fousekis (2020) investigated the relation between stock returns and changes in risk perceptions and showed that the association between the two variables is negative, contemporaneous, non-linear, and asymmetric with respect to both the sign and ~~to~~ the size of stock returns.

Well after Keynes (1936), a growing interest in determining what role sentiment and emotions play in investment decision making and how it drives stock prices has appeared. Dumas et al. (2009) documented the fact that this interest is receiving invigorating attention particularly in light of the excess volatility we are experiencing in global stock markets and our consistent~~ly~~ failure to link fundamentals with stock price variations. Research has now taken multiple paths to understand the role of sentiment in the stock market. Sentiment directly affects the mean-variance tradeoff on the market portfolio and can be a reason for extant literature to disagree on the nature of this significant relation (Gunathilaka, 2017). Frazzini and Lamont (2008), Schmeling (2009), Stambaugh et al. (2012), and Antoniou et al. (2013), found that investor sentiment contains useful economic information which can influence stock returns. Blasco et al. (2011), and Lemmon and Ni (2010) suggested that sentiment can incite investors to adopt feedback type strategies of buying and selling in tandem with the crowd. When sentiment is high, analysts' earnings forecasts are relatively more optimistic about uncertain firms. Banholzer et al. (2019) explored how sentiment information regarding internationalstock markets can be directly incorporated into the portfolio optimization procedure. Subsequently, they showed that sentiment information can be exploited by a trading strategy that takes into account a medium-term reversal effect of sentiment onreturns.

The challenge to these studies is that sentiment is essentially a qualitative disposition coming from inside a human being resulting from a myriad of unobservable factors and cannot be easily measured or quantified. However, the manifestation of sentiment on the decision-making of investors is ~~rather~~ quantifiable to some extent. All of these elements provide an important contribution in understanding how sentiment can influence stock price movements, but the mechanism by which it affects the demand of investors for risky assets is still not clear. The Baker and Wurgler (2006, 2007) paper attempted to explain the role sentiment plays on investors' decision-making and looked for an answer: "Now, the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects."

This article is connected to the large literature on investor sentiment. For instance, Sentana and Wadhwani (1992), Shiller (1984), and Cutler et al. (1990) proposed models that link behavior of sentiment-driven investors to variations in stock prices. Baker and Wurgler (2006, 2007) presented evidence regarding how to measure investor sentiment and quantify its effects on stock prices. They also showed that their constructed measure of investor sentiment based on principal component analysis (PCA) to extract the common sentiment component from sentiment indices demonstrates the mechanism by which investors' demand for risky assets is influenced. Chau et al. (2016) examined various sentiment measures based on the market and surveys. They found that only the latter plays a significant stock pricing role. This paper has extended these studies in an important way. We considered a new explanation of the question,"whether investor sentiment affects stock prices?" using a new time-varying investor sentiment index, as well as various other measures and looked deeply at the role sentiment plays on investors' decision-making. By this, we contributed to the existing literature in several ways. First, we critiqued the sentiment construct defined in finance (Baker & Wurgler, 2006, 2007) by proposing a novel measurement of time-varying investor sentiment. Second, we extended the idea of Chau et al. (2016) towards time-varying investor sentiment in the equity market. Third, we analyzed the effect of sentiment-driven trading ~~has~~ on different U.S. stock markets or large stock indices. Previous studies that used sentiment-driven trading focused mainly on its effect on one stock market index. This study also analyzed sentiment-driven trading to forecast or explain the stock prices, returns, volatility, trading activity and liquidity of the U.S. stock market. Fourth, we explored the role of sentiments in financial decision-making and attempts to employ well defined direct and indirect sentiment measures using psychology literature. It highlighted the need to incorporate sentiments in asset pricing as a

[1] The Securities and Exchange Commission (SEC) identifies and publicly discloses behavioral and sentiment factors that cause investors to make erroneous investment decisions which impact the economy (SEC Report, 2010): http://www.sec.gov/investor/locinvestorbehaviorreport.pdf.

systematic risk factor.

We have added to the current literature on sentiment by demonstrating that it is too early to accept the classical view that sentiment-driven investors are irrational and they lead to mispricing, particularly in light of evidence that investors can make sizeable profits if they understand what the underlying sentiment is in the stock market and trade as opposed to such sentiment when it can help drive profitability. Importantly, we have shown that sentiment-driven investors know when to go against the movement of the herd and make money by selling their positions when prices are vastly overinflated due to over bullish signs and overoptimistic sentiment. Alternatively, we believe low sentiment periods to be ~~a~~ good buying opportunities. Using U.S. data, our study has highlighted that investor sentiment is indeed important and that there is a group of sentiment-driven investors who play an important role in driving stock prices. We found that investor sentiment matters for several U.S. stock markets. Additionally, experienced market knowledge investors are more attracted to trade on the information content extracted from survey-based sentiment indicators rather than market-based ones. By focusing more on this subject, we found that such investors are trading primarily based on sentiment coming from individual surveys rather than institutional ones. Regarding the time-series dynamics of sentiment changes while taking into account buying and selling decisions of such investors, we have argued that they trade more aggressively during periods of declining sentiment than rises in sentiment of the same magnitude. Asymmetry is also noticeable in the role of sentiment when we ~~do~~ examine their behavior towards markets (Lakshina, 2020).

The rest of the paper unfolds as follows. The next section derives testable hypotheses from earlier literature. Section 3 presents the econometric framework in which we explored the role of investor sentiment and describes the data set. Section 4 shows empirical results and section 5 concludes.

2. Earlier literature and hypotheses

2.1. Explaining investor sentiment studies on price formation and returns

Throughout this section we will study the impact of sentiment on price formation and returns on the stock market according to some research. First, sentiment is defined in stock valuations by the difference between noise~~s~~ traders and arbitrageurs. The noise trader is a term that is used to describe a market participant who makes investment decisions without the use of fundamental principles, shows poor market timing, follows trends and tends to exaggeratedly or inadequately react to good and bad news. Indeed, noise~~s~~ traders is a concept introduced by Kyle (1985) and Black (1986). They describe noise-makers as stock market investors who do not trade on the basis of information and make irrational investment decisions. Lee and Ready (1991) demonstrate that noise-makers are active and that they influence market prices. In terms of rationality, traders can be classified according to rational (information traders) and irrational (noise traders) informational use. In addition, investor sentiment is overly optimistic or pessimistic, so it can have an increasingly binding effect on stock prices, whose fees and arbitrage risks are becoming higher and higher. Indeed, a pronounced impact of investor sentiment is a consequence of the risks affecting high arbitrage transactions. From this perspective, Bessière and Kaestner (2008) studied the link between optimism heuristic and under- and over-reaction phenomena to information in relation with the burst of internet bubbles (2000–2001). Based on ~~the~~ U.S. data, they have noticed that before the burst financial analysts seem to react to good news. After the burst, there appears to be a caution effect since over-reactions to extreme information and under-reactions to extreme negative information have decreased. Similarly, Bessière and Elkemali (2012) used European data, to show that analysts are optimistic before the burst and pessimistic after the burst with a very noticeable effect for high-tech firms. Furthermore, Baker and Wurgler (2006, 2007) predicted that broad waves of sentiment will have greater effects on hard to arbitrage and hard to value stocks.These stocks will exhibit high "sentiment beta." Sun et al. (2016) showed that the sentiment of high frequency investors also appears to have ~~a~~ significant economic value when assessed with temporal trading strategies of the market. In fact, behavioral finance literature highlights the undesirable effect of financial players' sentiment on financial market returns. Kothari and Shanken (1997) examined the relationship between the globalized accounting ratio (book to market) and the performance of US stocks over the period 1926–1941. They found that negative risk premiums are associated with higher book to market ratios in the market. They argued that the investor sentiment hypothesis could explain this evidence which is inconsistent with market efficiency. Baker and Wurgler (2000) have noted that the total number of new shares and the debts problem are also a strong contrarian predictor of U.S. stock market returns between 1928 and 1997.

Lee et al. (2002) pointed out, that the magnitude of bullish (bearish) shifts in sentiment, leads to higher (lower) excess market returns on a sample covering the period 1973–1995. Baker and Wurgler (2007) showed that investor sentiment has important and regular effects on individual firms and the stock market as a whole. Nevertheless, Brown and Cliff (2004) studied the correlation between sentiment and market performance and found that changes in survey measures composed of investor sentiment are highly correlated with contemporary market returns. In addition, Balcilar et al. (2017) showed that the effect of investor sentiment is more widespread in intraday volatility on the gold market than daily returns. Investor sentiment is used to model leaps in stock price volatility and manage risk. Zhu and Niu (2016) found that investor sentiment can alter both growth in expected earnings and the required rate of return. Also, they have noticed that the sentiment effect during the pessimistic period is obviously different from the one where sentiment is relatively high, especially for the required rate of return. Kim et al. (2014) used in-sample and out-of-sample analyses to demonstrate that investor sentiment has a significant impact on the stock market return predictability of disagreement. Frugier (2016) found that there are structural breaks on the returns of a single stock (Volkswagen). However, the volatility of all 46 shares is characterized by structural breaks at dates often different from one stock to another. The virtual absence of structural breaks on returns is an element that supports the stability of their model. Their study is empirical; thus volatility breaks do not create a modeling problem. They confirm that volatility

Table 1
Summary of previous research relevant to investor sentiment impact on asset prices and returns.

Authors	Sample	Data	Methodology	Results
Kim et al. (2014)	U.S. stock markets: NYSE, AMEX, and NASDAQ	market-based investor sentiment measure suggested by Baker and Wurgler (2007)	Regression models to examine the influence of investor sentiment on the relationship between disagreements among investors and future stock market returns.	Investor sentiment has a significant impact on the stock market return predictability of disagreement through in-sample and out-of-sample analyses.
Zhong-Xin et al. (2015)	Chinese A-share stock market	Investor sentiment index (SENT)	Employ panel quantile regression model to investigate the nonlinear effect of investor sentiment on monthly stock returns.	The influence of investor sentiment is significant from 1 month to 24 months vis-a-vis stock returns.
Kumari and Mahakud (2015)	Indian stock market	A new irrational aggregate sentiment index (IASI) based on Brown and Cliff (2004), Baker and Wurgler (2006), and Verma and Soydemir (2009).	The vector autoregression (VAR) carried out to analyze the relationship between the volatility of irrational aggregate sentiment index and stock market volatility.	-a unidirectional causality from sentiment to stock market volatility. -the significance of sentiment in explaining the stock market volatility in India
Da et al. (2015)	U.S. stock market	Construct a Financial and Economic Attitudes Revealed by Search (FEARS) index as a new measure of investor sentiment	Regression~~s~~ models to examine the relationship between FEARS and asset returns, stock market return volatility and fund flows.	FEARS index can predict short-term return reversals, temporary increases in volatility, and mutual fund flows out of equity funds and into bond funds.
Wei et al. (2015)	Taiwan stock market	Aggregate news sentiment index (ANSI): - Daily aggregate news sentiment index (DANSI) -Weekly aggregate news sentiment index (WANSI) -Monthly aggregate news sentiment index (MANSI)	Analyze the relationship between the ANSI and the market responses.	-Both the weekly and monthly ANSIs are leading indicators of market returns. -There is a strong correlation between ANSI and market returns (Taiwan Capitalization-weighted Stock Index (TAIEX)) which proves that ANSI levels and the resultant market responses are significantly correlated.
Zhu and Niu (2016)	Chinese A-share stock market	The method proposed by Baker and Wurgler (2006) based on (PCA) to develop the investor sentiment index of China's stock market.	Panel data regression models to investigate the joint effect of sentiment and accounting information on stock price and highlight the asymmetric effect of investor sentiment.	- Investor sentiment can change both the expected earnings growth and the required rate of return, thus affecting the stock price. - Investor sentiment effect during pessimistic periods is evidently different from that when sentiment is relatively high, especially for the required rate of return.
Sun et al. (2016)	U.S. stock market: S&P 500 index and bond index ETF (ticker symbol SPY)	Thomson Reuters MarketPsych Indices (TRMI) as an investor sentiment measure	Regression models to explore the predictive relation between high-frequency investor sentiment and stock market returns.	-Evidence that intraday S&P 500 index returns are predictable using half-hour lagged investor sentiment. The predictive power is also found in other stock and bond index ETFs. -High-frequency investor sentiment also appears to have significant economic value when evaluated with market timing trading strategies.
Yang and Zhou (2016)	Chinese A-share stock market: Shenzhen Composite Index, Shanghai Composite Index, and the CSI 300 Index	The first principle component by Baker and Wurgler (2006) to form the individual stock investor sentiment index using common variation in four underlying proxies of stock for sentiment.	Regression models to investigate the joint effects of individual stock crowded trades and individual stock investor sentiment on excess returns.	-The positive combined effect of individual stock crowded trades and individual stock investor sentiment on excess returns reveals the importance of anomaly factors in asset pricing. -Increasing individual stock buyer-initiated crowded trades will simultaneously increase excess returns and increasing individual stock seller-initiated crowded trades will decrease excess returns. -The importance of individual stock crowded trades and individual stock investor sentiment on the formation of stock prices.
Frugier (2016)	European blue chip stocks: daily closing prices of 46 shares composing the Euro Stoxx 50 index.	The CBOE put call ratio and the State Street Investor Confidence Index as measures of investor sentiment.	GARCH regression models to examine the performance of different portfolios composed of stocks of large European companies and to demonstrate a link between investor sentiment, stock volatility and future returns.	-Portfolios managed with investor sentiment have better returns and involve less risk under certain conditions. -The model seems stable and it does not modify the presence or absence of structural breaks on individual stocks, but the unconditional variance of managed

(*continued on next page*)

Table 1 (*continued*)

Authors	Sample	Data	Methodology	Results
				portfolios cannot be used for modeling time-varying returns.
Balcilar et al. (2017)	Gold market	The Financial and Economic Attitudes Revealed by Search (FEARS) index recently developed by Da et al. (2015) as a proxy for investor sentiment	GARCH-type models to examine nonlinear casual effects of sentiment on gold return and volatility.	- The effect of investor sentiment is more prevalent on intraday volatility in the gold market, rather than daily returns. - The investor sentiment could be utilized to model volatility jumps in safe haven assets that are often hard to predict and have significant implications for risk management as well as the pricing of options.
Xie and Wang (2017)	Chinese stock market	The Search Index of the Shanghai Stock Index, released by the website Baidu is used to measure investor sentiment on online platforms (denoted by SENINDEX).	Cointegration and Granger Causality Test between investor sentiment and the asset price movement.	- There is a cointegration relationship between online investor sentiment and asset return.The sentiment has a poor ability to predict the price, return, and volatility of asset price. - The empirical mode decomposition of online investor sentiment shows that high frequency components of online investor sentiment can be used to predict the asset price movement.
Li et al. (2018)	Chinese stock markets	The foreign sentiment proxy is originally extracted from Twitter by the Hedonometer Team, which analyses roughly 10% of all English tweets dating back to September 2008	Granger causality to examine the lead-lag relationship	- Foreign sentiment can only influence returns on market and industry indices when investors are in their extreme states of mind. - Significant sentiment contagion exists during the tranquil period, while no sentiment contagion exists during the turbulent period.
Qi et al. (2018)	Chinese Energy stock market: PetroChina Company Limited	Sentiment indicator of the 96,839 titles based on the BosonNLP sentiment analysis engine	Pearson correlation coefficient to test whether there is a correlation between investor sentiment fluctuation and stock price fluctuation.	Investor sentiment experienced stable fluctuations over the past five years, and stock returns fluctuated within the range of investors' acceptable volatility.

varies over time. Selected securities in managed portfolios should therefore not be the same throughout the study period. Kumari and Mahakud (2015) observed a significant effect of investor sentiment on stock market volatility and past returns. The pastinvestor sentiment affects the volatility negatively and positively. The negative investor sentiment influences volatility and supports the proposition that the noise traders' pessimism makes the markets highly volatile. They also suggest investor sentiment captures the volatility asymmetry patterns in the returns. Qi et al. (2018) examined the relationship between investor sentiment and stock price volatility, and showed that Petro China investor sentiment experienced stable fluctuations over the past five years, and stock returns fluctuated within the range of investors' acceptable volatility.

More recently with the quick development of online platforms that provide financial news and opinions, the question of whether investor sentiment expressed on Internet platforms has an impact on asset return has attracted the attention of recent researchers. Xie and Wang (2017) used the Baidu Searching Index as the variable agent to detect the effect of online investor sentiment on the asset price movement in the Chinese stock market. Theirstudy showed that although there is a cointegration relationship between online investor sentiment and asset return, the sentiment has a poor ability to predict the price, return, and volatility of the asset price. Based on the empirical mode decomposition of online investor sentiment, the authors found that high frequency components of online investor sentiment can be used to predict the asset price movement. Li et al. (2018) used a uniquely mismatched sample of investor sentiment extracted from Twitter and the Chinese stock markets, showed that foreign sentiment has a material impact on Chinese stock markets at both the market and industry levels. In particular, they found that (1) for the contemporaneous relationship, foreign sentiment can only influence returns on market and industry indices when investors are in their extreme states of mind, and (2) asignificant sentiment contagion exists during the tranquil period, while no sentiment contagion exists during the turbulent period. Table 1 concerns the relevant studies of investor sentiment linked to future asset prices and stock returns.

2.2. Hypotheses

As discussed above, the mechanism by which sentiment affects investors' demand for risky financial assets is not clear yet. Classical and behavioral finance authors (De Long et al., 1991, 1990; Ding et al., 2019; Rupande et al., 2019; Shiller, 2000; Shleifer & Vishny, 1997) reflected the view that sentiment-driven investors are primarily noise traders andirrational investors. However, it is very possible that these investors use information extracted from sentiment measures to make informed decisions. For instance, according to Soros (1987), the key to success is not to arbitrage when investors herd, but instead to ride the wave along with herding investors and sell out near the top. Therefore, it is not surprising that invested investors and investors who are awaiting an opportunity to invest have a wealth of analyst services, as well as survey-based indicators designed to gauge the overall sentiment in the market. Baker and Wurgler (2007) and others have shown the presence of sentiment-driven investors and their possible impact on stock price movements. Then, examining whether investors trade on sentiment and in which ways they do so provides a reasonable starting point for discussion. In other words, do investors respond to the information content of investor sentiment measures and how does their demand for risky assets vary along with changes in sentiment? This makes up our first hypothesis:

Hypothesis 1. There is sentiment-driven buying and selling in the different U.S. stock markets.

From the point of view of market timers, it is useful to know which sentiment measures are important and which ones are related to changes in risk aversion and future expectations. By knowing which measures of sentiment they must take into account, they can effectively position themselves either to engage in momentum strategies or to invest against such a sentiment. There is a very large number of market-based measures and survey-based measures of investor sentiment. Behavioral academic research has also constructed such measures in order to identify factors which influence sentiment and how such sentiment drives stock price movements (Baker & Wurgler, 2006). This large universe of sentiment measures reflects the growing demand for such measures from investors. This study has tried to answer the following research question: Are sentiment-driven investors actually using the measures constructed from investor surveys or market-based measures? We have assumed that the information content derived from survey-based indicators is more useful since it is compiled from potential investors' expectations and market outlook. We have further assumed that the information content of individual investor sentiment measuresis particularly important considering the individual investors may be more inclined toward irrationality and misinformation compared to their institutional counterparts. Whether or not they are more susceptible to these biases, this can provide good investing opportunities in both directions for intelligent investors. Verma and Verma (2008) argued that institutional investor sentiments are more rational than individual investor sentiments. In addition, Schmeling (2007) found that the sentiment of individual investors is closely watched by institutional investors because they considered it a potential source of noise trader risk when forming their expectations. Given these results, trading on the basis of survey-based sentiment measures from individual investors might be more useful since their forward-looking expectations are more subject to biases which can move away stock prices from fundamental values for an indefinite period of time. This forms our second hypothesis:

Hypothesis 2. The sentiment constructed from survey-based measures is what impacts the different U.S. stock markets.

It is also very interesting to see if the direction of sentiment changes impacts the buying and selling behavior of sentiment-driven investors differently. Baumeister et al. (2001), Peeters (1991), and Huynh et al. (2020) described negativity bias or negativity effect as a psychological phenomenon by which humans tend to give greater weight and emphasis to negative information rather than positive information of an equal magnitude. In light of this, sentiment-driven investors are expected to trade more aggressively on declining sentiment periods than on rising sentiment periods of approximately equal magnitude in regards to optimism or pessimism. Therefore, our third hypothesis is:

Hypothesis 3. There exists an asymmetry effect in the role sentiment plays. Sentiment-driven investors trade more aggressively during periods of declining sentiment in the different U.S. stock markets.

Finally, we turned our attention to see if there is asymmetry in the role of sentiment when incorporating business conditions whereby buying and selling is more pronounced during bear market periods. We considered that poor market conditions and declining stock prices may exacerbate irrational trading by individual investors (Lakshina, 2020). Thus, it is possible that prices move further from fundamentals leading to better than usual buying or selling opportunities for investors who keep a watchful eye on sentiment. This theoretical development leads us to postulate our fourth hypothesis:

Hypothesis 4. There exists an asymmetry effect in the role sentiment plays considering the market conditions and business cycles. Sentiment-driven investors trade more aggressively during periods of bear markets in the different U.S. stock markets.

3. Methodology and data

3.1. Theoretical framework

Based on the work of Chau et al. (2016), which represents an extension of the framework of Shiller (1984) and Sentana and Wadhwani (1992), a theoretical framework was used to explore the interaction of sentiment-driven investors with other heterogeneous investors and to test the above mentioned hypotheses. The relationship between investor sentiment and market returns can be described by the following equation:

$$R_t = \omega + \theta\sigma_t^2 + \left(\phi_0 + \phi_1\sigma_t^2\right)R_{t-1} + \gamma\sigma_t^2\Delta IS_{t-1} + \varepsilon_t \tag{1}$$

Where R_t is the return of actual period t, $\omega$is the risk-free rate of return, θ is the coefficient of relative risk aversion, and $\sigma_t^2$is the conditionalvariance (risk) in period t. According to a theory in finance,a positive and significant sign forθ denotes a positive risk-return tradeoff,

where$\phi_1 = -\rho\theta$ and $\gamma = -\lambda\theta$. The presence of risk-averse rational investors as described in equation (1) implies that θ is positive and statistically significant($\theta > 0$). However, if there is positive feedback trading, it is implied that ϕ_1 is negative and statistically significant.The coefficient ϕ_0 is also added to account for the autocorrelation due to non-synchronous trading or market inefficiencies. Finally, the presence of sentiment-driven investors who trade against the emotions of their peers would imply that γ is positive and statistically significant. If there is no sentiment-driven trading (i.e.$\gamma = 0$),then equation (1) reduces to the feedback trading model proposed by Sentana and Wadhwani (1992):

$$R_t = \omega + \theta\sigma_t^2 + \left(\phi_0 + \phi_1\sigma_t^2\right)R_{t-1} + \varepsilon_t \tag{2}$$

Hereafter, this model is referred to as the baseline model.Note that in the model associated with equation (1), the reaction of sentiment-driven traders to sentiment changes is symmetric. Such a symmetric reaction implicitly posits that positive and negative changes have the same effects on their demand for shares. This was named as the symmetric effects model throughout this research. As an alternative model, the possibility that their demand function is affected in an asymmetric way was also entertained:

$$S_t = \lambda^+\left(\Delta IS_{t-1}^+\right) + \lambda^-\left(\Delta IS_{t-1}^-\right) \tag{3}$$

Here in the indicator of sentiment change is decomposed into positive and negative terms such$\Delta S_{t-1} = \Delta IS_{t-1}^+ + \Delta IS_{t-1}^-$; whereby$\Delta IS_{t-1}^+ = \max(\Delta IS_{t-1}, 0)$ and $\Delta IS_{t-1}^- = \min(\Delta IS_{t-1}, 0)$.In this case, the reaction of sentiment-driven traders to variations in sentiment differs if$\lambda^+ \neq \lambda^-$. After substituting and rearranging, we get the following:

$$R_t = \omega + \theta\sigma_t^2 - \rho\left(\theta\sigma_t^2\right)R_{t-1} - \lambda^+\left(\theta\sigma_t^2\right)\Delta IS_{t-1}^+ - \lambda^-\left(\theta\sigma_t^2\right)\Delta IS_{t-1}^- + \varepsilon_t \tag{4}$$

Equation (4) can be re-parameterized and expressed in a simplified form as follows:

$$R_t = \omega + \theta\sigma_t^2 + \left(\phi_0 + \phi_1\sigma_t^2\right)R_{t-1} + \gamma^+\sigma_t^2\Delta IS_{t-1}^+ + \gamma^-\sigma_t^2\Delta IS_{t-1}^- + \varepsilon_t \tag{5}$$

Where$\phi_1 = -\rho\theta$, $\gamma^+ = -\lambda^+\theta$ and $\gamma^- = -\lambda^-\theta$. Hereafter equation (5) is referred to as the asymmetric effects model. In this analysis, a number of configurations for the original model were estimated to include the specification outlined by Sentana and Wadhwani (1992). This does not include the impact of sentiment-driven investors (i.e., the baseline model), and the symmetric effects and asymmetric effects models, respectively.Completion of these models requires a specification of the conditional variance(σ_t^2). In this paper, σ_t^2 was estimated using an exponential GARCH (EGARCH) process of order (1,1) (Nelson, 1991):

$$Ln\left(\sigma_t^2\right) = \alpha_0 + \alpha_1\left[\left(|Z_{t-1}| - E|Z_{t-1}|\right) + \delta Z_{t-1}\right] + \beta Ln\left(\sigma_t^2\right) \tag{6}$$

Where $Ln(\sigma_t^2)$are natural logarithms and $Z_{t-1} = \varepsilon_t/_{\sigma_t}$ are standardized residuals. The EGARCH (1,1) specification allows the conditional variance to be time-varying and to respond asymmetricallyto positive and negative return innovations. Additionally, it also has the advantage of requiring no non-negativity constraints to ensure a positive conditional variance.[2]

Given the initial values for ε_t and σ_t^2, the parameters of each model can be simultaneously estimated by maximum likelihood. The maximization technique used in this paper is based on the algorithm suggested by Berndt et al. (1974). It was assumed that the innovations were drawn from a normal density function. If error terms are not normally distributed, Bollerslev and Wooldridge (1992) robust standard errors are employed.[3]

3.2. Data

To empirically address the aforementioned hypotheses, monthly data for the period from January 1990 to December 2017 was used. A number of market- and survey-based investor sentiment measures were collected. These measures have been widely used in literature to gauge the sentiment of market participants. In addition to the sentiment measures, price series data on the S&P 500 index were obtained. These covered the nine different sectors used (S&P 500 global index, S&P 500 financial index, S&P 500 consumer discretionary index, S&P 500 consumer staples index, S&P 500 energy index, S&P 500 information technology index, S&P 500 utilities index, S&P 500 telecom index and S&P 500 materials index) to proxy for the overall performance of the U.S. stock markets. Continuously compounded returns from these price series were estimated for the period January 1990 to December 2015. The data were retrieved through use of the Thomson Reuters online database (Datastream).

3.2.1. Market-based investor sentiment measures

Market-based measures, which are sometimes called ~~as~~ indirect measures, rely on market data that correlate with investor sentiment. Baker and Wurgler (2006) combine several single market-based proxies into a composite sentiment index, S^{BW}.This index is constructed from the following six market-based variables: NYSE turnover (TURN), closed-end fund discount (CEFD), number of IPOs(NIPO), average first-day return on IPOs(RIPO), equity shares in new issues(S), and dividend premium(PDND), respectively. To remove the effect of business cycle variation, they regress each of these variables against a set of macroeconomic factors and use the first principal component of the residuals as an orthogonalized sentiment index.[4]*VIX* is another commonly used market-based measure. It is the implied volatility computed from S&P 500 index option prices and is often known as the investor fear gauge (the Chicago Board Options Exchange's volatility index). The VIX index is constructed fromimplied volatilities of S&P 500 index options and has often been used by traders as a sentiment indicator since its introduction in 1993 (Whaley, 2000, 2009). The monthly series of the VIX index was retrieved from Datastream[5] for the period of January 1990 to December 2015.

3.2.2. Survey-based investor sentiment measures

Survey-based or direct measures are constructed by gathering the responses of people regarding their expectations of the stock market and the general economic condition. Their attitudes and perceptions reveal their views as optimistic or pessimistic. Popular survey-based measures include but are not limited to Investor Intelligence (*II*), Association of Individual Investors (*AAII*), Consumer Confidence Index (*CCI*), Michigan Consumer Sentiment Index (*MS*). All these measures, except II, represent the individual investor sentiment since they are targeted at individual investor~~s'~~ perception. Contrarily, II can be viewed as institutional investor sentiment since investment newsletters are mainly written by professionals (Brown & Cliff, 2004).

Three additional survey-based measures of individual investor sentiment were employed.*AAII* collect market participant responses on a weekly basis by asking their members whether they think the stock market in the next six months will increase, decrease or remain unchanged, and so ~~to~~ capture the bullish, bearish or neutral mood of investors.This index has been published since July 1987 and has been adopted in work such as Wang et al. (2006). Wang et al. (2006) was followed and a ratio of the bullish percentage to the bearish percentage was computed as the measure of sentiment for individual investors.[6]

The consumer confidence index (*CCI*) and consumer sentiment index by the University of Michigan (*MS*) are monthly survey-based measures of investor sentiment that have been used concurrently in many studies since both indices reveal consumer confidence towards the overall economic conditions. *CCI* is created by mailing the questionnaire to the targeted household every month. The consumers indicate their current view and expectation regarding business conditions and employment as well as their expected family income. Thus, *CCI* reveals the current and future economic conditions from the consumer perspective.

MS, on the other hand, is concerned more about the expected change in the general economy. Apart from this, the survey asks about the respondents' current and expected personal financial conditions and their view regarding buying durable goods at the present economic condition. The monthly series of *CCI* was extracted from the Bloomberg terminal and *MS*has been published by the University of Michigan[7] since 1952 for the period between January 1990 and December 2015, for which both consumer confidence surveys are available monthly.[8]

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[3] Our estimation can also be interpreted as a quasi-maximum likelihood method.

[4] See Baker and Wurgler (2006) for more details on the construction of this market-based sentiment index. The monthly series of the orthogonalized index of investor sentiment is available from August 1965 to December 2014 at Jeffrey Wurgler's website (http://pages.stern.nyu.edu/~jwurgler/).

[5] VIX is available from January 1990 to December 2017.

[6] For the empirical analysis in this paper, the weekly AAII survey results were collected from http://www.aaii.com/available for the period between July 24, 1987 and December 31, 2017.

[7] See http://www.sca.isr.umich.edu/tables.html.

[8] These consumer confidence indicators are computed using a set of questionnaire results about the participants' view and outlook for the U.S. economy. However, the earlier parts of CCI and MS indices were not published monthly. The CCI was released every two months prior to January 1977 and the MS was released every quarter prior to January 1978. Further information about these two indices is available at https://www.conference-board.org/and http://www.sca.isr.umich.edu/.

3.2.3. Construction of Baker and Wurgler (2006, 2007) investor sentiment index (S^{BW})

To construct the US sentiment index(S^{BW}), Baker and Wurgler's (2006, 2007) methodology based on the extraction of the common sentiment component from six investor sentiment proxies was used. These proxies included dividend premium (PDND), average first-day returns on IPOs (RIPO), the number on IPOs (NIPO), the closed-end fund discount (CEFD), market turnover (TURN) and the equity share in new issue (S). Specifically, the principal component analysis (PCA) was employed and the index was defined as the first principal component of the six underlying investor sentiment proxies for the whole sample period.

For this end, a number of statistical procedures were adopted. First, the various sentiment proxies were clearly measured on different scales. Hence, each indicator was standardized before it was used for further analysis. The standardization procedure removed the (undesirable) deterministic trend and also helped to ensure the stationarity of the time series. Second, prior literature noted that shifts in these sentiment proxies have both a rational component and an irrational one. The rational component relates to the changes in macro fundamental, as sentiment investor receives a noisy signal about the overall economy. To remove, or at least alleviate, the rational effect, Baker and Wurgler (2006) and Verma and Soydemir (2009)'s orthogonalization procedure was followed. This regressed each individual proxy on a set of macro variables (namely the growth of industrial production (ΔINDPRO), real growth of durable consumption (ΔCONSDUR), real growth of nondurable consumption (ΔCONSNON), real growth of services consumption (ΔCONSSERV), and growth in employment (ΔEMPLOPY))as shown below:

$$S_{i,t}^{BW} = \alpha_i + \beta_{1,i}INDPRO_{i,t} + \beta_{2,i}CONSDUR_{i,t} + \beta_{3,i}CONSNON_{i,t} + \beta_{4,i}CONSSERV_{i,t} + \beta_{5,i}EMPLOPY_{i,t} + \varepsilon_{i,t} \tag{7}$$

In this regression, ($SENT_{i,t}$) is one of the many sentiment proxies as described above. Consistent with related literature (Baker & Wurgler, 2006, 2007; Brown & Cliff, 2004), the residuals ($\varepsilon_{i,t}$) of the orthogonalization procedure are then the proxies for the irrational part of investor sentiment. Summary statistics of the individual orthogonalized sentiment proxies are presented in Table 2.

Correlations between all orthogonalized sentiment proxies are reported in Table 3. Results show that the sentiment proxies are strongly correlated.

Third, the principal component approach (PCA) was adopted for measuring the common variations and to isolate the common components in these six sentiment proxies. The principal component analysis filters out idiosyncratic noise in the orthogonal sentiment proxies and captures their common component. Also, the relative timing of the given orthogonalized proxies may reflect a given shift in the sentiment earlier than others. Following Baker and Wurgler (2006, 2007), all the respective proxies and their lags were sent as inputs for the PCA to estimate the first principal component of these proxies and their lags which were referred to as the first stage index. Subsequently, correlations were computed between the first stage index and the current and lagged proxies. The final sentiment index was then calculated as the first principal component of the correlation matrix of the input orthogonalized sentiment proxies and each respective proxy's lead or lag, whichever had higher correlation with the first-stage index. Thus, the sentiment index, denoted as (S_t^{BW}) was constructed from their respective sentiment proxies. The factor loadings of the sentiment index constructed on the basis of PCA are shown in Table 4. The first component explains (67.45%) of the sample variance, capturing the co-movement of individual sentiment proxies. All six proxies have the expected sign, confirming the positive relation with the principal component. As expected, positive correlations were found for all proxies.

3.2.4. Construction of rolling window investor sentiment index

Similar proxies were used in this study to construct an improved investor sentiment index, S^{RW}. The updated monthly data of S^{BW}, sentiment proxies and macroeconomic variables used to remove the business cycle component from the sentiment proxies were obtained from Jeffrey Wurgler's website.[9] For this paper, index $S^{RW}$was constructed on a rolling window basis and hence excluded obsolete information. Following Baker and Wurgler (2006, 2007), principal component analysis (PCA) was used in this study to extract the common component that is related to investor sentiment from different sentiment proxies. The main difference between this index and S^{BW} is that, $S^{RW}$was constructed on a rolling window basis to effectively capture the dynamic contributions of sentiment components to S^{RW}. Following Baker et al. (2012) and Finter, Niessen-Ruenziand Ruenzi (2012), this study adopted contemporaneous proxies in the construction ofS^{RW}. Fig. 1 clearly depicts the construction of this index.

A window length of three years[10]was used in the construction of S^{RW} with the first window running from January 1990 until December 1992. As in Baker and Wurgler (2006, 2007), each proxy was first orthogonalized against a set of 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($\Delta CONSSERV$), and growth in employment($\Delta EMPLOPY$). This was done to remove the components that are related to macroeconomic conditions. The resulting residuals were standardized to have zero mean and unit variance before being applied to the principal component analysis (PCA). A new series of investor sentiment indices, which were

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

[10] Literature demonstrates that theoretically the effect of investor sentiment differs across different market states. A full business cycle published by National Bureau of Economic Research (NBER) is on average close to 6 years. Thus, the empirical contribution of each sentiment component may change greatly every half of the business cycle (3 years). For an unreported result, the robustness check on the effect of different window lengths (i.e. 1 year, 2 years, 3 years, 4 years, and 5 years) shows that 3 years window length has the most significant results across different prediction horizons even though the use of different window lengths also exhibit a negative effect of investor sentiment on future stock market returns. This implies that 3 years' window length optimally captures the changes in investor sentiment.

Table 2
Descriptive statistics of orthogonalized sentiment proxy variables.

Sentiment Proxies	Mean	Median	Max	Min	Stdev	Skew	Kurt	Obs
TURN	0.0000	0.0633	1.7617	−2.3615	0.9169	−0.4809	2.6329	336
CEFD	0.0000	0.3197	1.4698	−2.3473	0.9057	−0.8530	2.8027	336
NIPO	0.0000	−0.2400	3.7108	−1.7034	0.9547	1.2854	4.8234	336
RIPO	0.0000	0.0007	3.0303	−2.8466	0.9613	0.6196	4.9701	336
S	0.0000	0.3491	1.4337	−2.6335	0.9181	−0.9454	2.8168	336
PDND	0.0000	−0.1108	2.9979	−1.7150	0.9609	0.6781	3.4100	336

Notes:This table reports descriptive statistics of orthogonalized sentiment proxy variables used for analysis. The sentiment proxies included the market turnover *(TURN)*, the closed-end fund discount *(CEFD)*, the number on IPOs *(NIPO)*, the average first-day returns on IPOs *(RIPO)*, the equity share in new issue *(S)*, and the dividend premium *(PDND)*. *Stdev* denotes standard deviation, *Min* is the minimum value, *Max* is the maximum value, *Skew* is theSkewness, *Kurt* is the Kurtosis and *Obs* is the number of observations. The sample period spans for 336 months, from January 1990 until December 2017.

Table 3
Correlations between orthogonalized sentiment proxy variables.

	PDND	S	RIPO	NIPO	CEFD	TURN
PDND	1					
S	0.14	1				
RIPO	0.03	0.23*	1			
NIPO	0.19*	0.29*	0.04	1		
CEFD	0.53*	0.14	0.05	0.44*	1	
TURN	0.49*	0.09	0.11*	0.34*	0.89*	1

Notes: This table reports Pearson correlations for the orthogonalized sentiment proxy variables used for analysis. The sentiment proxies included the dividend premium *(PDND)*, the equity share in new issue *(S)*, the average first-day returns on IPOs *(RIPO)*, the number on IPOs *(NIPO)*, the closed-end fund discount *(CEFD)*, and the market turnover *(TURN)*. The sample period spans for 336 months, from January 1990 to December 2017. * denotes statistical significance at the level of 5%.

Table 4
Characteristics of Sentiment Index Constructed using PCA Methodology.

Factor Loadings	S_t^{BW} index	
	PDND(-1)	0.223
	S	0.180
	RIPO (−1) NIPO	0.329
	TURN (−1) CEFD (−1)	0.294
		0.411
		0.265
Explained Variance by the PC1	67.45%	

Notes: This table reports the factor loadings of the sentiment index constructed on the basis of PCA. The sentiment index is the Baker and Wargelconstructed index (S_s^{BW}). The sentiment proxies included the lagged dividend premium *(PDND(-1))*, the current equity share in new issue *(S)*, the lagged average first-day returns on IPOs *(RIPO(-1))*, the current number on IPOs *(NIPO)*, the lagged closed-end fund discount *(CEFD(-1))*, and the lagged market turnover *(TURN(-1))*. The sample period is from January 1990 to December 2017.

estimated as the first principal component (PCA1) of the correlation matrix of five proxies, were generated in each window. $S^{RW}$was constructed by retaining only the last observation in each window in order to accommodate for the time-varying contribution of sentiment component to the index. Hence, it can be viewed as a series of updated investor sentiment utilizing only the most relevant and updated information in every rolling window.In sum, computing investor sentiment index using the PCA approach on a rolling window basis does not suffer from a limited number of observations and timing issues. Thus, it can better capture the dynamic of investor sentiment.

The construction of an improved investor sentiment index, referred to as the rolling window investor sentiment index (S^{RW}),optimally captured the dynamic property of investor sentiment components by assigning a greater weight for each time to those components that are more related to investor sentiment.

This study constructed a new investor sentiment index, (S^{RW}). The construction of this index is closely related to the work of Baker and Wurgler (2006) who employed the principal component analysis (PCA) to extract the common sentiment component from the sentiment proxies. There is, however, an important methodological difference. Instead of allocating constant weight, which are estimated from the whole sample period, to each sentiment component, the (S^{RW}) was constructed by allowing the weights of sentiment components to change through time on a rolling window basis with the strict assumption of future information as unknown. This allowed the dynamic investor sentiment components to be accurately captured for each time period as the index rolled over to the next

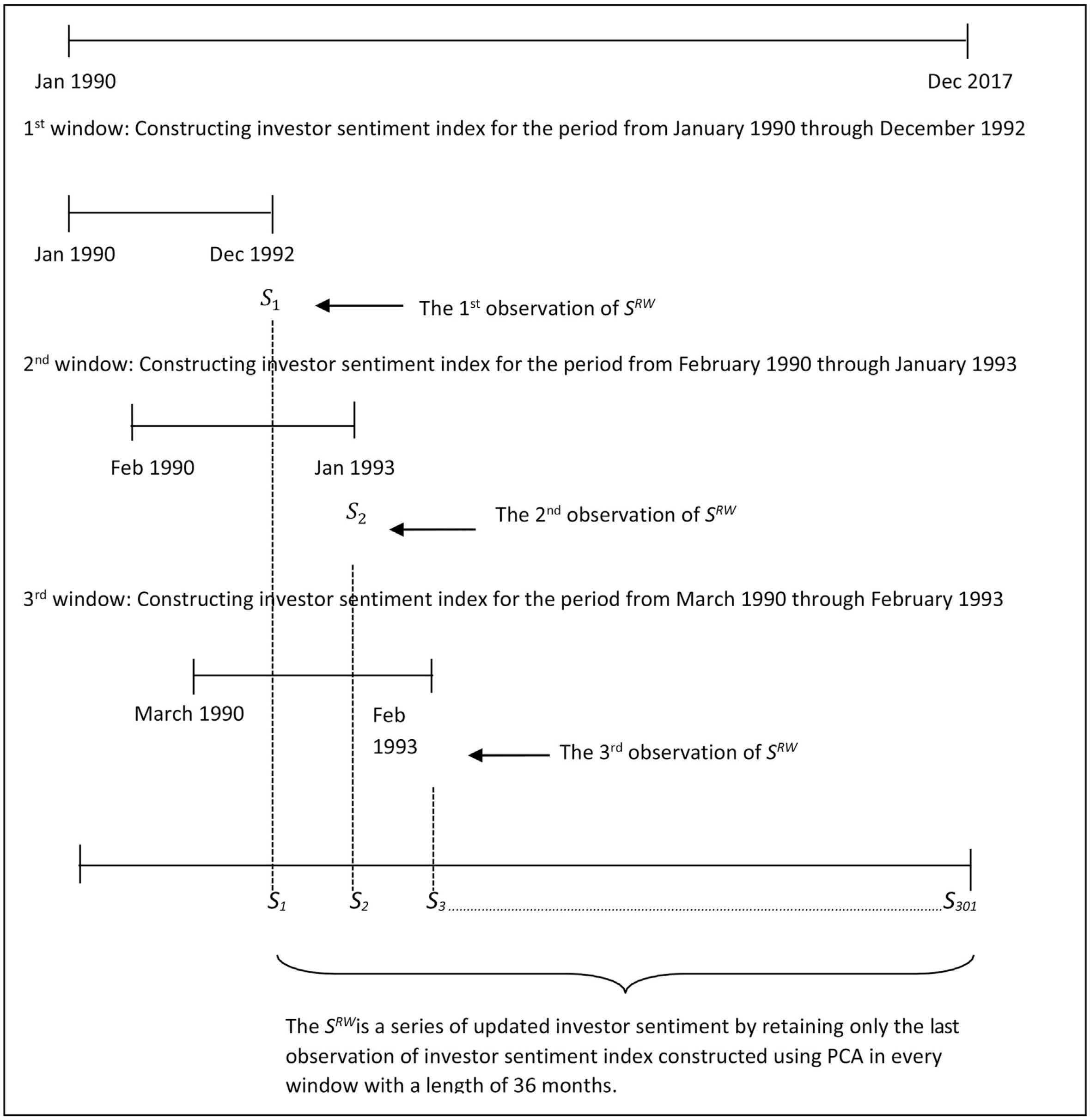

Fig. 1. The construction of rolling window investor sentiment index($\mathbf{S^{RW}}$).

period. This study differs from previous studies (e.g. Chau et al., 2016; Chung et al., 2012; Li et al., 2017)[11] in that, the dynamic feature of investor sentiment was modeled through time-varying weights in the index components.

4. Results

4.1. Descriptive statistics

Tables 5 and 6 provide the summary statistics for all variables used, which include investor sentiment indices and S&P 500 ~~sectors'~~ price returns. The sample period of this study spans from January 1990 through December 2017. The statistics reported are,

[11] These studies examined the asymmetry effect of investor sentiment, which is measured by SBW, on stock returns in different market states. Therefore, they focused on the changes of the slope coefficient associated with investor sentiment without considering ~~on~~ the time-varying ability of each component in optimally capturing ~~the~~ investor sentiment.

Table 5
Descriptive statistics of investor sentiment measures.

	Survey − basedmeasures			*Market − basedmeasures*		
	CCI	*MS*	*AAII*	S^{BW}	S^{RW}	*VIX*
PanelA : Summarystatistics						
μ	144.745	86.567	17.003	0.238	0.128	20.136
σ	25.313	12.553	42.012	0.605	0.618	8.093
S	−0.102	−0.390	0.671	0.721	0.749	1.932
K	−0.588	−0.629	−0.059	0.457	0.466	6.948
JB	7.514** (0.023)	14.836*** (0.001)	82.568*** (0.008)	32.701*** (0.000)	35.950*** (0.000)	675.460*** (0.000)
$LB(12)$	3,318.64*** (0.000)	3,230.67*** (0.000)	6,864.10*** (0.000)	3,280.51*** (0.003)	3,277.45*** (0.000)	946.330*** (0.005)
$LB^2(12)$	3,474.34*** (0.000)	3,962.20*** (0.000)	5,920.30*** (0.000)	2,133.65*** (0.010)	2,124.97*** (0.000)	522.793*** (0.002)
ARCH	383.016*** (0.000)	364.722*** (0.000)	107.104*** (0.000)	351.355*** (0.000)	356.892*** (0.000)	148.625*** (0.000)
JOINT	374.620***	361.810***	105.390***	332.744***	338.512***	153.860***
PanelB : Autocorrelation						
b_0	2.015**	3.025**	0.114***	0.014	0.025***	2.601***
b_1	1.002***	0.907***	1.083***	0.987***	0.997***	0.856***
b_2	−0.057	−0.058	−0.126**	0.010	0.008***	−0.079
b_3	−0.023	0.041	−0.009	0.020	0.018***	0.006
b_4	0.038	0.001	−0.068	0.082	0.090	0.151*
b_5	−0.003	0.036	0.033	−0.117***	−0.112***	−0.030
$F-$ *statistic*	1134.22***	788.03***	2091.10***	1479.53***	1536.75***	142.68***

Notes: This table provides descriptive statistic s of investor sentiment measures for the full sample (N = 336). Survey-based sentiment measuresincluded Consumer Confidence Index (*CCI*), Michigan Consumer Sentiment Index (*MS*) and Association of Individual Investors (*AAII*). Market-based sentiment measures included Baker and Wargel index (S^{BW}), rolling window basis index (S^{RW}), and implied volatility index *(VIX)*.The statistics reported are the mean (μ), standard deviation (σ), measures for skewness (S) and excess kurtosis (K), and Jarque-Bera (JB) test statistic. LB(12) and $LB^2(12)$ are the Ljung-Box autocorrelation test for the level and squared sentiment indices, respectively.The test statistics follow Chi-square distribution with 12 degrees of freedom. ARCH is the Lagrange Multiplier test for the ARCH (1) effect. The JOINT test is Engle and Ng's (1993) test for the potential asymmetries in conditional variance.The numbers in parentheses correspond to the probability (p-values) of rejecting the null hypothesis. The autocorrelation parameters (b1 through b5) are estimated from the autoregressive model, AR(5).The test statistic is an F-statistic for the null hypothesis of $b_1 = b_2 = b_3 = 0$ of the regression. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 6
Descriptive statistics ofS&P 500 sectors returns.

S&P 500 *global* index	*S&P* 500 *financial*index	*S&P* 500 *consumer discretionary*index	*S&P* 500 *consumer staples*index	*S&P* 500 *energy*index	*S&P* 500 *utilities*index	*S&P* 500 *materials*index	*S&P* 500 *information technology*index		*S&P* 500 *telecom*index
PanelA : *Summarystatistics*									
μ	0.560	0.465	0.358	0.186	0.317	0.240	0.349	0.818	0.266
σ	6.227	5.375	5.083	1.656	2.735	2.325	2.977	9.281	2.035
S	−0.831	−0.627	−0.594	−0.090	−0.465	−0.191	−0.746	−0.160	−0.708
K	3.697	3.885	4.123	3.327	4.049	3.697	4.552	3.539	3.196
JB	272.15*** (0.000)	212.30*** (0.000)	185.67*** (0.000)	146.19*** (0.000)	122.54*** (0.000)	167.47*** (0.000)	171.83*** (0.000)	313.69*** (0.000)	155.43*** (0.000)
$LB(12)$	11.799 (0.972)	10.671 (0.815)	9.433 (0.425)	10.420 (0.251)	9.155 (0.147)	9.715 (0.822)	10.006** (0.020)	11.402 (0.123)	9.270 (0.466)
$LB^2(12)$	80.502*** (0.000)	73.506*** (0.000)	67.418*** (0.000)	65.078*** (0.000)	62.791*** (0.000)	63.506*** (0.000)	70.093*** (0.000)	77.248*** (0.000)	60.816*** (0.000)
$ARCH$	23.100*** (0.000)	69.764*** (0.000)	9.865*** (0.000)	5.120*** (0.000)	6.350*** (0.000)	24.251*** (0.002)	50.545*** (0.000)	36.698*** (0.000)	57.990*** (0.000)
$JOINT$	39.480***	32.701***	30.410***	24.057***	28.002***	26.791***	33.370***	38.145***	29.161***
PanelB : *Autocorrelation*									
b_0	0.520**								
b_1	0.061								
b_2	0.073								
b_3	0.019								
b_4	0.031								
b_5	0.074								
$F-$ *stat*	1.580								

Notes: This table provides descriptive statistics of S&P 500 returns for the full sample (N = 336). The S&P 500 indices include S&P 500 global index,S&P 500 financial index, S&P 500 consumer discretionary index, S&P 500 consumer staples index, S&P 500 energy index,S&P 500 utilities index,S&P 500 materials index,S&P 500 information technology index, and S&P 500 telecom index. The statistics reported are the mean (μ), standard deviation (σ), measures for skewness (S) and excess kurtosis (K), and Jarque-Bera (JB) test statistic. LB(12) and LB[21](12) are the Ljung-Box autocorrelation test for the level and squared stock returns, respectively.The test statistics follow Chi-square distribution with 12 degrees of freedom. ARCH is the Lagrange Multiplier test for the ARCH (1) effect. The JOINT test is Engle and Ng's (1993) test for the potential asymmetries in conditional variance.The numbers in parentheses correspond to the probability (p-values) of rejecting the null hypothesis. The autocorrelation parameters (b1 through b5) are estimated from the autoregressive model, AR(5).The test statistic is an F-statistic for the null hypothesis of $b_1 = b_2 = b_3 = 0$ of the regression *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

respectively, the mean (μ), standard deviation (σ), measures for skewness (S) and excess kurtosis (K), Jarque-Bera (JB) test statistic, Ljung-Box (LB) statistic for12 lags, *ARCH* test, and the *JOINT* test statistic which tests for volatility asymmetry.

Consistent with the literature, there is ~~a~~ clear evidence of departures from normality in the stock market returns series and sentiment indicators (as indicated by significant JB and ARCH statistics). Particularly, we see that the monthly return of all stock market indices on S&P 500 are negatively skewed and highly leptokurtic. This observation is consistent with the volatility feedback hypothesis of Campbell and Hentschel (1992) which suggests that large negative stock market returns are more common than large positive returns. Likewise, the investor sentiment measures also display a skewed and leptokurtic pattern. The LB statistics provide evidence of significant temporal dependencies of both the levels and the squared values of all sentiment indicators. The JOINT test of Engle and Ng (1993) suggests that significant time-variations and asymmetries exist in conditional volatility, supporting our use of the asymmetric EGARCH specification as a method to model the conditional variance. Nevertheless, to examine the extent of interaction between serial correlation and volatility, further investigation is required. To obtain an initial idea on the degree of sentiment on feedback trading and the S&P 500 stock market index, it would be helpful to estimate a simple autoregressive model, AR (5). The results reported in Panel B of Table 5 show that all coefficients for sentiment measures are highly persistent and exhibit significant first-order autocorrelations that are positive.

4.2. *Regression analysis*

This section presents our results in four main parts. The first part reviews the notion that sentiment-driven buying and selling that exhibit contrarian-type investing exists in the U.S. stock markets. It also shows that survey-based measures of sentiment are the most important inputs which affect the buying and selling decisions of sentiment-driven investors. Additionally, it determines if the intensity of sentiment-driven buying and selling differs with respect to rising and declining sentiment (tests for asymmetry effects). The second part examines the robustness of our results by attempting to use returns on the different S&P 500 sectors as a proxy for the market portfolio and see how sentiment measures can explain the behavior of sentiment-driven investors.The third part provides additional robustness checks of our results by controlling for year and industry fixed effects. Finally, the fourth part seeks to determine how sentiment-driven investors behave during bull and bear markets as well as periods of high and low sentiment, respectively.

4.2.1. *Evidence on sentiment-driven trading in S&P 500 stock market index*

Table 7 reports the maximum likelihood estimates of the feedback trader models (Sentana & Wadhwani, 1992) described by equations (1)–(5), incorporating the possible presence of sentiment driven investors (i.e., $\gamma \neq 0$), and providing a comparison across the mean equation parameter estimates with the symmetric effects (1) and asymmetric effects (5) models, respectively.[12] It can be seen that the coefficients describing the conditional mean process naturally exhibit observable qualitative differences because of the many different types of sentiment indicators that are used.We have *CCI*, *MS* and *AAII* as survey-based sentiment measures whereby we consider symmetric effects and asymmetric effects models, respectively. We haveS^{BW},S^{RW} and *VIX* as market-based sentiment measures where we also consider symmetric effects and asymmetric effects models, respectively.

The parameter of interest in this case isγ. Particularly, if γ is positive and statistically significant, it implies that there are certain sentiment-driven investors who trade against the emotions and feelings of the herd. For the symmetric effects model (1) we find that γ is indeed positive and statistically significant when *CCI*, *MS*, *AAII*and S^{RW}, respectively, are used to proxy for sentiment. The coefficient γ is not significant when either S^{BW} or *VIX* are used as sentiment measures. These results have implications for the first hypothesis about whether investor sentiment-driven buying and selling exists in the stock market, and for the second hypothesis which concerns survey based measures of sentiment as important inputs affecting the buying and selling decisions of sentiment-driven investors. More precisely, regarding Hypothesis 1, coefficient γ is positively significant meaning that it explains time-series variations in stock returns and supports the view that sentiment-driven investors affect prices. In equation (1), $\gamma = -\lambda\theta$. Thus, on the basis of the positively significant coefficients of 0.008, 0.003, 0.052 and 0.015 in Table 7 from the symmetric effects model for *CCI*, *MS*, *AAII*and S^{RW}, respectively, there is a negative relation between the quantity demand for stock and sentiment levels. This result provides novel insight into the behavior of sentiment-driven traders because they have been assumed to have irrational behavior. Surprisingly, there is now evidence from coefficient γ that as investor sentiment begins to rise connected to the rising coupled stock price, the demand for shares held by sentiment-driven investors begins to decline. This may arise from either their fear linked to the reasons for rises in stock prices and their anticipation of the occurrence of a reversal or, from a bubble burst, for example, the extreme cases of 2000 and 2008–2009, respectively. Unlike feedback trading or trading in herds, in which investors buy when everyone else is buying (prices are going up) and sell when everyone else is selling (prices are going down), these results demonstrate that sentiment-driven investors behave like contrarians. This is consistent with the trading view proposed by Soros (1987) which says that it is essentia~~lly~~ to trade against the herd ~~and~~ particularly during periods of over-inflated prices as a result of irrational market exuberance. The asymmetric effects model tests for asymmetry while incorporating rising and declining investor sentiment, γ^{+} andγ^{-}, respectively. The asymmetric effects model for each of the sentiment proxies is a useful estimation because it allows us to determine if the intensity of sentiment-driven buying and selling differs

[2] Pagan and Schwert (1990) evaluated several competing volatility models and concluded that EGARCH provides the best overall 'fit' for return volatility. As a robustness check, in our empirical application we also estimated the process by replacing equation (1) and (1) with a GJR-GARCH(1,1) model. We found that our main results are robust to different specification choices of the conditional variance.

[12] Regarding the soundness of the instrument used in this study, one month lags (R_(t-1)) are included to mitigate the endogeneity problem. Thus, there is no endogeneity issue in the model and estimates are methodologically robust.

Table 7
Regression results from evidence on sentiment-driven trading in S&P 500.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	−0.129 [-0.153]	1.094* [1.904]	0.612 [0.761]	0.794 [1.372]	0.450 [0.363]	0.770 [0.315]	0.325 [0.135]	0.170 [0.315]	0.121** [2.027]	0.387 [0.958]	1.782 [0.507]	1.627 [1.301]
θ	0.019* [1.899]	0.023*** [-2.806]	0.004 [0.260]	0.003 [0.225]	0.004 [0.381]	−0.003 [1.127]	0.005 [0.664]	0.009 [1.127]	0.007** [-2.100]	0.008 [1.189]	−0.022 [0.265]	−0.020 [-0.219]
ϕ_0	−0.090 [-0.824]	0.154** [2.380]	1.000*** [56.521]	0.154*** [2.739]	0.012 [0.390]	0.087 [1.047]	0.046 [0.784]	0.052 [1.047]	0.093 [0.233]	0.046 [1.097]	0.024 [0.111]	−0.024 [1.588]
ϕ_1	−0.000*** [-6.124]	0.005*** [13.882]	−0.000 [-0.390]	0.005*** [14.279]	−0.000 [-0.495]	0.005*** [18.090]	−0.000 [-1.041]	0.006*** [18.090]	−0.001 [-3.538]	0.006*** [20.492]	−0.001 [-0.454]	0.005*** [13.679]
γ	0.008*** [3.993]		0.003*** [2.952]		0.052*** [2.741]		−0.064 [0.208]		0.015*** [-4.963]		−0.011 [-1.442]	
γ^+		−0.013 [0.151]		−0.013 [-0.781]		−0.076 [0.505]		0.040 [0.505]		0.033 [0.439]		−0.008 [-1.519]
γ^-		0.003** [-1.528]		0.003*** [2.596]		0.003*** [5.886]		0.228 [0.781]		0.246*** [6.799]		−0.004 [1.225]
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.54	0.59	0.98	0.60	0.47	0.66	0.36	0.66	0.49	0.61	0.30	0.44
DW	1.95	2.19	2.05	2.28	1.97	1.93	1.99	1.93	1.88	2.14	1.96	1.50

Notes: This table reports maximum likelihood estimates for our two augmented models, the symmetric effects model given by equation (1) and the asymmetric effect model given by equation (5).The objective is to detect the presence of sentiment-driven trading in the S&P 500 global sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models. Investor sentiment measures comprised survey-based and market-based measures. The survey-based sentiment measures included Consumer Confidence Index *(CCI_S,CCI_A)*, Michigan Consumer Sentiment Index *(MS_S,MS_A)* and Association of Individual Investors*($AAII_S$, $AAII_A$)*with symmetric and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wurgler index*(S_s^{BW}, S_A^{BW})*, rolling window basis index *(S_s^{RW}, S_A^{RW})*, and implied volatility index *(VIX_S, VIX_A)* with symmetric and asymmetric effects, respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient ϕ_0 accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^- indicate rising and declining investor sentiment, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 8
Robustness checking with sentiment-driven trading in S&P 500 financial index.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	1.217* [1.886]	1.119* [2.184]	0.439 [0.655]	0.493 [0.736]	1.424 [0.022]	0.970 [-0.051]	0.017 [-0.135]	−0.036 [-0.276]	−0.095 [1.148]	−0.192 [0.588]	0.768** [2.535]	0.388* [1.785]
θ	−0.023 [-1.487]	0.003 [0.216]	−0.009 [-0.976]	−0.022 [-1.554]	−0.029 [0.202]	0.005 [-0.054]	0.002 [0.450]	−0.001 [-0.371]	0.005* [-1.925]	−0.004 [0.636]	−0.020*** [-3.634]	0.008 [0.350]
ϕ_0	−0.210*** [-3.158]	−0.249*** [-2.693]	−0.036 [-0.293]	−0.021 [-0.171]	−0.344 [-0.469]	−0.385 [-0.529]	−0.006 [-0.152]	−0.069 [-0.358]	−0.021 [-0.195]	−0.048 [-0.379]	−0.024*** [-3.368]	−0.044*** [-3.927]
ϕ_1	−0.004 [-0.103]	0.000 [0.947]	−0.001* [1.770]	0.000* [1.827]	0.002 [0.872]	0.002 [0.958]	0.001 [0.271]	0.001 [0.795]	0.000 [0.000]	0.001 [0.725]	−0.009*** [4.534]	0.000*** [4.017]
γ	0.015*** [12.151]		0.014*** [4.251]		0.279*** [-4.912]		−0.024 [0.826]		0.056** [-2.333]		−0.009 [-1.462]	
γ^+		0.010*** [5.134]		0.020 [0.787]		−0.510 [0.316]		0.070* [1.679]		0.270 [-0.756]		−0.019*** [-8.720]
γ^-		0.024*** [8.188]		0.006*** [3.158]		0.128*** [2.959]		−0.063 [-0.442]		0.042*** [-5.534]		−0.003 [-0.480]
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.46	0.49	0.11	0.11	0.01	0.01	0.01	0.02	0.13	0.18	0.39	0.50
DW	1.93	1.99	2.29	2.27	1.98	1.98	2.01	1.98	2.22	2.20	1.68	1.50

Notes: This table reports maximum likelihood estimates for two augmented models: the symmetric effects model given by equation (1) and the asymmetric effects model given by equation (5). The objective is to detect the presence of sentiment-driven trading in the S&P 500 financial sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models. Investor sentiment measures comprised survey-based and market-based measures. The survey-based sentiment measures included Consumer Confidence Index *(CCI_S,CCI_A)*, Michigan Consumer Sentiment Index *(MS_S,MS_A)* and Association of Individual Investors*($AAII_S$, $AAII_A$)*with symmetric and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wurgler index *(S_s^{BW}, S_A^{BW})*, rolling window basis index *(S_s^{RW}, S_A^{RW})*, and implied volatility index *(VIX_S, VIX_A)* with symmetric and asymmetric effects, respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient ϕ_0 accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^- indicate rising and declining investor sentiment, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 9
Robustness checking with sentiment-driven trading in S&P 500 consumer discretionary index.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	−0.134 [-0.245]	−0.178 [-0.328]	0.275 [0.439]	0.240 [0.384]	0.900 [0.256]	0.788 [0.266]	0.164 [0.233]	0.173 [0.163]	0.149 [1.531]	0.105 [0.973]	1.021 [1.537]	0.631 [1.461]
θ	0.027*** [2.661]	0.043*** [3.071]	0.007 [0.520]	−0.014 [-0.778]	−0.012 [0.826]	0.025 [0.799]	0.010 [0.894]	0.011 [0.460]	0.011 [-1.263]	0.007 [1.089]	−0.018 [-0.990]	0.018** [2.055]
ϕ_0	−0.242*** [-2.932]	−0.251 [-0.999]	−0.115 [-1.231]	−0.090 [-0.954]	−0.265 [-1.485]	−0.268 [-1.476]	−0.146 [-1.388]	−0.146 [-1.485]	−0.142 [-1.174]	−0.154 [-1.355]	−0.108*** [-3.004]	−0.120*** [-3.317]
ϕ_1	0.001** [-2.462]	0.001*** [2.961]	0.001** [2.570]	0.001** [2. 542]	0.002 [1.675]	0.002 [1.624]	0.001 [1.373]	0.001 [1.525]	0.001 [-0.365]	0.001 [0.358]	−0.000*** [4.411]	0.000*** [4.211]
γ	0.016*** [8.213]		0.012*** [2.953]		0. 239*** [3.052]		−0. 089 [-0.598]		−0.047*** [-3.538]		−0.007 [-1.522]	
γ^+		0.015*** [3.373]		0.022 [0.054]		−0.654 [-0.560]		−0.101 [0.282]		0.043*** [-0.228]		−0.025*** [-8.307]
γ^-		0.021*** [5.634]		0.000** [2.822]		0.065* [1.815]		−0.082 [-0.915]		0.106*** [-5.114]		−0.001 [-1.455]
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.282	0.293	0.061	0.073	0.021	0.021	0.018	0.021	0.079	0.155	0.203	0.329
DW	1.902	2.925	2.198	2.160	1.979	1.980	1.995	1.982	2.211	2.271	1.935	1.700

Notes: This table reports maximum likelihood estimates for two augmented models: the symmetric effects model given by equation (1) and the asymmetric effects model given by equation (5). The objective is to detect the presence of sentiment-driven tradingin S&P 500 consumer discretionary sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models. Investor sentiment measures comprised survey-base and market-based measures. The survey-based sentiment measures included Consumer Confidence Index *(CCI_S,CCI_A)*, Michigan Consumer Sentiment Index *(MS_S,MS_A)* and Association of Individual Investors*($AAII_S$, $AAII_A$)*with symmetric effects and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wurgler index *(S_s^{BW}, S_A^{BW})*, rolling window basis index *(S_s^{RW}, S_A^{RW})*, and implied volatility index *(VIX_S, VIX_A)* with symmetric effects and asymmetric effects, respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient ϕ_0 accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^- indicate rising and declining investor sentiment, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 10
Robustness checking with sentiment-driven trading in S&P 500 consumer staple index.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	0.526 [1.242]	0.651* [1.751]	0.300 [0.658]	0.276 [0.599]	0.575 [0.809]	0.526 [0.808]	0.364 [0.894]	0.374 [0.493]	0.410 [0.827]	0.239 [0.772]	0.401 [1.278]	0.373 [1.260]
θ	0.002 [0.089]	0.030 [0.200]	0.009 [0.425]	−0.006 [-0.208]	−0.007 [0.362]	0.055 [0.182]	0.008 [0.246]	0.006 [0.987]	0.006 [0.039]	0.030 [0.929]	0.001 [-0.294]	0.024** [0.912]
ϕ_0	−0.042 [-0.401]	−0.012 [-0.160]	0.042 [0.370]	0.041 [0.358]	−0.082 [-0.336]	−0.127 [-0.349]	−0.038 [-0.358]	−0.041 [-0.009]	−0.043 [0.488]	−0.001 [0.544]	0.055 [-0.722]	0.060 [-1.203]
ϕ_1	−0.002 [-1413]	−0.041*** [-5.466]	−0.001 [-0.385]	−0.000 [-0. 349]	0.002 [1.295]	0.002 [1.160]	0.002 [0.853]	0.002 [0.082]	0.002 [-1.070]	0.000 [-1.059]	−0.002 [1.317]	−0.002 [1.419]
γ	0.022*** [5.807]		0.007** [2.556]		0. 313*** [2.943]		−0. 394* [-1.950]		0.211 [0.792]		−0.005*** [-3.649]	
γ^+		0.009 [1.515]		0.016 [1.167]		−1.226 [-1.530]		−0.375 [-1.599]		−0.422 [-1.502]		−0.024*** [-6.712]
γ^-		0.035*** [4.887]		0.003* [1.807]		0.009* [1.918]		−0.417 [-0.102]		0.020** [2.085]		0.003 [0.092]
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.170	0.328	0.021	0.024	0.061	0.061	0.036	0.043	0.019	0.039	0.083	0.217
DW	2.012	2.011	2.064	2.045	1.939	1.940	1.974	1.968	2.051	2.130	1.965	1.966

Notes: This table reports maximum likelihood estimates for two augmented models: the symmetric effects model given by equation (1) and the asymmetric effects model given by equation (5). The objective is to detect the presence of sentiment-driven tradingin S&P 500 consumer staple sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models. Investor sentiment measures comprised survey-based and market-based measures. The survey-based sentiment measures included Consumer Confidence Index *(CCI_S,CCI_A)*, Michigan Consumer Sentiment Index *(MS_S,MS_A)* and Association of Individual Investors*($AAII_S$, $AAII_A$)*with symmetric effects and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wurgler index *(S_s^{BW}, S_A^{BW})*, rolling window basis index *(S_s^{RW}, S_A^{RW})*, and implied volatility index *(VIX_S, VIX_A)* with symmetric and asymmetric effects, respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient ϕ_0 accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^- indicate rising and declining investor sentiment, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 11
Robustness checking with sentiment-driven trading in S&P 500 energy index.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	−0.238 [-0.315]	−0.138 [-0.186]	0.358 [0.438]	0.42 [0.523]	1.524 [0.006]	0.984 [-0.040]	0.005 [-0.287]	−0.033 [-0.226]	−0.236*** [2.772]	−0.187 [0.622]	2.330** [2.054]	0.560 [1.434]
θ	0.020 [1.046]	0.023** [2.419]	0.000 [0.008]	0.024 [0.912]	−0.036 [0.509]	0.026 [0.315]	0.011 [0.816]	0.008 [0.361]	0.017*** [-2.824]	0.009 [0.932]	−0.062* [-1.897]	0.028 [1.300]
ϕ_0	0.110 [1.218]	0.061 [0.682]	0.059 [0.594]	0.035 [0.342]	−0.058 [1.049]	−0.077 [0.997]	0.108 [1.438]	0.104 [1.229]	0.151 [0.030]	0.135 [-0.423]	0.003 [-0.652]	−0.038 [-0.925]
ϕ_1	−0.000 [-1.361]	−0.000 [-0.327]	−0.000 [-0.986]	−0.000 [-1.091]	0.001* [-1.641]	0.000 [-1.182]	−0.001** [-2.285]	−0.001 [-1.317]	−0.002*** [-4.021]	−0.002 [-1.233]	−0.003* [1.871]	−0.000 [0.106]
γ	0.013*** [4.907]		0.004* [1.848]		0.403*** [6.775]		0.131 [1.046]		0.194*** [-5.452]		−0.015 [-0.946]	
γ^+		0.002 [0.536]		−0.007 [-0.770]		−0.897 [0.785]		0.226 [1.302]		0.294 [0.089]		−0.031*** [-9.027]
γ^-		0.026*** [5.042]		0.009*** [1.800]		0.006** [2.319]		0.069 [0.588]		0.113*** [-6.961]		0.000 [-0.081]
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.18	0.18	0.04	0.05	0.04	0.04	0.05	0.05	0.17	0.25	0.23	0.36
DW	1.93	1.94	2.01	2.05	1.99	1.99	2.00	2.00	2.14	2.24	2.00	1.88

Notes: This table reports maximum likelihood estimates for two augmented models: the symmetric effects model given by equation (1) and the asymmetric effects model given by equation (5). The objective is to detect the presence of sentiment-driven tradingin S&P 500 energy sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models. Investor sentiment measures comprised survey-based and market-based measures. The survey-based sentiment measures included Consumer Confidence Index *(CCI_S,CCI_A)*, Michigan Consumer Sentiment Index *(MS_S,MS_A)* and Association of Individual Investors*($AAII_S$, $AAII_A$)*with symmetric effects and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wurgler index *(S_s^{BW}, S_A^{BW})*, rolling window basis index *(S_s^{RW}, S_A^{RW})*, and implied volatility index *(VIX_S, VIX_A)* with symmetric and asymmetric effects, respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient ϕ_0 accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^- indicate rising and declining investor sentiment, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 12
Robustness checking with sentiment-driven trading in S&P 500 information technology index.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	−0.182	−0.059	−0.159	−0.089	−0.006	0.002	−0.024	−0.021	0.029 [0.542]	0.053 [0.558]	0.380	0.377 [0.029]
	[-0.247]	[-0.081]	[-0.221]	[-0.125]	[-0.033]	[-0.029]	[0.040]	[0.074]			[-0.009]	
θ	−0.002	0.007 [1.109]	−0.001	0.014*	−0.005	−0.007	−0.002	0.002	−0.003**	0.001 [1.270]	−0.009	0.007
	[-0.442]		[-0.300]	[1.918]	[-0.643]	[0.258]	[-0.862]	[0.138]	[-2.063]		[-1.077]	[-1.094]
ϕ_0	−0.122	−0.048	−0.145	−0.089	−0.070	−0.054	−0.145	−0.106	−0.150**	−0.130	−0.307	−0.113
	[-1.005]	[-0.578]	[-1.215]	[-1.022]	[-1.207]	[-1.264]	[-1.242]	[-1.504]	[-2.542]	[-1.464]	[-0.564]	[-0.630]
ϕ_1	0.000	−0.000*	0.000 [0.361]	0.000 [0.343]	−0.000	0.000	−0.000	−0.000	−0.000**	−0.000	0.000	−0.000*
	[0.260]	[-1.914]			[-0.193]	[-1.301]	[-0.242]	[-1.350]	[-2.052]	[-0.606]	[-1.340]	[-1.769]
γ	0.001*		0.005***		0.046**		0.097***		0.087***		−0.008	
	[1.712]		[2.804]		[2.545]		[2.580]		[-4.966]		[-0.890]	
γ^+		−0.005		−0.003		−0.033		0.033		0.024 [0.201]		−0.024
		[-1.503]		[-0.968]		[0.519]		[0.421]				[-0.711]
γ^-		0.002**		0.016***		0.056**		0.164**		0.149***		0.001
		[2.445]		[3.542]		[2.363]		[2.555]		[-5.892]		[-1.573]
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.02	0.05	0.06	0.08	0.05	0.05	0.05	0.06	0.13	0.19	0.03	0.03
DW	2.04	2.04	2.01	2.06	2.04	2.16	2.05	2.15	2.01	2.13	2.05	2.09

Notes: This table reports maximum likelihood estimates for two augmented models: the symmetric effects model given by equation (1) and the asymmetric effects model given by equation (5). The objective is to detect the presence of sentiment-driven tradingin S&P 500 information technology sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models. Investor sentiment measures comprised survey-based and market-based measures. The survey-based sentiment measures included Consumer Confidence Index (CCI_S,CCI_A), Michigan Consumer Sentiment Index (MS_S,MS_A) and Association of Individual Investors($AAII_S$, $AAII_A$)with symmetric and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wurgler index (S_s^{BW}, S_A^{BW}), rolling window basis index (S_s^{RW}, S_A^{RW}), and implied volatility index (VIX_S, VIX_A) with symmetric effects and asymmetric effects each one respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient ϕ_0 accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^- indicate rising and declining investor sentiment, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 13
Robustness checking with sentiment-driven trading in S&P 500 utilities index.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	0.287 [0.084]	0.094 [0.160]	0.307 [0.476]	0.253 [0.392]	1.217 [0.002]	0.806 [-0.346]	0.001 [0.048]	−0.222 [-0.269]	0.030 [1.592]	−0.172 [1.030]	1.061** [2.077]	0.682 [1.460]
θ	−0.004 [-0.262]	0.041* [1.956]	−0.007 [-0.440]	0.033 [1.374]	−0.045 [0.417]	0.020 [0.118]	0.006 [0.271]	0.002 [-0.358]	0.004** [-2.036]	−0.007 [0.136]	−0.040*** [-2.769]	0.003 [1.074]
ϕ_0	0.140* [1.779]	−0.010 [-0.102]	0.141* [1.680]	0.085 [0.750]	0.021 [1.315]	−0.062 [1.620]	0.111 [1.345]	0.183* [1.859]	0.123 [1.117]	0.213 [0.332]	0.092 [0.290]	0.036 [-0.664]
ϕ_1	−0.002** [-2.343]	0.001 [-0.542]	−0.002** [-1.801]	−0.002 [-1.590]	0.001*** [-2.803]	−0.000** [-2.540]	−0.001*** [-2.947]	0.002** [-2.320]	−0.003*** [-3.358]	−0.003** [-2.116]	−0.003 [1.001]	−0.002 [-0.151]
γ	0.011*** [5.160]		0.005** [2.229]		0.418** [2.317]		0.235 [1.157]		0.175*** [-3.509]		−0.011 [-1.033]	
γ^+		0.002 [0.661]		−0.016 [-1.424]		−1.045 [1.190]		0.483** [2.429]		0.468 [-0.396]		−0.033*** [-8.900]
γ^-		0.026*** [5.161]		0.033*** [2.616]		0.044* [1.906]		0.180 [0.622]		0.082*** [-4.582]		−0.002 [-0.525]
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.15	0.18	0.04	0.06	0.06	0.07	0.06	0.08	0.11	0.16	0.25	0.38
DW	1.95	2.03	1.98	2.06	1.94	1.05	1.90	2.03	2.05	2.23	2.15	1.99

Notes: This table reports maximum likelihood estimates for two augmented models: the symmetric effects model given by equation (1) and the asymmetric effects model given by equation (5). The objective is to detect the presence of sentiment-driven tradingin S&P 500 utilities sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models. Investor sentiment measures comprised survey-based and market-based measures. The survey-based sentiment measures included Consumer Confidence Index (CCI_S,CCI_A), Michigan Consumer Sentiment Index (MS_S,MS_A) and Association of Individual Investors($AAII_S$, $AAII_A$)with symmetric and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wargel index (S_s^{BW}, S_A^{BW}), rolling window basis index (S_s^{RW}, S_A^{RW}), and implied volatility index (VIX_S, VIX_A) with symmetric and asymmetric effects, respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient ϕ_0 accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^- indicate rising and declining investor sentiment, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 14
Robustness checking with sentiment-driven trading in S&P 500 telecom index.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	−0.572 [-0.805]	−0.759 [-1.091]	−0.309 [-0.412]	−0.310 [-0.412]	0.563 [-0.575]	0.349 [-0.577]	−0.572 [-0.503]	−0.443 [-0.379]	−0.386 [0.907]	−0.294 [0.569]	0.666 [0.829]	0.427 [0.501]
θ	0.007 [0.323]	0.049** [2.171]	−0.006 [-0.283]	−0.007 [-0.251]	−0.034 [-0.083]	−0.016 [-0.015]	0.007 [-0.175]	−0.009 [-0.674]	−0.004** [-2.205]	−0.017 [-0.885]	−0.043 [-1.129]	−0.021 [-0.718]
ϕ_0	0.189 [1.479]	0.144 [1.150]	0.168 [1.244]	0.168 [1.237]	−0.080 [1.406]	−0.064 [1.407]	0.189 [1.311]	0.194 [1.108]	0.182 [0.751]	0.157 [1.526]	0.221 [-0.632]	0.194 [-0.504]
ϕ_1	−0.002* [-1.666]	−0.001 [-0.999]	−0.002 [-1.465]	−0.002 [-1.453]	0.001* [-1.693]	0.000* [-1.665]	−0.002 [-1.434]	−0.003 [-0.920]	−0.002*** [-3.398]	−0.002*** [-2.943]	−0.005 [0.623]	−0.004 [0.404]
γ	0.013*** [4.749]		0.008* [1.753]		0.412*** [7.152]		0.006 [-0.311]		−0.028*** [-5.149]		−0.018 [-0.054]	
γ^+		0.003 [0.390]		0.008 [0.935]		−0.536 [-0.084]		−0.018 [0.659]		0.125*** [-3.963]		−0.027*** [-4.913]
γ^-		0.027*** [5.057]		0.008* [1.745]		0.314* [1.916]		0.021 [-0.920]		0.138** [2.271]		−0.013*** [-3.390]
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.14	0.18	0.04	0.04	0.03	0.03	0.03	0.03	0.15	0.16	0.24	0.25
DW	1.98	1.99	2.10	2.10	2.03	2.03	2.03	2.00	2.17	2.20	2.01	2.96

Notes: This table reports maximum likelihood estimates for two augmented models: the symmetric effects model given by equation (1) and the asymmetric effects model given by equation (5). The objective is to detect the presence of sentiment-driven tradingin S&P 500 telecom sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models. Investor sentiment measures comprised survey-based and market-based measures. The survey-based sentiment measures included Consumer Confidence Index *(CCI_S,CCI_A)*, Michigan Consumer Sentiment Index *(MS_S,MS_A)* and Association of Individual Investors*($AAII_S$, $AAII_A$)*with symmetric effects and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wurgler index *(S_s^{BW}, S_A^{BW})*, rolling window basis index *(S_s^{RW}, S_A^{RW})*, and implied volatility index *(VIX_S, VIX_A)* with symmetric and asymmetric effects, respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient ϕ_0 accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^- indicate rising and declining investor sentiment, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 15
Robustness checking with sentiment-driven trading in S&P 500 materials index.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	−0.160	−0.465	0.077	0.020	−0.006	0.429	−0.024	−0.106	0.031 [0.917]	−0.177	0.380 [1.566]	0.367 [0.746]
	[-0.255]	[-0.760]	[0.108]	[0.031]	[-0.050]	[-0.148]	[-0.094]	[-0.246]		[0.523]		
θ	0.021 [1.489]	0.060***	0.010	−0.014	−0.006	0.042	−0.003	0.012	−0.004	0.004*	−0.011	0.034***
		[3.387]	[0.617]	[-0.667]	[0.942]	[0.667]	[0.953]	[0.234]	[-0.565]	[1.834]	[-1.221]	[-3.325]
ϕ_0	−0.081	−0.128	−0.024	0.053	−0.070	−0.220	−0.145	−0.013	−0.150	−0.029	−0.307*	0.014***
	[-0.882]	[-1.419]	[-0.235]	[0.673]	[-0.589]	[-0.144]	[-0.360]	[-0.356]	[0.325]	[0.183]	[-1.741]	[1.588]
ϕ_1	0.001 [1.330]	0.002***	0.001*	0.001	−0.000*	0.003	−0.000	0.002*	−0.000	0.002***	0.000***	0.000***
		[2.815]	[-1.702]	[1.519]	[1.761]	[1.638]	[1.207]	[1.723]	[0.490]	[0.426]	[3.862]	[4.630]
γ	0.016***		0.009**		0.048*		0.097		0.088***		−0.009	
	[7.652]		[2.230]		[-1.869]		[-0.495]		[-2.826]		[-1.651]	
γ^+		0.007***		0.020		−0.963		−0.059		0.143		−0.034
		[2.114]		[2.701]		[-0.346]		[0.935]		[-6.163]		[-9.650]
γ^-		0.030***		−0.005		−0.067		−0.189		−0.216		0.003 [-1.235]
		[6.511]		[-0.494]		[-1.122]		[-1.340]		[1.039]		
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.26	0.31	0.05	0.06	0.02	0.02	0.01	0.02	0.05	0.19	0.26	0.40
DW	1.906	1.966	2.139	2.119	1.975	2.037	2.016	2.075	2.168	2.416	1.979	1.940

Notes: This table reports maximum likelihood estimates for two augmented models: the symmetric effects model given by equation (1) and the asymmetric effects model given by equation (5). The objective is to detect the presence of sentiment-driven tradingin S&P 500 materials sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models. Investor sentiment measures comprised survey-based and market-based measures. The survey-based sentiment measures included Consumer Confidence Index *(CCI_S,CCI_A)*, Michigan Consumer Sentiment Index *(MS_S,MS_A)* and Association of Individual Investors*($AAII_S$, $AAII_A$)*with symmetric and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wurgler index *(S_s^{BW}, S_A^{BW})*, rolling window basis index *(S_s^{RW}, S_A^{RW})*, and implied volatility index *(VIX_S, VIX_A)* with symmetric and asymmetric effects, respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient $\phi_0$accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^-indicate rising and declining investor sentiment, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 16
Regression results from evidence on sentiment-driven trading in S&P 500with year and industry dummy interaction.

Baseline	Survey-based measures						Market-based measures					
	CCI_s	CCI_A	MS_s	MS_A	$AAII_s$	$AAII_A$	S_s^{BW}	S_A^{BW}	S_s^{RW}	S_A^{RW}	VIX_s	VIX_A
ω	−0.108 [-0.172]	1.073* [1.893]	0.591 [0.640]	0.773 [1.251]	0.429 [0.342]	0.759 [0.294]	0.304 [0.114]	0.149 [0.294]	0.100** [2.006]	0.366 [0.937]	1.761 [0.486]	1.606 [1.100]
θ	0.016* [1.798]	0.020** [-2.306]	0.003 [0.239]	0.002 [0.205]	0.003 [0.360]	−0.002 [1.015]	0.004 [0.436]	0.008 [1.015]	0.006** [-2.012]	0.007 [1.068]	−0.021 [0.244]	−0.019 [-0.202]
ϕ_0	−0.076 [-0.903]	0.133** [2.561]	1.000*** [37.301]	0.133*** [2.956]	0.010 [0.372]	0.066 [0.926]	0.035 [0.683]	0.041 [0.926]	0.072 [0.211]	0.035 [0.977]	0.023 [0.090]	−0.023 [1.357]
ϕ_1	−0.000*** [-4.103]	0.004*** [10.691]	−0.000 [-0.190]	0.004*** [11.578]	−0.000 [-0.285]	0.004*** [15.263]	−0.000 [-0.994]	0.005*** [15.263]	−0.001 [-2.847]	0.005*** [17.681]	−0.001 [-0.343]	0.004*** [10.429]
γ	0.007** [2.495]		0.002** [2.271]		0.051** [2.045]		−0.063 [0.207]		0.014** [-2.382]		−0.010 [-1.461]	
γ^+		−0.012 [0.150]		−0.012*** [-2.585]		−0.075 [0.506]		0.039 [0.506]		0.032 [0.431]		−0.007 [-1.518]
γ^-		0.002** [-1.569]		0.002** [2.391]		0.002** [2.026]		0.227* [1.094]		0.245** [2.290]		−0.003 [1.185]
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IndusFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.63	0.68	0.99	0.69	0.56	0.75	0.45	0.75	0.58	0.70	0.39	0.53
DW	2.04	2.28	2.14	2.37	2.06	2.02	2.08	2.02	1.97	2.23	2.05	1.59

Notes: This table reports maximum likelihood estimates for our two augmented models: the symmetric effects model given by equation (1) and the asymmetric effects model given by equation (5) after controlling for the possible year and industry fixed effects. The objective is to detect the presence of sentiment-driven trading in the S&P 500 global sectorindex and to compare across the mean equation parameter estimates with the symmetric and asymmetric effects models after controlling for year and industry fixed effects. Investor sentiment measures are comprised of survey-based measures and market-based measures. The survey-based sentiment measures included Consumer Confidence Index *(CCI_S,CCI_A)*, Michigan Consumer Sentiment Index *(MS_S,MS_A)* and Association of Individual Investors*($AAII_S$, $AAII_A$)*with symmetric and asymmetric effects, respectively. The market-based sentiment measures included Baker and Wurgler index *(S_s^{BW}, S_A^{BW})*, rolling window basis index *(S_s^{RW}, S_A^{RW})*, and implied volatility index *(VIX_S, VIX_A)* with symmetric and asymmetric effects, respectively.ω is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient $\phi_0$accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading,γ indicates the presence of sentiment driven investors, andγ^+ and γ^-indicate rising and declining investor sentiment, respectively. *(Year FE)* and *(Indus FE)* are year and industry dummy variables, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

Table 17
Regression results from evidence on sentiment-driven trading with respect to market conditions and business cycles.

	Market Conditions (Bull/Bear)		Business Cycles (Expansion/Recession)	
	Symmetric	Asymmetric	Symmetric	Asymmetric
Panel A: Meanequation				
ω	0.7414** (2.083)	0.6269 (1.356)	0.7582* (1.669)	0.4798 (0.814)
θ	0.0003 (0.009)	0.0164 (0.505)	−0.0022 (−0.074)	0.0256 (0.493)
ϕ_0	−0.0902 (−1.087)	−0.1211 (−1.180)	−0.1145 (−1.271)	−0.1624 (−1.403)
ϕ_1	0.0002 (0.107)	0.0013 (0.475)	0.0010 (0.325)	0.0032 (0.612)
γ_{UP}	0.0018** (1.999)		0.0044 (0.898)	
γ_{DOWN}	0.0054*** (2.892)		0.0066*** (2.954)	
γ^+_{UP}		0.0015 (0.332)		0.0047 (0.806)
γ^+_{DOWN}		0.0060 (0.503)		0.0012 (0.240)
γ^-_{UP}		0.0068 (0.829)		0.0066 (0.887)
γ^-_{DOWN}		0.0088*** (2.793)		0.0085** (2.245)
Panel B: Likelihood ratio Tests				
LR	127.0619*** [0.000]		4.5630*** [0.008]	
LR^+		0.2958 [0.619]		0.0625 [0.914]
LR^-		6.3074** [0.022]		4.0030** [0.028]

due to rising or declining sentiment. Looking at the asymmetric effects model (equation (5)) when *CCI*, *MS*, *AAII*and$S^{RW}$are used to proxy for sentiment,the coefficients describing the declining sentiment γ^- for *CCI*, *MS*, *AAII*and $S^{RW}$are all positive and highly significant. This implies that sentiment-driven investors buy more aggressively during periods of declining sentiment than they sell during periods of rising sentiment. It is important to note that they are providing liquidity to the market since declining sentiment periods on average push average investors to mass sell their positions. Coefficient γ in equation (1) demonstrates that sentiment-driven investors exhibit contrarian-type behavior. There is also asymmetry in terms of how investors buy and sell regarding rises and declines in overall market sentiment. This finding thus confirms hypothesis (3) about the existence of an asymmetry effect. A reasonable or probable argument explaining why this asymmetry exists is not obvious. Initially, sentiment-driven investors may be aware of the fact that declines in the market due to bad news and declining sentiment are more severe than rises. They perceive declining sentiment (fall in stock prices) as a better trading opportunity and will buy when other investors are selling. Psychology literature claiming that negative information has a tendency to outweigh positive information in the minds of individuals explains why market declines are more severe and consequently present possible better buying opportunities. Next, Akhtar et al. (2011),Baumeister et al. (2001) and Huynh et al. (2020) have observed this so called negativity bias or negativity effect in psychology literature among market participants when making investment decisions. From a practical standpoint, negative news and poor sentiment are watched more closely by investors and could be portrayed even more vividly by the media, thus encouraging investors to react quickly exiting from the market. In addition, this appears not to contradict the concept of loss aversion in behavioral economics and decision theory. Kahneman and Tversky (1992) describe investors having a stronger preference for avoiding potential losses compared to their desire to acquire equivalent gains. The coefficients of $S^{BW}$and*VIX* continue to not be significant for either the symmetric effects model (parameter γ related to equation (1)) or the asymmetric effects model (parameters γ^+ and γ^-related to equation (5)). Here, we do not find any significant relationship between the level of market sentiment defined by both $S^{BW}$and*VIX* and the investment decision-making of sentiment-driven investors. These results are consistent with Hypothesis 2, supporting the idea that the information content of survey-based investor sentiment measures is what impacts the U.S. stock market, particularly sentiment-driven investors. This is made obvious by the sign and significance of parameters γ and $\gamma^-$for S^{RW} in Table 7. This does not mean that such market-based measures of investor sentiment are not important. Rather, it shows that survey-based measures may be perceived as less noisy, truly forward-looking indicators of future investors' expectations about the state of the economy. They tend to elicit opinions and attitudes towards current consumers and households which are least likely to be prone to intraday fluctuations and noise that is common across financial assets, such as stocks and options.

4.2.2. Robustness checks and further discussion: evidence on sentiment-driven trading in eight S&P 500 stock market sectors indices

A variety of robustness checks were performed. The results for models as specified in equations (1) and (5) covering eight different S&P 500 sectors are given in Tables 8–15. As one might expect, the parameter γ for the symmetric effects model (1) is positive and statistically significant when investor sentiment is captured by survey-based measures *CCI*, *MS* and *AAII* in the following S&P 500 sectors: financial index, consumer discretionary index, consumer staples index, energy index, information technology index, utilities index, telecom index and materials index. This parameter γ is partially significant when market-based measures S^{BW},S^{RW} and *VIX* are used as investor sentiment. This implies that sentiment-driven investors exhibit contrarian-type behavior. Thus, survey-based measures of sentiment play a relatively more significant role in influencing the behavior of investors when it comes to their buying and selling decisions as well as their demand for risky assets in the various market sectors of the Standard and Poor's 500 Index. When comparing the significance of the γ parameters between survey-based measures (*CCI*, *MS* and *AAII*) and sentiment versus market-based measures (S^{BW},$S^{RW}$and *VIX*), we see that sentiment-driven investors tend to trade on the survey-based, rather than market-based, sentiment measures. This finding supports the conjecture that the information content of survey sentiment indices is particularly important to consider because the investor sentiment survey may be less prone to irrationality and misinformation compared to their market measure counterparts. Thus, they can be exploited by sentiment-driven investors. In the case of the asymmetric effects model (5), similar results were found to Table 7.The parameter $\gamma^-$is consistently higher in significance as one would expect, and a stronger positive relationship between *CCI*, *MS*, *AAII*and $S^{RW}$was found when used as proxy for sentiment and returns in the studied S&P 500 sector indices. Overall, the sign and significance of the parameters γ^- in Tables 8–14 are findings which are qualitatively analogous to hypothesis (3) for the existence of an asymmetry effect and that sentiment-driven investors trade more aggressively during periods of declining sentiment. In other words, they may have their demand for shares rise~~s~~ when sentiment declines and other investors are selling and, conversely, they may have their demand for shares drops when sentiment rises and other investors are buying.

4.2.3. Additional robustness checks: controlling for year and industry fixed effects

It can now be seen that survey-based measures of sentiment are important inputs affecting the buying and selling decisions of sentiment-driven investors. In addition, sentiment driven trading of investors exhibits contrarian-type behavior, which is more intense during declining market periods. In this sub-section, the robustness of the results will be examined by including year and industry dummies, to control for inter-temporal and industry variation in measures of investor sentiment and stock prices. For this process, industries are defined on the basis of two digit SIC codes. Table 16 presents the sensitivity of the asymmetric and symmetric effect of sentiment-driven trading regression to the inclusion of year and industry fixed-effects. Looking at the 1990–2017 sample, the results show that when OLS is applied to the symmetric effects model, the coefficient γ is positive and significant at the 5% level when *CCI*, *MS*, *AAII*and S^{RW}, respectively, denote the sentiment of individual investors. The negative insignificant effect also holds when S^{BW}or *VIX*in sentiment proxies were used. The common interpretation of this result is that it confirms the presence of sentiment-driven investors who exhibit contrarian-type investing. Furthermore, it shows survey-based estimates of investor sentiment matter most by playing a relatively more significant role in influencing these investor~~s'~~demands for risky assets. When year and industry fixed-effects are included in the asymmetric effects model, the γ-coefficient is positive and significantly very similar to that reported by Table 7. Specifically, the coefficient γ-is positive and highly significant for *CCI*, *MS*, *AAII*, and S^{RW}, at the 5% level and S^{BW}, at the 10% level. These results are in line with ~~our~~ earlier findings, and highlight the fact that contrarian-type trading behavior of sentiment-driven investors becomes more pronounced during periods of declining sentiment. The evidence presented in the columns of Table 16 are qualitatively similar to those presented for the S&P 500 index in Table 7, despite the relatively smaller and less significant estimates for γ and γ-. In other words, even when controlled for year or industry influences, sentiment driven trading is still somewhat present in the stock market. This trading is asymmetric with respect to declining and rising sentiment and utilizes *CCI*, *MS*, and *AAII*as a means of investing. Thus, the results are not particularly driven by the choice of methods in estimating augmented trader models. This positive correlation among estimates for parameters γ and γ-confirm the hypotheses and is robust to different estimation techniques (OLS) as well as year and industry specific effects.

4.2.4. Evidence on the sentiment-driven trading with respect to additive effect of market conditions and business cycles

From the viewpoint of investors, it's imperative to understand not only what sentiment measures are important, but when does sentiment most affect the decision-making process of investors and what are the expectations of their future benefits. By knowing this information before they invest thousands of dollars, sentiment-driven investors can effectively position themselves. Hypothesis 4 examines such an important empirical issue and the results are shown in Table 17.

The focus here is to test if sentiment-driven investors respond asymmetrically to sentiment measures depending upon the impact of market conditions and business cycles. Note that poor market conditions and falling stock prices may exacerbate individual investor~~s'~~ pessimistic sentiment, therefore pushing prices above fundamentals. This can provide a valuable buying opportunity for those investors with an open eye. The aim is to explore this possibility using the monthly CCI and operating the indicator of changes in sentiment (ΔIS_{t-1}) with a dummy variable serving as business cycles and market conditions as seen in the following equations:

$$R_t = \omega + \theta\sigma_t^2 + \left(\phi_0 + \phi_1\sigma_t^2\right)R_{t-1} + \gamma_{UP}(D_t)\sigma_t^2\Delta IS_{t-1} + \gamma_{DOWN}(1-D_t)\sigma_t^2\Delta IS_{t-1} + \varepsilon_t \tag{8}$$

$$R_t = \omega + \theta\sigma_t^2 + \left(\phi_0 + \phi_1\sigma_t^2\right)R_{t-1} + \gamma_{UP}^{+}(D_t)\sigma_t^2\Delta IS_{t-1}^{+} + \gamma_{DOWN}^{+}(1-D_t)\sigma_t^2\Delta IS_{t-1}^{+} + +\gamma_{UP}^{-}(D_t)\sigma_t^2\Delta IS_{t-1}^{-} + \gamma_{DOWN}^{-}(1-D_t)\sigma_t^2\Delta IS_{t-1}^{-} + \varepsilon_t \tag{9}$$

Where $D_t$is a dummy variable that is equal to 1 in an expansion or bull market period and 0 in a recession or bear market period. The business cycle dating chronology provided by the National Bureau of Economic Research (NBER) was used. (Recessions and Expansions are dated by the NBER indicator in the U.S. economy). With regard to market conditions, the moving average approach as used by Chen (2011)'s technical analysis was followed. Here, bull and bear markets were identified by using the mean S&P500 return over the last six periods. Particularly, a period was defined as a bull market when its moving average return is much greater than zero. The response of sentiment-driven traders to changes in sentiment is authorized to differ within the macroeconomic cycles whether $\gamma_{UP} \neq \gamma_{DOWN}$; $\gamma_{UP}^{+} \neq \gamma_{DOWN}^{+}$; and/or $\gamma_{UP}^{-} \neq \gamma_{DOWN}^{-}$. Given that a dummy variable to identify recessions and expansions in equations (8) and (9) was added to the symmetric and asymmetric effects model specifications, the likelihood ratio test (LR) could be calculated in testing such constraints.

Within the context of the models proposed, an explanation will be provided for plausible values for the parameters of interest $\gamma_{UP}$and γ_{DOWN}illustrating the intensity of sentiment-driven trading in recessions (bull market) as well as in expansions (bear market). An examination of the sign and significance of these key parameters in Table 16 is consistent with earlier findings that significant sentiment-driven trading exist against the crowd's emotions and that investors tend to trade more aggressively on declining sentiment than on upswings in sentiment of equal magnitude. Moreover, as the likelihood ratio test statistics (LR) indicated practical significance, their responses to changes in sentiment are revealed to be rather different according to macroeconomic and business cycles. More precisely, sentiment-driven trading is more pronounced during bear and recessionary market conditions. Recall that sentiment-driven investors are more likely to trade (increasing liquidity) on the survey-based sentiment of individual investors since those same investors are more prone to excessive optimistic/pessimistic attitudes which might be misaligned with fundamental and objective facts at hand.

Notes: This table reports mean equation and maximum likelihood estimates for our two augmented models:the symmetric effects model given by equation (8) and the asymmetric effect model given by equation (9). The objective is to test if sentiment-driven investors respond asymmetrically to sentiment measures considering the impact of market conditions and business cycles, by operating the indicator of change in sentiment (ΔIS_{t-1}) with dummy variables describing market conditions (Bull/bear) and business cycles (Expansion/recession). $\omega$is the risk-free rate of return, $\theta$is the coefficient of relative risk aversion, the coefficient $\phi_0$accounts for the autocorrelation due to non-synchronous trading or market inefficiencies,ϕ_1 accounts for feedback trading, $\gamma_{UP}$and γ_{DOWN}illustrate the intensity of sentiment-driven trading in expansions (bear market) and recessions (bull market), respectively,$\gamma^{+}_{UP}$and γ^{+}_{DOWN}indicate rising investor sentiment in expansions and recessions, respectively, and$\gamma^{-}_{UP}$and γ^{-}_{DOWN}indicate declining investor sentiment in expansions and recessions, respectively.LR, LR+, and LR-are the likelihood ratio statistics for testing the restrictions in models H_0: $\gamma_{up} \neq \gamma_{down}$, H_0: $\gamma^{+}_{up} \neq \gamma^{+}_{down}$, and H_0: $\gamma^{-}_{up} \neq \gamma^{-}_{down}$, respectively. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample period covers from January 1990 to December 2017.

5. Conclusion

As sentiment plays an important role in the decision-making of investors and stock price~~s~~ movements, we have aimed at understanding the mechanism by which sentiment affects investors~~'~~ demand for risky assets. Previous work highlight~~s~~ that sentiment-driven investors are primarily noise traders and irrational. Nevertheless, it's quite possible that these investors make great informed decisions using information extracted from sentiment measures. In this paper, we have analyzed this possibility and empirically tested if and to what extent investor sentiment impacts such investors~~'~~ trading behaviour and performance. More importantly, we have investigated the extent to which rational utility maximizers, smart money professionals, positive feedback traders, or sentiment-driven investors influence stock prices in the different U.S. stock markets. The research design includes Sentana and Wadhwani (1992), Cutler et al. (1990) and Chau et al. (2016) models to give a generalized approach for investigating the influence of these investors and to what extent their behavior drives changes in stock prices. In particular, this work has addressed whether investors trade on sentiment, what sentiment measures are important to investors, and when is sentiment more important. To achieve this, we have used some market and survey-based measures which are available at a monthly and weekly frequency and that have been widely used in both research and by practitioners to gauge the sentiment and opinions of market participants.

Our main results can be summarized as follows. First, we have observed that investor sentiment is indeed important and that there is a group of sentiment-driven investors who~~se~~ play an important role in driving stock prices. Second, investors are more likely to trade on the information content extracted from investor surveys rather than market-based, sentiment measures. Third, we have found that sentiment-driven investing is asymmetric with regard to decline and rise of sentiment in the market. In addition, we have acknowledged a discernible asymmetry while trying to understand their behaviors vis-à-vis bearish and bullish markets by which they are culturally more prone to sentiment-driven trading in bear markets.

These study's findings bear implications for investors and policymakers. For investors, the fact that volatility is priced, including the sentiment-driven component, means that their strategies should include a sentiment factor when measuring the total risk. Given the significant positive risk-premium, investors need to hold well-diversified portfolios to be rewarded for the component of risk as per CAPM. For policymakers, volatility persistence may have a negative impact on the functioning of markets and the pricing of assets. This impact may be amplified by changes in investor sentiment, leading to capital outflows and financial instability as investors seek better quality markets. Therefore, policymakers need to not only focus on established fundamental drivers of volatility but also on investor sentiment. The significant leverage effects imply that policymakers need to pay more attention to negative shocks and changes in investor sentiment as volatility is amplified. Understanding the role of cognition and information processing in affecting investor sentiment urges regulators to play a more proactive role in asset markets. They can help investors make better decisions by improving investor education and rules of information disclosure to enhance unbiased information processing. The need for pricing investor sentiment cannot be shunned away.

Overall, these robustness results with several different specifications provide important insights into the price formation process for market practitioners. They show that such sentiment-driven investors are not irrational as in the classical framework of asset pricing theory. Rather, they know when to go against the crowd in trading and make money and, can even play a role of liquidity providing when buying overly sold stock during periods of declining sentiment and bear market conditions. The behavior of sentiment-driven investors influences a wide range of trading policies in financial markets. It is time to reconsider this phenomenon in future behavioral study. The implementation of sentiment-driven trading hypothesis will lead to more specific findings.We acknowledge some limitations in our study. We encountered some problems obtaining information. On the one hand, there is a lack of validity for other implications due to measurement difficulties and data. On the other hand, the sample size and the lack of information concerning certain periods of the exercise has limited the accuracy of our estimates. Future research in this area can build on the obtained results and take inspiration from recent news and upcoming events to limit these limits and errors.

CRediT authorship contribution statement

Bouteska Ahmed: Conceptualization, Methodology, Funding acquisition, Data curation, Formal analysis, Data curation, Writing - original draft.

Declaration of competing interest

I declare that me Ahmed Bouteska first and corresponding author has no any conflict of interests.

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