Does investor sentiment really matter?

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Abstract

We examine the role sentiment plays and its manifestation in the trading behavior of investors in the U.S. stock market. Our findings support the notion that sentiment-induced buying and selling is an important determinant of stock price variation. While 'classical' asset pricing categorizes investors who trade in ways not consistent with mean-variance optimization as 'irrational,' we show that this traditional view should not hastily be evoked to characterize sentiment-driven investing. We instead show that sentiment-driven investors can trade against the herd and sell when prices are overinflated as a result of over-bullishness and vice versa. The asset pricing implications of this paper are that sentiment is linked to shifts in risk tolerance and this triggers contrarian-type behavior. In sum, we uncover the following regarding the behavior of sentiment-driven investors; firstly, they are more apt to trade on survey-based indicators rather than market-based indicators. Secondly, they trade on the basis of information extracted from individual, rather than institutional, investor surveys. Thirdly, they respond asymmetrically to shifts in sentiment and trade more aggressively during periods of declining sentiment. Finally, there is asymmetry in the role of sentiment with respect to business conditions whereby such buying and selling is more pronounced during bear markets.

1. Introduction

Does investor sentiment really matter? The answer to this question has sweeping implications for academics, practitioners and regulators alike. Traditional asset pricing theory explicitly assumes the answer is 'no' in order to establish equilibrium relations and to tractably identify the linkages between stock price movements and intertemporal variation in relevant state factors (Merton, 1973, 1980). On the other hand, practitioners expend considerable resources to extract investor sentiment measures in order to gauge levels of pessimism or optimism. There are at least two reasons why a good understanding of sentiment is important to practitioners; firstly, sentiment refers to the general attitude or tone of investors toward a particular security or the market. By extension, this tone or mood can drive prices in ways that do not reflect fundamentals or changes in the investment opportunity set (Edelen et al., 2010). Thus, practitioners need to monitor their portfolios for shifts that can occur even in the absence of news pertaining to underlying fundamentals. Secondly, sentiment and investor psychology in general can spread quickly throughout the market and this in turn affects investors' risk aversions independently of intrinsic cash flow prospects or measures for fundamental value. Given how quickly sentiment can spread, regulators are directly interested in the role sentiment plays for its involvement in some of the manias, bubbles and 'black swan' type of events which have undermined our financial infrastructure.[1]

The finance profession has a long tradition of categorizing investors as either rational and informed or irrational and sentiment-driven. Classical theory argues that rational mean-variance optimizers dominate in the long-run (Markowitz, 1959). Information diffusion is also assumed to disseminate unrestrictedly to all market participants and thus we can deduce market participants compete equally and fairly. This leads to equilibrium and to 'fairly' priced securities which reflect only fundamental value whereby mispricing is transitory and quickly corrected by arbitrageurs at virtually no cost or risk (Friedman, 1953).

This classical line of reasoning, although refraining from explicitly rejecting the existence of sentiment-driven investors, leaves little room for a rigorous analytic discussion in terms of their role. The argument that arbitrageurs can effortlessly eliminate mispricing is also dubious

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[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 our economy (see SEC Report, 2010): *http://www.sec.gov/investor/locinvestorbehaviorreport.pdf*. Bernanke (2002) has also publicly spoken on how investor irrationality can lead to the formation of bubbles and the difficulties associated with 'pricing' them: *http://www.federalreserve.gov/boarddocs/speeches/2002/20021015/default.htm*.

since their resources may be limited (Shleifer and Vishny, 1997), they may be incapable of deciphering real information from 'noise' (Black, 1986), or are hesitant to attack mispricing given the possibility prices will further deviate from fundamentals (De Long et al., 1990a, 1990b, 1991; Figlewski, 1979; Shleifer and Summers, 1990). Wurgler and Zhuravskaya (2002) argue that since stocks are imperfect substitutes, it is not possible to eliminate such risk. Finally, Abreu and Brunnermeier (2002, 2003) reason that arbitrageurs are incapable of coordinating and synchronizing their efforts in order to become a stronger driving force in the market to correct mispricing.

As early as Keynes (1936), there has been interest in determining what role sentiment and emotions have on the decision-making of investors and how it drives stock prices. This interest is receiving invigorating attention especially in light of the excess volatility we are experiencing in stock markets globally and our inability to consistently link fundamentals with stock price variations (Dumas et al., 2009; Shiller, 2000).[2]

Studies now take various paths in order to understand the role of sentiment in the stock market. Yu and Yuan (2011) show that sentiment directly influences the mean-variance tradeoff on the market portfolio and may be a reason why extant literature cannot agree on the nature of this important relation. Other authors find that sentiment contains useful economic information which can impact stock returns (Antoniou et al., 2013; Baker and Wurgler, 2006; Frazzini and Lamont, 2008; Schmeling, 2009; Stambaugh et al., 2012). Other authors argue that sentiment can lead investors to engage in feedback-type strategies of buying and selling in tandem with the 'crowd' (Blasco et al., 2011; Lemmon and Ni, 2010). Hribar and McInnis (2012) find that when sentiment is high, analysts' forecasts are relatively more optimistic for 'uncertain' firms.

What is fascinating (and not to mention challenging) to researchers is that sentiment is essentially a qualitative disposition arising from inside an individual stemming from a myriad of unobservable factors and cannot easily be measured or quantified. What is quantifiable however, to some extent, is the manifestation of sentiment on the decision-making of individuals. The aforementioned have contributed significantly to our understanding of how sentiment can affect

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[2] Interest in the role of sentiment is indeed growing. Testament to this are the growing number of articles related to investor sentiment. For example, a quick search on the Social Science Research Network (SSRN) for articles which have titles containing the key words "investor sentiment" gives back approximately 600 results. Likewise, if we search only titles containing the popular key word "CAPM," we get approximately 1,500 results (a little more than double). This search result is as of the summer of 2015. It should be noted that there is also a growing literature that studies the macro-financial determinants of investor sentiment (Lutz, 2015), however the identification of driving forces of sentiment is beyond the scope of this paper.

stock price movements. What is still not clear is the mechanism by which it influences investors' demand for risky assets. Baker and Wurgler (2007, pp.130) make this very point: *"...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."* Thus, this paper attempts to expound on this and looks at the role sentiment plays on investors' decision-making.

We show it is too premature to accept the classical view that sentiment-driven investors are irrational and that they contribute to mispricing, especially in light of evidence that investors can reap sizeable profits by understanding what the underlying sentiment is in the stock market and trading against such sentiment when it is profitable to do so (Soros, 1987). In particular, we find that sentiment-driven investors can trade against the 'herd' and sell their positions when prices are overinflated as a result of over-bullishness and overoptimistic sentiment. Conversely, periods of low sentiment can present excellent buying opportunities. The asset pricing implications of this paper are that sentiment is linked to shifts in risk tolerance and this triggers contrarian-type behavior.

Given that there is great demand for survey- and market-based indicators of sentiment, it is no surprise that sophisticated investors would use such information to make more informed decisions. We find in our paper that investor sentiment indeed matters and that such investors are more apt to trade on the information content extracted from survey-, rather than market-based, sentiment indicators. When focusing more in-depth on this, we specifically find that such investors trade on sentiment extracted from individual, rather than institutional, surveys. In terms of the time-series dynamics of sentiment changes with respect to such investors' buying and selling decisions we find that they trade more aggressively during periods of declining sentiment than rises in sentiment of equal magnitude. Asymmetry is also discernible when we look at their behavior with respect to bear versus bull markets whereby they are more prone to sentiment-driven trading during bearish markets. The findings herein are strikingly robust to various econometric specifications and suggest that we ought to take a closer look at the role sentiment plays in the decision-making of investors and how this drives stock prices.

The remainder of this paper is structured as follows. In Section 2 we develop our testable hypotheses and review some background literature. Section 3 describes our analytical framework. Section 4 describes the investor sentiment data used and the sample characteristics.

In section 5 we discuss our major findings and their robustness. Finally, in Section 6, we provide concluding remarks.

2. Testable Hypotheses

As discussed in the introduction, it is still not clear the mechanism by which sentiment impacts investors' demand for risky assets. The classical view in finance is sentiment-driven investors are essentially 'noise traders' and irrational (De Long et al., 1990a, 1990b, 1991; Shiller, 2000; Shleifer and Vishny, 1997). However, it is quite possible that these investors use information extracted from sentiment measures to make informed decisions. For example, Soros (1987) argues that the key to success is not to arbitrage against herding investors, but instead to 'ride the wave' along with them and sell out near the top. Thus, it is no surprise that there is a wealth of analyst services available to investors as well as survey-based indicators designed to gauge the overall sentiment in the market among invested investors as well as those on the sidelines who are awaiting an opportunity to invest.

Baker and Wurgler (2007), among others, have identified the presence of sentiment-driven investors and their possible influence on stock price movements. A reasonable starting point for discussion is therefore to examine whether investors trade on sentiment and in what ways they do so. In other words, do they respond to the information content from sentiment measures and how does their demand for risky assets change along with shifts in sentiment. This leads us to the first hypothesis of this paper:

Hypothesis 1: Investor sentiment matters and there exists sentiment-driven buying and selling in the stock market.

From the perspective of market timers, it is of use to know which sentiment measures matter and which are actually linked to shifts in risk aversion and future expectations. By knowing which sentiment measures to look at they can effectively position themselves in order to either engage in momentum type strategies, or, to invest against such sentiment. There is already a very large universe of market-based measures as well as measures constructed from investor surveys. Academic research has also constructed such measures in order to identify factors which impact sentiment and how such sentiment drives stock price movements (Baker

and Wurgler, 2006). This large supply of sentiment measures reflects the growing demand for such measures on the part of investors. The next question naturally is, what type of sentiment actually matters and is used by sentiment-driven investors? We conjecture that the information content extracted from survey-based indicators is more useful given that it is compiled from investors' forward-looking expectations and outlook of the market.

We further conjecture that the information content of individual investor sentiment measures is particularly important to consider because individual investors may be more prone to irrationality and misinformation compared to their institutional counterparts. If they are more prone to such biases, this can present excellent investment opportunities in either direction for vigilant investors. Verma and Verma (2008) find that institutional investor sentiments are more rational than individual investor sentiments. Likewise, Schmeling (2007) argues that institutional investors closely watch the sentiment of individual investors, which presents a potential source of noise trader risk, in order to form their expectations.

In light of these findings, it may be useful to trade on the basis of survey-based sentiment measures from individual investors since their forward-looking expectations may be more prone to biases that can drive stock prices away from fundamentals for an indefinite period of time. This leads us to our next hypothesis:

Hypothesis 2: The sentiment extracted from survey-based measures and, in particular, individual sentiment measures, is what matters.

It is of further interest to see whether the direction of sentiment changes impacts the buying and selling behavior of sentiment-driven investors differently. The so-called 'negativity effect' in psychology is a cognitive bias which refers to a phenomenon whereby individuals tend to put greater weight and emphasis on negative information rather than positive information of equal magnitude (Baumeister et al., 2001; Peeters, 1991). Given this tendency, we would expect sentiment-driven investors to trade more aggressively on declining sentiment than on upswings in sentiment of equal magnitude. This leads us to our third hypothesis:

Hypothesis 3: There is asymmetry in the role sentiment plays whereby sentiment-driven trading is more pronounced during periods of declining sentiment.

Finally, we want to examine whether sentiment-driven investors respond more or less to sentiment measures with respect to market conditions. It is possible that poor market conditions and declining stock prices may exacerbate individual investors' irrationality. This may result from noise traders' insufficient liquidity on hand and inability to meet their margin calls. Such a scenario can push prices further from fundamentals and may presents better than usual buying or selling opportunities for those with an eye on sentiment. This leads us to our last hypothesis:

Hypothesis 4: There is asymmetry in the role sentiment plays with respect to market conditions whereby sentiment-driven trading is more pronounced during bear markets.

3. Analytical Framework

This paper extends the framework of Shiller (1984) and Sentana and Wadhwani (1992) to provide a generalized framework for exploring the interaction of sentiment-driven investors with other heterogeneous investors and to directly address the aforementioned hypotheses to discover (i) *whether* investors trade on sentiment; (ii) *which* sentiment indicators matter to investors; (iii) *whose* sentiment matters; (iv) *when* does sentiment matter most.

In particular, building on the intertemporal capital asset pricing model (ICAPM), we develop a model to accommodate the heterogeneous trading behavior of three distinct groups of investors; rational utility maximizers, or 'smart money' investors, positive feedback traders, and sentiment-driven investors, respectively.

The demand for shares by the first group (rational or 'smart-money') investors in period t, Q_t, is consistent with the maximization of expected mean-variance utility:

$$Q_t = \frac{[E_{t-1}(R_t) - \omega]}{\theta \sigma_t^2} \quad ; \quad \theta > 0 \tag{1}$$

where $E_{t-1}(R_t)$ is the expected return of period *t* given the information available at period *t-1*, ω is the risk-free rate of return, θ is the coefficient of relative risk aversion, σ_t^2 is the conditional variance (risk) in period *t*. According to theory, a positive and significant sign for θ denotes a positive tradeoff between risk and return.

The second group of investors we integrate into our model are known as 'feedback traders.' Their demand for shares, F_t, depends on the previous period's return:

$$F_t = \rho R_{t-1} \quad ; \quad \rho > 0 \tag{2}$$

where R_{t-1} is the return in the previous period, ρ is the feedback parameter and is expected to be a positive value ($\rho > 0$) for the case of positive feedback, or 'trend-chasing' traders, who buy (sell) after price increases (decreases).[3]

Finally, as an extension to the framework of Sentana and Wadhwani (1992), we model the demand of sentiment-driven investors who base their investment decisions on the basis of overall market sentiment. The fraction of shares held by this group in period t, S_t, is a function of the changes in investor sentiment and is given by:

$$S_t = \lambda(\Delta IS_{t-1}) \quad ; \quad \lambda < 0 \tag{3}$$

whereby ΔIS_{t-1} is an indicator of change in investor sentiment and is defined as $IS_{t-1} - \overline{IS}_{t-3}$ where IS_{t-1} and $\overline{IS}_{t-3}$ are the sentiment level in period $t-1$ and its previous three-month average value, respectively. In the empirical analysis we also calculate a 'weighted' rolling average of the sentiment level for the previous three months as follows: (3/6)*sentiment$_{t-1}$ + (2/6)*sentiment$_{t-2}$ + (1/6)*sentiment$_{t-3}$. This is to allow more weight on the most recent sentiment observation.[4] The demand for shares by this group of investors depends on the sensitivity of their demand to sentiment changes (as given by the λ coefficient). For instance, if $\lambda < 0$ it suggests that sentiment is considered by this group of investors as a 'contrarian' market timing tool; i.e., they lower their demand for shares following an increase in investor sentiment and vice versa.

In equilibrium, all shares must be held by these three groups of investors:[5]

$$Q_t + F_t + S_t = 1 \tag{4}$$

Or, alternatively,

$$\frac{[E_{t-1}(R_t) - \omega]}{\theta \sigma_t^2} + \rho R_{t-1} + \lambda(\Delta IS_{t-1}) = 1 \tag{5}$$

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[3] This type of trading behavior may result from portfolio insurance strategies or stop-loss orders and has often been blamed for moving prices away from their fundamental value (Shleifer, 2000). Nofsinger and Sias (1999) provide evidence supporting the existence of positive feedback trading among individual and institutional investors.

[4] However, as shown in section 5.4, our main results remain unchanged when we use a simple arithmetic average. For robustness checks, we also consider alternative periods based on one and five month lags and find that our results continue to hold.

[5] Note that if all investors are rational 'smart-money' investors (i.e., $Q_t = 1$), then market equilibrium would yield the familiar ICAPM of Merton (1973): $E_{t-1}(R_t) - \omega = \theta \sigma_t^2$.

Equation (5) can be converted into a regression model with a stochastic error term. Thus, if we assume the rational expectation, $R_t = E_{t-1}(R_t) + \varepsilon_t$, and substitute this back into (5) and rearrange the equation, we have the following:

$$R_t = \omega + \theta\sigma_t^2 - \rho(\theta\sigma_t^2)R_{t-1} - \lambda(\theta\sigma_t^2)\Delta IS_{t-1} + \varepsilon_t \qquad (6)$$

whereby ε_t is a stochastic error term. The term $-\rho(\theta\sigma_t^2)R_{t-1}$ implies that in a market with positive feedback traders the returns would exhibit negative autocorrelation and the degree of autocorrelation is proportional to the conditional variance of returns, σ_t^2. Equation (6) can further be re-parameterized and expressed in a simplified form as follows:

$$R_t = \omega + \theta\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \gamma\sigma_t^2\Delta IS_{t-1} + \varepsilon_t \qquad (7)$$

whereby φ_1 = -$\rho\theta$ and γ = -$\lambda\theta$. The presence of risk-averse rational investors as described in equation (1) implies that θ is positive and statistically significant. However, if there is positive feedback trading it implies 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 (7) reduces to the feedback trading model proposed by Sentana and Wadhwani (1992), $R_t = \omega + \theta\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t$. Hereafter in our paper, this model is referred to as the 'baseline model.'

Note that in the model associated with equation (7), 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. We therefore name this as the 'symmetric effects model' throughout the paper. As an alternative model, we also entertain the possibility that their demand function is affected in an *asymmetric* way:

$$S_t = \lambda^+(\Delta IS_{t-1}^+) + \lambda^-(\Delta IS_{t-1}^-) \qquad (8)$$

Herein the indicator of sentiment change is decomposed into positive and negative terms such that $\Delta S_{t-1} = \Delta IS_{t-1}^+ + \Delta IS_{t-1}^-$; 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 $\lambda^+ \neq \lambda^-$.[6] After substituting (1), (2) and (8), respectively, into (4) and rearranging, we get the following:

$$R_t = \omega + \theta\sigma_t^2 - \rho(\theta\sigma_t^2)R_{t-1} - \lambda^+(\theta\sigma_t^2)\Delta IS_{t-1}^+ - \lambda^-(\theta\sigma_t^2)\Delta IS_{t-1}^- + \varepsilon_t \qquad (9)$$

Equation (9) can be re-parameterized and expressed in a simplified form as follows:

$$R_t = \omega + \theta\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \gamma^+\sigma_t^2\Delta IS_{t-1}^+ + \gamma^-\sigma_t^2\Delta IS_{t-1}^- + \varepsilon_t \qquad (10)$$

whereby $\varphi_1 = -\rho\theta$, $\gamma^+ = -\lambda^+\theta$ and $\gamma^- = -\lambda^-\theta$. We hereafter refer to equation (10) as the 'asymmetric effects model'.

As we discuss in greater detail in section 5, in our analysis we estimate a number of configurations of the original model in (4) to include the specification outlined by Sentana and Wadhwani (1992), which does not include the impact of sentiment-driven investors (i.e., the 'baseline model'), and the 'symmetric effects' and 'asymmetric effects' models, respectively. The latter two of the models are estimated and compared in order to examine whether sentiment-driven investors behave differently in recessionary market conditions.

Completion of these models requires a specification of the conditional variance (σ_t^2). In our paper, we estimate σ_t^2 using an exponential GARCH (EGARCH) process of order (1,1) (Nelson, 1991):

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1[(\left|z_{t-1}\right| - E\left|z_{t-1}\right|) + \delta z_{t-1}] + \beta\ln(\sigma_{t-1}^2) \qquad (11)$$

whereby *ln(.)* are natural logarithms and $z_t = \varepsilon_t/\sigma_t$ are standardized residuals. The EGARCH(1,1) specification allows the conditional variance to be time-varying and to respond asymmetrically to positive and negative return innovations. In addition, it also has the advantage of requiring no non-negativity constraints to ensure a positive conditional variance.[7] Given the initial values for ε_t and σ_t^2, the parameters of each model can be estimated simultaneously by maximum likelihood. The maximization technique used in this paper is based on the algorithm suggested by Berndt et al. (1974). We assume that the innovations are drawn from a normal density function.

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[6] Note that when $\lambda^+ = \lambda^- = \lambda$ then equation (3) is obtained as a special case.

[7] Pagan and Schwert (1990) evaluate several competing volatility models and conclude that the EGARCH provides the best overall 'fit' for return volatility. As a robustness check, in our empirical application we also estimate the process by replacing equation (11) with a GJR-GARCH(1,1) model. We find that our main results are robust to different specification choices of the conditional variance.

If error terms are not normally distributed, Bollerslev and Wooldridge (1992) robust standard errors are employed.[8]

4. Sentiment Data and Sample Characteristics

To empirically test our hypotheses we obtain a number of market- and survey-based measures that have been widely used in the literature to gauge the sentiment of market participants. The first measure is the index of investor sentiment provided by Baker and Wurgler (2006) (hereafter referred to as 'BW'). This index is constructed from the following six market-based variables: NYSE turnover, closed-end fund discount, number of IPOs, first-day return on IPOs, the equity share in the new issues, and the dividend premium, 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.[9]

The second investor sentiment proxy we consider is investors' forward-looking expectations of market volatility, captured by the VIX (the Chicago Board Options Exchange's volatility index, also known as the 'investor fear gauge'). The VIX index is constructed from implied volatilities of S&P 500 index options and has often been used by traders as a sentiment indicator since its introduction in 1993 (Whaley, 2009). The monthly series of the VIX index is obtained from Datastream for the period of January 1993 to December 2011. In addition to this market-based indicator of sentiment, we employ two additional survey-based measures: the Consumer Confidence Index (CCI) compiled by the Conference Board and the University of Michigan (MS) consumer sentiment index, respectively. Unlike the BW index and VIX, both the CCI and MS surveys gather their information solely from consumers in order to gauge their expectations about future business conditions, the general level of prices and overall prospects of the economy. Such indexes have proven successful in predicting household spending (Ludvigson, 2004; Garrett et al., 2005) and are considered a reliable barometer of sentiment in the aggregate market (Fisher and Statman, 2003; Antoniou et al., 2013). The monthly series of CCI and MS are extracted directly from the Euromonitor International Economic Observer

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[8] Hence, our estimation can also be interpreted as a quasi-maximum likelihood method.
[9] 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 2010 at Jeffrey Wurgler's website (*http://pages.stern.nyu.edu/~jwurgler/*).

database for the period between January 1978 and December 2011, for which both consumer confidence surveys are available at the monthly frequency.[10]

We also use two commonly cited surveys available on a weekly basis to capture the changing moods and emotions of different groups of market participants. The first is the survey conducted by the American Association of Individual Investors (AAII). This association has been conducting its weekly sentiment survey for its members since July 1987 whereby participants are asked whether they are bullish, bearish, or neutral about the stock market over the next six months. Since this survey is targeted towards individuals, it can be interpreted as a measure of *individual* investor sentiment. Specifically, we follow Wang et al. (2006) and use a ratio of the bullish percentage to the bearish percentage as our measure of sentiment for individual investors. Another sentiment index used in this paper is based on the survey data provided by Investors Intelligence (II) which has compiled its weekly sentiment data since 1964. Unlike that of AAII, the respondents to this survey are independent newsletter writers and market professionals. We thus use the ratio of bullish to bearish responses for the II index as a proxy of *institutional* investor sentiment.[11]

In addition to the sentiment measures, we collect price series data on the S&P 500 index to proxy for the overall performance of the U.S. stock market. We estimate continuously compounded returns from these price series for the period January 1978 to December 2011.[12]

Descriptive statistics of all the variables discussed in this section are provided in table 1. The statistics reported are, respectively, the mean (μ), standard deviation (σ), measures for skewness (S) and excess kurtosis (K), Jarque-Bera (JB) test statistic, Ljung-Box (LB) statistic for 12 lags, ARCH test, and the JOINT test statistic which tests for volatility asymmetry. As indicated by the significant JB test statistics, the stock market return series and sentiment indicators display a clear departure from normality. In particular, we see that the monthly return on S&P 500 index is negatively skewed and highly leptokurtic. This observation is consistent

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[10] Both 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 at the monthly frequency. 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/*.

[11] Although the II index is available from 1964, for the empirical analysis in this paper we collect the weekly AAII and II survey results from *http://www.aaii.com/* and *http://www.investorsintelligence.com/* for the period between July 24, 1987 and December 29, 2011 because of the changes in the II reporting frequency and the unavailability of AAII prior to 1987.

[12] We also examine the robustness of our main results using the Dow Jones Industrial Average (DJIA) index. The results (reported in Table 5) confirm that our conclusions hold for these alternative stock market indices. It should however be noted that the frequency of data and the sampling period for the ensuing analysis vary due to data availability of investor sentiment indicators. The starting and ending dates for each sentiment indicator are reported in Table 1.

with existing literature and ties in with the volatility feedback hypothesis which finds that large negative stock market returns are more common than large positive returns (Campbell and Hentschel, 1992). Likewise, the investor sentiment measures also display a skewed and leptokurtic pattern. The Ljung-Box (LB) statistics provide evidence of significant temporal dependencies in both the levels and the squared values of all sentiment indicators. The regression results reported in panel C of table 1 show that all the sentiment measures are highly persistent and exhibit substantial first-order autocorrelations that are positive.

Visual inspection of figure 1 suggests there is some degree of persistence in the time-series behavior of investor sentiment. The results of the ARCH and JOINT tests suggest that significant time-variations and asymmetries exist in the conditional volatility, supporting the use of an asymmetric EGARCH specification as a method of modelling the conditional variance.

Panel B of table 1 presents the correlations of our monthly measures of investor sentiment (both the market- and survey-based indicators) and the returns on the S&P 500 index, as well as the correlation between the weekly surveys of *individual* (AAII) and *institutional* (II) investor sentiments.

Consistent with Fisher and Statman (2003), the correlation coefficient between the two survey-based indicators, CCI and MS, is 0.84 and statistically significant. It is also not surprising to see that, understandably, there is some correlation between individual and institutional investors' expectations about future states of the economy. However, it appears that CCI exhibits a statistically insignificant correlation with returns on the S&P 500 index.

The ups and downs of consumer confidence and the S&P 500 index from January 1978 through December 2011 are presented in Figure 1. Visual inspection reveals at least two important observations: (i) Consumer confidence fluctuates substantially over time, with troughs in periods corresponding to times of economic uncertainty. (ii) A discernible relation between confidence measures and returns on the S&P 500 is more ostensible after the mid-1990s when volatility in the market became more and more pronounced. The burst of the 2000 tech bubble and the 2008-2009 crash following the collapse of Lehman Brothers are time periods where market prices dropped precipitously and are also associated with out-of-the-ordinary drops in

investor sentiment. In these time periods, based on visual inspection, the association between sentiment and market prices is indeed strongest.[13]

The two market-based sentiment proxies, BW and VIX, exhibit a limited degree of co-movement with one another; the correlation coefficient between the two is 0.075 and statistically insignificant. This suggests that they also may encompass different sets of information intended for somewhat disparate types of investors. While the BW index subsumes macro-level types of characteristics, such as mutual fund flows, the VIX captures options data characteristics which fluctuate more aggressively and can be used by intraday traders.

Consistent with the volatility feedback effect of Campbell and Hentschel (1992), there is a negative and statistically significant relation between returns on the S&P 500 index and the implied volatilities of S&P 500 index options (as captured by the VIX). From an asset pricing point of view, this suggests a negative time-series relation between risk and return. From a behavioral finance perspective, this type of a relation manifests because rises in the VIX reflect fear and uncertainty. As the VIX rises, investors sell their underlying positions and this leads to declining stock prices. Conversely, when the VIX is historically low, it signals complacency and bullishness. While the former scenario presents a potential buying opportunity for contrarians, the latter may be a good time to exit the market. This is why the VIX is also generally referred to as a market-based barometer of 'investor fear' and is used by contrarians to time market entry and exit points.

Finally, we also find a positive and significant relation between the two respective measures of consumer confidence. The correlation coefficient between AAII (which reflects *individual* investor sentiment) and II (which reflects *institutional* investor sentiment) is 0.37. As mentioned, a priori, this is to be expected given that there is some degree of similarity in the expectations among these two classes of investors.

[Insert table 1]

[Insert figure 1]

5. Main Findings and Robustness Checks

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[13] Fisher and Statman (2003) argue that the declines in stock prices are likely to erode consumer confidence because of the detrimental effects of the declining stock prices on investors' income and total wealth. While it remains difficult to assert whether the collapse of consumer confidence was the cause or the consequences of the recent global financial crisis, most academics and policy makers agree the erosion of confidence has ensured the depth and longevity of the crisis regarded by many economists as the worst financial crisis since the Great Depression (Pendery, 2009).

5.1. Evidence of sentiment-driven trading

Our first hypothesis tests the notion that sentiment-driven buying and selling exists in the stock market. Testing this hypothesis is naturally a first step before delving deeper into our following three hypotheses that seek to determine *which* sentiment measures matter more for investors and *how* sentiment-driven investors behave during bull and bear markets as well as periods of high and low sentiment, respectively.

Table 2 thus reports, among the other models that we will discuss in turn, the parameter estimates for our baseline model. As mentioned, our baseline model is analogous to the feedback trading model by Sentana and Wadhwani (1992) and assumes that no sentiment-driven investing exists in the stock market (i.e., $\gamma = 0$). The baseline model is described using equation (7), with the restriction that $\gamma = 0$, and provides a comparison with the symmetric effects (equation 7) and asymmetric effects (equation 10) models, respectively, which test for the presence of sentiment-driven investors. Such a comparison can be made across the mean equation parameter estimates in panel A of table 2. It is important to note that panel B of table 2 reports parameter estimates for the EGARCH specification in equation (11) which correspond with the respective models in panel A. As mentioned, the conditional mean and variance equations are estimated simultaneously because time-series estimates of the conditional variance are used to produce conditional mean parameter estimates for each of the models.

The conditional mean equation parameter estimates (in panel A) naturally exhibit observable qualitative differences, which we will discuss, as a result of the different sentiment measures that are used. This can be deduced by observing the parameters across the columns. For example, for survey-based sentiment measures we have CCI and MS whereby we consider symmetric effects and asymmetric effects models, respectively. For the market-based sentiment measures we have BW and VIX where we also consider symmetric effects and asymmetric effects models, respectively. For the EGARCH parameter estimates (in panel B), however, we generally find that the conditional variance at time t is a statistically significant function of past innovations and with its past values. This is indicated by parameters α_1 and β, respectively, and supports the view that volatility responds to shocks and is persistent across time. The asymmetry parameter, δ, is generally insignificant across the models. This may be an artifact of using monthly data which 'averages out' important time-series characteristics of the data. In the weekly data we will discuss later on (in table 3) we find that δ is consistently negative and

significant – consistent with the notion that negative shocks lead to more volatility than positive shocks of equal magnitude. It has been argued that asymmetry in the conditional variance arise due to, at least in part, the presence of positive feedback (or trend-chasing) trading behaviour (Antoniou et al., 2005).

Let us now turn our attention more closely at the baseline model before delving deeper into the sentiment-based models. The very first column of table 2 reports parameter estimates for this model for the monthly data we examine. The baseline model is described by equation (7) but with the restriction $\gamma = 0$. It is essentially the feedback trading model of Sentana and Wadhwani (1992) which assumes the existence of 'rational' (mean-variance optimizing) investors and feedback traders as the only investors who affect prices.

The parameters θ and φ_1 for this model, which denote the presence of rational and feedback investors, respectively, are positive although insignificant. This suggests, for the monthly data that is examined, that the presence of these two types of investors alone cannot explain the time-series variations in stock returns. This finding contrasts with Sentana and Wadhwani (1992) who find feedback trading in daily price data series but is consistent with the finding by Koutmos (2012) who shows that feedback trading may be undetectable in monthly time-series price data. A plausible reason is there are other investors whose trades impact stock returns in a material way.

We posit that such investors are driven by sentiment. The survey-based (CCI and MS) and market-based (BW and VIX) columns report on the impact of these types of investors given the respective measures that are used to proxy for sentiment. The parameter of interest in this case is γ. Specifically, 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 (equation 7) we find that γ is indeed positive and statistically significant when CCI and MS, respectively, are used to proxy for sentiment. The coefficient γ is not significant when either BW or VIX are used as sentiment measures.

These findings have implications for the first hypothesis, which is concerned with whether investor sentiment matters, and for a portion of the second hypothesis, which contends that survey-based measures matter for investors. Specifically, in regards to the first hypothesis, the coefficient γ is positive and significant which means that it explains time-series variations in stock returns and supports the view that sentiment-driven investors affect prices. However, how

can we interpret the sign of γ? If we re-visit our earlier discussion of equation (7), we mention that $\gamma = -\lambda\theta$. Therefore, in the case of our positive and significant coefficients of 0.0057 and 0.0151 in table 1 for the symmetric effects model for CCI and MS, respectively, we can conclude that there exists a negative relation between the quantity demand for stock and sentiment levels (recall from equation 4 that the total quantity of shares is dictated by the respective demand functions of 'rational,' feedback and sentiment-driven investors). This provides novel insight into the behavior of sentiment-driven traders because, up until now, they are assumed to be irrational. We instead show from the coefficient γ that as investor sentiment begins to rise, which is coupled by rising stock prices (see figure 1), the demand for shares held by sentiment-driven investors begins to decline. This may stem from their apprehension as to the reasons for rises in stock prices and their anticipation of a reversal or, as in the extreme cases of 2000 and 2008-2009, respectively, a bubble burst.

Therefore, unlike feedback traders who 'follow the herd' and buy when everyone else is buying (prices are rising) and selling when everyone else is selling (prices are falling), we show that sentiment-driven investors behave like contrarians. This view is consistent with the trading philosophies detailed by Soros (1987) who argues that, at times, it is lucrative to trade against the herd and especially during periods where prices are overly-inflated as a result of exuberance.

Expounding on this further, let us see what we can deduce from the asymmetric effects model (equation 10) when CCI and MS are used to proxy for sentiment. As mentioned, the asymmetric effects model tests for asymmetry with respect to rising and declining investor sentiment. Estimating the asymmetric effects model for each of the sentiment proxies is useful because it allows us to determine whether the intensity of sentiment-driven buying and selling differs with respect to rising and declining sentiment. In table 2, the coefficients γ^+ and γ^-, respectively, correspond with rising and declining sentiment. For CCI and MS, the coefficient γ^- is positive and statistically significant. This suggests that sentiment-driven investors buy more aggressively during periods of declining sentiment than they sell during periods of rising sentiment. In some sense, based on their behavior, it can thus be argued that they are providing liquidity to the market because, on average, periods of declining sentiment cause average investors to sell their positions *en masse*.

This is an interesting finding because, although we can deduce from the coefficient γ in equation (7) that sentiment-driven investors exhibit contrarian-type behavior, we show that there

is asymmetry in terms of how they buy and sell with respect to rises and declines in overall market sentiment. This finding thus confirms hypothesis (3) where we posit such asymmetry.

A plausible explanation as to why this asymmetry exists is not readily apparent. It may be that sentiment-driven investors are aware of the fact that declines in the market are more severe than rises, as a result of bad news and declining sentiment. Thus, they perceive declining sentiment (falling stock prices) as a better trading opportunity and will buy when other investors are selling.

An explanation as to why market declines are more severe and thus possibly present better buying opportunities can be found in psychology literature which finds that negative information has a tendency to outweigh positive information in the minds of individuals. This observation is known as the 'negativity bias' or 'negativity effect' in psychology literature and has been detected among market participants when making investment decisions (Akhtar et al., 2011; Baumeister et al., 2001). From a practical investment perspective, negative news and poor sentiment is watched more closely by investors and can be portrayed more vividly by the media, thus coercing investors to act quickly to exit the market. This is also consistent with the notion of 'loss aversion' in economics and decision theory which finds that investors have a stronger preference for avoiding losses relative to their desire for acquiring gains (Kahneman and Tversky, 1992).

Both in the symmetric effects (equation 7) and asymmetric effects (equation 10) models we do not detect significance in the parameter γ (for the symmetric effects model) or in the parameters γ^+ and γ^- (for the asymmetric effects model). This finding is consistent with hypothesis 2 where we posit that the sentiment from survey evidence is what matters for sentiment-driven investors. Although BW and VIX have some explanatory power in the cross-section of stock returns, we find here that they have no statistically significant bearing on the investment decision-making of sentiment-driven investors as we have them defined here in our paper. This does not mean that such measures are not important. Instead, it suggests that survey-based measures may be perceived as less noisy forward-looking indicators of investors' expectations regarding future states of the economy because they elicit the opinions and attitudes of actual consumers and households - opinions and attitudes that are less prone to intraday fluctuations and 'noise' which is common in financial assets such as stocks and options.

[Insert table 2]

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5.2. Effects of individual and institutional sentiments

We have shown that survey-based measures of sentiment are important inputs which affect the buying and selling decisions of sentiment-driven investors. We have also shown that sentiment-driven investors exhibit contrarian-type behavior.

What is still unsaid is *whose* sentiment plays a relatively more significant role in influencing these investors' demand for risky assets. Hypothesis 2 directly addresses this important question where we posit that survey-based estimates of individual investor sentiment matter.

To test this hypothesis, we collect weekly data on AAII and II, which are both survey-based measures and denote the sentiment of individual and institutional investors, respectively. Following Wang et al. (2006) and Kurov (2008), we compute an investor sentiment index as a ratio of the percentage of bullish investors to the percentage bearish investors. As can be seen by the sign and significance of the parameters γ and γ^- in table 3, sentiment-driven investors trade more aggressively during periods of declining sentiment - a finding that is qualitatively analogous to the findings reported in table 2. As in table 2, the interpretation for their demand function is also the same; their demand for shares rises when sentiment declines and other investors are selling and, conversely, their demand for shares drops when sentiment rises and other investors are buying.

When comparing the significance of the γ coefficients between AAII (individual) sentiment versus II (institutional) sentiment, we see that sentiment-driven investors tend to trade on the individual, rather than institutional, sentiment surveys. This finding supports our conjecture that the information content of individual investor sentiment (as captured by AAII) is particularly important to consider because individual investors may be more prone to irrationality and misinformation compared to their institutional counterparts. In other words, they may be overly optimistic or pessimistic at various periods of time as a result of influences other than fundamentals. These attitudes may lead to uniformed decisions in the short- and medium-run and can be exploited by sentiment-driven investors. Shiller (2000) points out that the average investor in the market makes investment decisions on a myriad of subjective factors which may bear little correlation with underlying fundamentals. Thus, if individual investors lack the information and research access which institutional investors benefit from and are more prone to

overly optimistic or pessimistic attitudes, it may be easier to exploit these attitudes in the short- and medium-run.

<center>[Insert table 3]</center>

5.3. Sentiment-driven trading across market conditions and business cycles

From the perspective of market timers, it is important to know not only whether (and whose) sentiment measures matter but also *when* does sentiment matter the most in influencing the decision-making of investors and their future expectations. By knowing when to look at such information, sentiment-driven investors can effectively position themselves accordingly. Hypothesis 4 examines this issue and empirical findings are presented in table 4.

The aim here is to see whether sentiment-driven investors respond asymmetrically to sentiment measures with respect to market conditions and business cycles. As mentioned, it is plausible that poor market conditions and declining stock prices may exacerbate individual investors' (pessimistic) sentiment thereby pushing prices further from fundamentals and thus providing a good (buying) opportunity for those investors with an eye on sentiment. We explore this possibility by focusing on the monthly CCI and interacting the indicator of sentiment change (ΔIS_{t-1}) with a dummy variable describing business cycles and market conditions, as follows:

$$R_t = \omega + \theta\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \gamma_{UP}(D_t)\sigma_t^2\Delta IS_{t-1} + \gamma_{DOWN}(1-D_t)\sigma_t^2\Delta IS_{t-1} + \varepsilon_t \qquad (12)$$

$$R_t = \omega + \theta\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \gamma_{UP}^+(D_t)\sigma_t^2\Delta IS_{t-1}^+ + \gamma_{DOWN}^+(1-D_t)\sigma_t^2\Delta IS_{t-1}^+$$
$$+ \gamma_{UP}^-(D_t)\sigma_t^2\Delta IS_{t-1}^- + \gamma_{DOWN}^-(1-D_t)\sigma_t^2\Delta IS_{t-1}^- + \varepsilon_t \qquad (13)$$

where D_t is a dummy variable that is equal to 1 in a period of expansion or bull market and 0 in a period of recession or bear market. The indicator used to identify recessions and expansions in the U.S. economy is the National Bureau of Economic Research (NBER) business cycle indicator.[14] In this case the reaction of sentiment-driven traders to sentiment changes is allowed to differ over the macroeconomic cycles if $\gamma_{UP} \neq \gamma_{DOWN}$; $\gamma_{UP}^+ \neq \gamma_{DOWN}^+$ and/or $\gamma_{UP}^- \neq \gamma_{DOWN}^-$. Given that the new model specifications in equations (12) and (13) are nested in our symmetric and

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[14] As a robustness check, we also classify each period as recession or expansion by comparing the current economic activity (as measured by the Chicago Fed National Activity Index, CFNAI) to a rolling average of the previous three-month activity level. The results (not reported here) confirm that our main conclusions hold for this alternative macroeconomic condition indicator. In terms of market conditions, we follow Chen (2011) and use the moving average approach whereby bull and bear markets are identified by using the mean S&P500 return over the last six periods. In particular, we define a period as the bull market if its moving average return is greater than zero.

asymmetric effects models, the likelihood ratio (LR) statistics can be computed to test such restrictions.

For the sake of brevity, we will concentrate on the interpretation of the values for parameters of interest γ_{UP} and γ_{DOWN} which indicate the intensity of sentiment-driven trading during expansion (or bull market) and recession (or bear market), respectively. An inspection of the sign and significance of these key parameters in table 4 confirms our earlier findings that there are significant sentiment-driven trading against the emotions of the crowd and that they tend to trade more aggressively on declining sentiment than on upswings in sentiment of equal magnitude. More importantly, as indicated by the significance of LR test statistics, it also shows that their responses to sentiment changes are indeed different across the macroeconomic cycles. Specifically, sentiment-driven trading is more pronounced during recessionary and bear market conditions. This again is a recurring theme in our paper. It seems that sentiment-driven investors are more apt to trade on the survey-derived sentiment of individual investors because it is these very investors who are more prone to excessive optimism or pessimism - attitudes that can be misaligned with fundamentals and with the objective facts at hand.

[Insert table 4]

5.4. Robustness and additional tests

In this sub-section we examine the robustness of our results by attempting to (a) use returns on the Dow Jones Industrial Average (DJIA) as a proxy for the market portfolio and see how CCI can explain the behavior of sentiment-driven investors; (b) use a rolling weighted average calculation method for the sentiment change indicator ($\Delta IS'_{t-1}$); (c) use a measure of sentiment that is orthogonalized by using the residual from a regression of CCI against a constant and the rolling three-month average value of Chicago Fed National Activity Index (CFNAI) in order to remove the influence of macroeconomic factors on investor sentiment.

Let us now turn our attention to the first columns of table 5 where we focus on the results of the CCI measure for our symmetric and asymmetric effects models, respectively, whereby returns on the DJIA now serves as a proxy for the market portfolio. Overall, the results are qualitatively similar to those presented for the S&P 500 index in Table 2; specifically, they confirm the presence of sentiment-driven investors who exhibit contrarian-type investing and whose trading behavior becomes more pronounced during periods of declining sentiment.

Let us now examine the middle columns where we use $\Delta IS'_{t-1}$ as a measure for sentiment to explain returns on the market portfolio. We estimate $\Delta IS'_{t-1}$ as the weighted rolling average of the sentiment level for previous three months: $\left(\frac{3}{6}\right) \times sentiment_{t-1} + \left(\frac{2}{6}\right) \times sentiment_{t-2} + \left(\frac{1}{6}\right) \times sentiment_{t-3}$, rather than the simple moving average approach. Consistent with our earlier findings, estimates for the parameters γ and γ^- confirm our hypotheses that investor sentiment matters and there exists sentiment-driven trading in the stock market which is asymmetric with respect to declining and rising sentiment. Thus, our results are not particularly driven by the choice of methods in calculating sentiment change.

Finally, consideration is also given to the potential influence of macroeconomic factors on investor sentiment by regressing CCI on a constant and the rolling three-month average value of Chicago Fed National Activity Index (CFNAI) and using the residual from this auxiliary regression as the orthogonalized sentiment measure.[15] The evidence, presented in the final columns of table 5, show that, in general, the results of the 'unorthogonalized' CCI carry over to the orthogonalized measure, albeit the relatively smaller and less significant estimates for γ and γ^-. In other words, even when we control for macroeconomic influences, we see that sentiment-driven trading is still somewhat present and that they utilize the CCI as a means of investing.

[Insert table 5]

6. Concluding Remarks

While a growing number of studies have shown that sentiment plays an important role on the decision-making of investors and stock prices dynamics, less is known about the mechanism by which sentiment impacts investors' demand for risky assets. The classical view is that sentiment-driven investors are essentially 'noise traders' and irrational. However, it is quite possible that these investors use information extracted from sentiment measures to make informed decisions. This paper examines this possibility and empirically tests whether and to what extent investor sentiment influences the trading behavior of such investors. In particular, we investigate the

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[15] We chose the Chicago Fed National Activity Index (CFNAI) as a measure of the overall economic activity because it has been shown that this index often provides useful information on the current and future courses of U.S. economic activity and inflation (cf., Chau and Deesomsak, 2014). The CFNAI is constructed using principal components of 85 monthly indicators for employment, production, personal consumption, sales & inventories, and corresponds to the economic activity index developed by Stock and Watson (1999). Further details on the CFNAI are available at https://www.chicagofed.org/publications/cfnai/index

extent to which rational utility maximizers, or 'smart money', investors, positive feedback traders, and sentiment-driven investors drive stock prices in the U.S. stock market.

The economic framework nests the Sentana and Wadhwani (1992) and Cutler et al. (1990) models to provide a generalized framework for exploring the influence of these investors and to what extent their behavior drives variations in stock prices. Specifically, our hypotheses seek to address (i) *whether* investors trade on sentiment; (ii) *which* sentiment indicators matter to investors; (iii) *whose* sentiment matters; (iv) *when* does sentiment matter more. To accomplish this, we utilize a number of market- and survey-based measures that are available at both monthly and weekly frequencies and which have been widely used in the literature and by practitioners to gauge the sentiment of market participants.

The key findings of this paper can be summarized as follows. Firstly, we show that investor sentiment indeed matters and that there exists a group of sentiment-driven investors whose action play a significant role in driving stock prices. Secondly, we find that these investors are more apt to trade on the information content extracted from survey-, rather than market-based, sentiment indicators. Thirdly, we show that investors trade on sentiment extracted from individual, rather than institutional, investor surveys. Finally, sentiment-driven investing is asymmetric with respect to declining and rising sentiment in the market. This asymmetry is also discernible when we look at their behavior with respect to bear versus bull markets whereby they are more prone to sentiment-driven trading during bearish markets.

The findings herein are robust to various econometric specifications and have important implications to market practitioners. Specifically, we need to recognize that such sentiment-driven investors are not irrational as in the context of classical asset pricing theory but instead play a role in trading against the crowd and, in times of declining sentiment and bear conditions, can even act as liquidity providers by buying overly sold stock.

References

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

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

Antoniou, A., Koutmos, G., Pericli, A., 2005. Index futures and positive feedback trading: evidence from major stock exchanges. Journal of Empirical Finance 12, 219–238.

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

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

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

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

Baumeister, R.F., Bratslavsky, E., Finkenauer, C., Vohs, K.D., 2001. Bad is stronger than good. Review of General Psychology 5, 323-370.

Bernanke, B., 2002. Asset Price "Bubbles" and Monetary Policy. Remarks by Ben Bernanke before the New York Chapter of the National Association for Business Economics, New York, NY.

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

Blasco, N., Corredor, P., Ferreruela, S., 2011. Market sentiment: a key factor of investors' imitative behavior. Accounting & Finance 51, 1-27.

Bollerslev, T., Wooldridge, J., 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. Econometric Reviews 11, 143–172.

Campbell, J., Hentschel, L., 1992. An asymmetric model of changing volatility in stock returns. Journal of Financial Economics 31, 281-318.

Chau, F., Deesomsak, R., 2014. Does linkage fuel the fire? The transmission of financial stress across the markets. International Review of Financial Analysis 36, 57-70.

Chen, S., 2011. Lack of consumer confidence and stock returns. Journal of Empirical Finance 18, 225-236.

Cutler, D.M., Poterba, J.M., Summers, L.H., 1990. Speculative dynamics and the role of feedback traders. AEA Papers and Proceedings. American Economic Review 80, 63-68.

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

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

De Long, B.J., Shleifer, A., Summers, L.H., Waldmann, R.J., 1991. The survival of noise traders in financial markets. Journal of Business 64, 1-19.

Dumas, B., Kurshev, A., Uppal, R., 2009. Equilibrium portfolio strategies in the presence of sentiment risk and excess volatility. Journal of Finance 64, 579-629.

Edelen, R.M., Marcus, A.J., Tehranian, H., 2010. Relative sentiment and stock returns. Financial Analysts Journal 66, 20-32.

Figlewski, S., 1979. Subjective information and market efficiency in a betting market. Journal of Political Economy 87, 75-88.

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

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

Friedman, M., 1953. The case for flexible exchange rates, in Milton Friedman (ed.), Essays in Positive Economics. University of Chicago Press. Chicago, IL.

Garrett, T.A., Hernandez-Murillo, R., Owyang, N.T., 2005. Does consumer sentiment predict regional consumption? Federal Reserve Bank of St. Louis Review 87, 123-135.

Hribar, P., McInnis, J., 2012. Investor sentiment and analysts' earnings forecast errors. Management Science 58, 293-307.

Kahneman, D. and Tversky, A., 1992. Advances in prospect theory: cumulative representation of uncertainty. Journal of Risk and Uncertainty 5, 297-323.

Keynes, J.M., 1936. The General Theory of Employment, Interest and Money. London: Macmillan.

Koutmos, D., 2012. An intertemporal capital asset pricing model with heterogeneous expectations. Journal of International Financial Markets, Institutions & Money 22, 1176-1187.

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

Lemmon, M., Ni, S.X., 2010. The effects of investor sentiment on speculative trading and prices of stock and index options. SSRN working paper.

Ludvigson, S.C., 2004. Consumer confidence and consumer spending. Journal of Economic Perspectives 18, 29-50.

Lutz, C., 2015. The impact of conventional and unconventional monetary policy on investor sentiment. Journal of Banking and Finance 61, 89–105.

Markowitz, H., 1959. Portfolio selection: efficient diversification of investments. New York: Wiley.

Merton, R.C., 1973. An intertemporal capital asset pricing model. Econometrica 41, 867-888.

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

Pagan, A.R. and Schwert, G.W., 1990. Alternative models for conditional stock volatility. Journal of Econometrics 45, 267-290.

Peeters, G., 1991. Evaluative inference in social cognition: the roles of direct versus indirect evaluation and positive-negative asymmetry. European Journal of Social Psychology 21, 131-146.

Pendery, D., 2009. Three top economists agree 2009 worst financial crisis since great depression: risks increase if right steps are not taken. Business Wire News.

Schmeling, M., 2007. Institutional and individual sentiment: smart money and noise trader risk? International Journal of Forecasting 23, 127-145.

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

Securities and Exchange Commission, 2010. Behavioral Patterns and Pitfalls of U.S. Investors. Report by the Federal Research Division, Library of Congress, Washington, D.C.

Shiller, R.J., 2000. Irrational Exuberance. Princeton University Press, Princeton, New Jersey.

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

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

Soros, G., 1987. The Alchemy of Finance. New Jersey: Wiley.

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

Verma, R., Verma, P., 2008. Are survey forecasts of individual and institutional investor sentiments rational? International Review of Financial Analysis 17, 1139-1155.

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

Whaley, R., 2009. Understanding the VIX. Journal of Portfolio Management 35, 98-105.

Wurgler, J., Zhuravskaya, E., 2002. Does arbitrage flatten demand curves for stocks? Journal of Business 75, 583-608.

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

Table 1: Descriptive statistics of S&P 500 returns and investor sentiment measures

	Monthly					Weekly	
		Survey-based		Market-based		Survey-based	
	S&P500	CCI	MS	BW	VIX	AAII	II
Start Date	01/1978	01/1978	01/1978	01/1978	01/1993	24/07/1987	24/07/1987
End Date	12/2011	12/2011	12/2011	12/2010	12/2011	29/12/2011	29/12/2011
Panel A: Summary statistics							
μ	0.639	93.066	85.916	0.222	20.307	1.561	1.540
σ	4.530	24.756	13.109	0.708	7.905	0.651	0.966
S	-0.943	-0.204	-0.391	0.705	1.948	0.646	2.122
K	3.662	-0.505	-0.612	0.461	6.929	-0.060	7.719
JB	284.19 ***	7.05 **	16.54 ***	36.28 ***	679.34 ***	87.17 ***	4,041.60 ***
LB(12)	11.41	3,423.82 ***	3,233.78 ***	3,274.51 ***	940.33 ***	6,880.71 ***	1,761.54 ***
$LB^2(12)$	82.97 ***	3,561.01 ***	3,298.41 ***	2,120.79 ***	510.30 ***	5,942.42 ***	789.89 ***
ARCH	33.00 ***	380.07 ***	365.64 ***	355.64 ***	150.52 ***	1,061.09 ***	127.12 ***
JOINT	47.37 ***	369.52 ***	362.73 ***	339.23 ***	156.68 ***	1,039.56 ***	214.52 ***
Panel B: Correlation Coefficients							
S&P500	1						
CCI	0.080	1					
MS	0.136 ***	0.839 ***	1				
BW	-0.048	0.079	0.104 **	1		AAII 1	
VIX	-0.389 ***	-0.171 ***	-0.251 ***	0.075	1	II 0.370 ***	1
Panel C: Autocorrelation							
b_0	0.551 **	2.386 **	3.043 **	0.010	2.510 ***	0.100 ***	0.409 ***
b_1	0.064	1.023 ***	0.925 ***	0.977 ***	0.843 ***	1.073 ***	0.357 ***
b_2	-0.077	-0.056	-0.057	0.009	-0.077	-0.112 **	0.148 ***
b_3	0.054	-0.031	0.054	0.019	0.007	-0.008	0.155 ***
b_4	0.041	0.041	0.000	0.074	0.143 *	-0.063	0.071
b_5	0.078	-0.004	0.042	-0.113 **	-0.041	0.047	0.004
F-test	1.61	1305.23 ***	806.30 ***	1519.75 ***	133.85 ***	2095.03 ***	136.10 ***

Notes: This table provides descriptive statistics of S&P500 returns and investor sentiment measures. 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 test of autocorrelation for the level and squared returns and sentiment indices; the test statistics follow Chi-square distribution with 12 degree of freedom. ARCH is the Lagrange Multiplier test for ARCH (1) effect. The JOINT test is Engle and Ng's (1993) test for the potential asymmetries in conditional variance. The autocorrelation parameters (b_1 through b_5) are estimated from the autoregressive model, AR(5). *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 1: Time series plots of investor sentiment and S&P 500 price level

Panel A: Monthly sentiment series
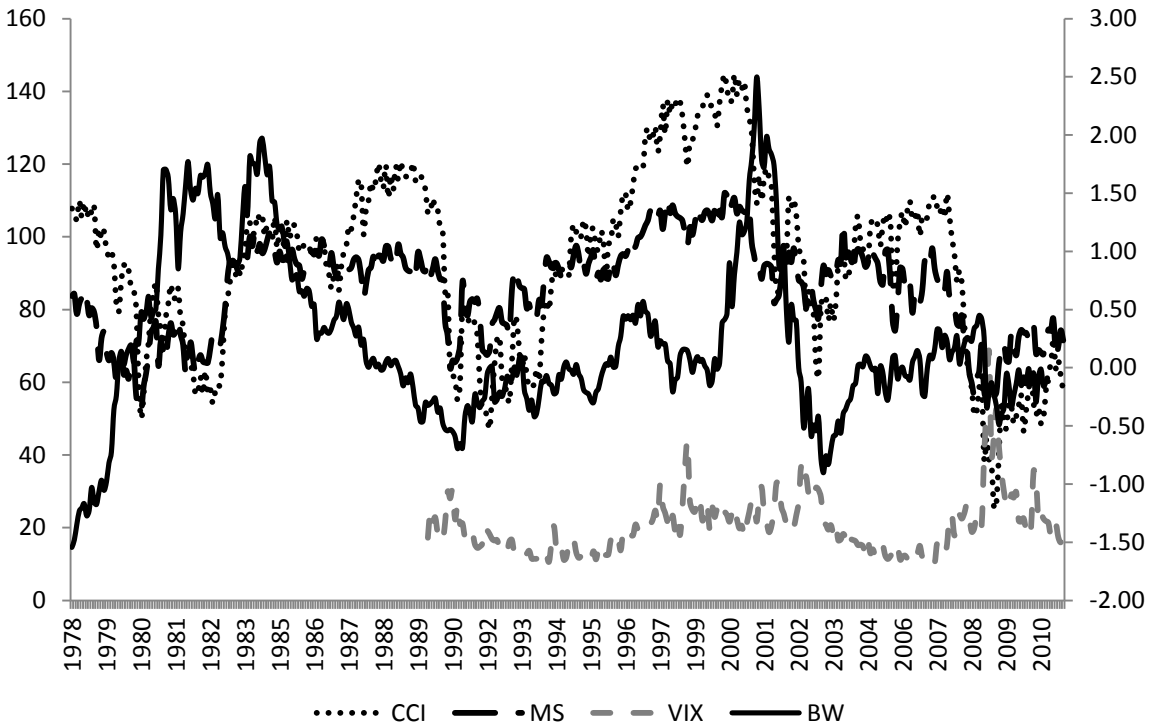
Panel B: S&P 500 Index
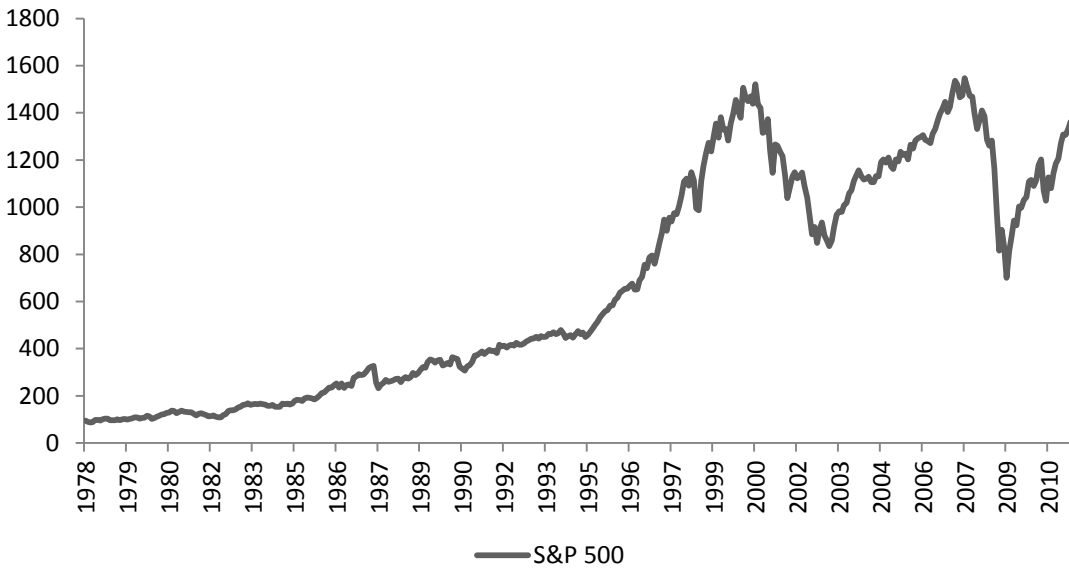
Notes: This figure depicts time series variation in the investor sentiment indices (Panel A) and in the stock market (Panel B). Panel A shows the levels of survey-based sentiment measures (CC and MS) on the left scale, and the market-based indicators (BW and VIX) on the right scale.

Table 2: Evidence on sentiment-driven trading

		MONTHLY SENTIMENT MEASURES							
		Survey-based				Market-based			
		CCI		MS		BW		VIX	
	Baseline	Symmetric	Asymmetric	Symmetric	Asymmetric	Symmetric	Asymmetric	Symmetric	Asymmetric
Panel A : Mean equation									
ω	0.5571	0.6438	0.5519 ***	0.8084 **	0.7811 *	0.6253	0.6145	0.6141 *	0.5339
	(1.254)	(1.551)	(12.005)	(1.999)	(1.908)	(1.462)	(1.105)	(1.756)	(1.404)
θ	0.0082	0.0038	0.0221 ***	-0.0029	0.0138	0.0033	0.0105	0.0055	0.0186
	(0.308)	(0.155)	(5.393)	(-0.115)	(0.469)	(0.129)	(0.229)	(0.205)	(0.507)
φ_0	-0.1329	-0.1272	-0.1567 ***	-0.1629	-0.1926 *	-0.1299	-0.1377	-0.1326	-0.1378
	(-1.429)	(-1.298)	(-6.667)	(-1.629)	(-1.849)	(-1.370)	(-1.395)	(-1.450)	(-1.478)
φ_1	0.0044	0.0018	0.0027 ***	0.0015	0.0025	0.0043	0.0046	0.0042	0.0039
	(1.573)	(0.615)	(3.290)	(0.456)	(0.707)	(1.524)	(1.205)	(1.140)	(1.063)
γ		0.0057 **		0.0151 ***		-0.0298		0.0008	
		(2.133)		(3.552)		(-0.357)		(0.225)	
γ^+			0.0031		0.0089		-0.1149		-0.0023
			(1.264)		(1.015)		(-0.577)		(-0.489)
γ^-			0.0096 ***		0.0219 ***		0.0294		0.0033
			(5.680)		(3.076)		(0.180)		(0.430)
Panel B : Variance equation									
α_0	0.1486 **	0.1294 **	0.1344 ***	0.1322 *	0.1167 *	0.1302 **	0.1394	0.2927 **	0.2766 **
	(2.032)	(2.000)	(76.009)	(1.953)	(1.773)	(1.971)	(1.301)	(2.411)	(2.305)
α_1	0.2403 ***	0.2403 ***	0.2402 ***	0.2618 ***	0.2520 ***	0.2415 ***	0.2376 ***	0.4012 ***	0.4005 ***
	(3.357)	(3.439)	(8.505)	(3.459)	(3.398)	(3.398)	(7.039)	(2.963)	(2.984)
β	0.9510 ***	0.9576 ***	0.9557 ***	0.9558 ***	0.9619 ***	0.9580 ***	0.9546 ***	0.8889 ***	0.8949 ***
	(38.404)	(44.176)	(171.534)	(41.174)	(42.353)	(43.114)	(22.552)	(19.901)	(20.315)
δ	-0.1660	-0.1520	-0.1888 *	-0.0849	-0.0663	-0.1384	-0.1617	-0.4417 *	-0.4331 *
	(-0.975)	(-0.865)	(-1.812)	(-0.568)	(-0.412)	(-0.843)	(-0.498)	(-1.908)	(-1.905)

Notes: This table reports maximum likelihood estimates for the Sentana and Wadhwani (1992) heterogeneous trader model (i.e., baseline model) and our two augmented models (i.e. symmetric effects model given by equation (7) and asymmetric effect model given by equation (10)) that allow us to detect the presence of sentiment-driven trading. The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3: Effects of individual and institutional sentiments

		WEEKLY SENTIMENT MEASURES			
		Survey-based			
		AAII (Individual)		II (Institutional)	
	Baseline	Symmetric	Asymmetric	Symmetric	Asymmetric
Panel A : Mean equation					
ω	0.1328 **	0.1195	0.1232	0.1141	0.1163
	(2.006)	(1.560)	(1.382)	(1.632)	(1.536)
θ	0.0103	0.0160	0.0240	0.0082	0.0122
	(0.532)	(0.941)	(1.036)	(0.507)	(0.676)
φ_0	-0.0955 ***	-0.1156 ***	-0.1154 ***	-0.1166 ***	-0.1179 ***
	(-254.939)	(-2.827)	(-3.297)	(-2.743)	(-2.796)
φ_1	0.0021	0.0012	0.0011	0.0025	0.0025
	(0.941)	(0.354)	(0.255)	(0.663)	(0.855)
γ		0.1453 ***		0.0160	
		(2.805)		(1.032)	
γ^+			0.0663		0.0036
			(0.520)		(0.133)
γ^-			0.2105 **		0.0292
			(2.331)		(0.980)
Panel B : Variance equation					
α_0	0.0855 ***	0.0899 ***	0.0900 ***	0.0858 **	0.0858 ***
	(2.638)	(4.112)	(6.106)	(2.522)	(2.684)
α_1	0.2238 ***	0.2241 ***	0.2251 ***	0.2151 ***	0.2152 ***
	(4.318)	(5.154)	(8.580)	(4.234)	(4.219)
β	0.9426 ***	0.9393 ***	0.9393 ***	0.9419 ***	0.9419 ***
	(44.661)	(63.873)	(91.670)	(43.814)	(45.304)
δ	-0.5709 ***	-0.5883 ***	-0.5778 ***	-0.6880 ***	-0.6882 ***
	(-4.032)	(-4.018)	(-5.680)	(-3.684)	(-4.669)

Notes: This table reports maximum likelihood estimates for the Sentana and Wadhwani (1992) heterogeneous trader model (i.e., baseline model) and our two augmented models (i.e. symmetric effects model given by equation (7) and asymmetric effects model given by equation (10)) when we use the two commonly cited weekly surveys of AAII and II to measure the sentiments of individual and institutional investors. The variance equation is given by equation (11). The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4: Sentiment-driven trading across business cycles and market conditions

	MONTHLY SENTIMENT MEASURE (CCI)			
	Market Conditions (Bull vs. Bear)		Business Cycles (Expansion vs. Recession)	
	Symmetric	Asymmetric	Symmetric	Asymmetric
Panel A : Mean equation				
ω	0.7521 *	0.6339	0.7699	0.4874
	(1.746)	(1.471)	(1.560)	(0.762)
θ	0.0000	0.0140	-0.0021	0.0236
	(0.000)	(0.458)	(-0.067)	(0.474)
φ_0	-0.0924	-0.1222	-0.1158	-0.1514
	(-1.170)	(-1.193)	(-1.257)	(-1.352)
φ_1	0.0004	0.0014	0.0012	0.0030
	(0.110)	(0.432)	(0.295)	(0.572)
γ_{UP}	0.0032 *		0.0033	
	(1.688)		(0.861)	
γ_{DOWN}	0.0067 **		0.0055 **	
	(2.129)		(2.230)	
γ^{+}_{UP}		0.0016		0.0042
		(0.306)		(0.749)
γ^{+}_{DOWN}		0.0040		0.0013
		(0.532)		(0.227)
γ^{-}_{UP}		0.0048		0.0055
		(0.931)		(0.774)
γ^{-}_{DOWN}		0.0077 **		0.0074 *
		(2.429)		(1.770)
Panel B : Variance equation				
α_0	0.1214	0.1069 *	0.1148	0.1252
	(1.145)	(1.669)	(1.354)	(0.954)
α_1	0.2441 ***	0.2475 ***	0.2496 ***	0.2388 ***
	(6.626)	(3.489)	(8.369)	(5.382)
β	0.9599 ***	0.9653 ***	0.9624 ***	0.9590 ***
	(23.513)	(44.578)	(30.380)	(18.976)
δ	-0.1170	-0.1208	-0.1333	-0.1942
	(-0.402)	(-0.729)	(-0.497)	(-0.554)

Table 4: Sentiment-driven trading across business cycles and market conditions (Cont'd)

	MONTHLY SENTIMENT MEASURE (CCI)			
	Market Conditions (Bull vs. Bear)		Business Cycles (Expansion vs. Recession)	
	Symmetric	Asymmetric	Symmetric	Asymmetric
Panel C : Likelihood ratio tests				
LR	129.0796 *** <0.000>		4.9712 ** <0.026>	
LR$^+$		0.2834 <0.594>		0.0517 <0.820>
LR$^-$		5.8998 ** <0.015>		3.1342 * <0.077>

Notes: This table reports maximum likelihood estimates for our two augmented models when we interact the indicator of sentiment change (ΔIS_{t-1}) with a dummy variable describing business cycles and market conditions (i.e. symmetric effects model given by equation (12) and asymmetric effects model given by equation (13)). The variance equation is given by equation (11). LR, LR$^+$, and LR$^-$ are the likelihood ratio statistics for testing the parameter restrictions 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.

Table 5: Robustness and additional tests

| | MONTHLY SENTIMENT MEASURES (CCI) | | | | | |
| | DJIA | | $\Delta IS'_{t-1}$ | | CFNAI | |
	Symmetric	Asymmetric	Symmetric	Asymmetric	Symmetric	Asymmetric
Panel A : Mean equation						
ω	4.1482	4.1416	0.7183 *	0.5946	0.6297	0.6030
	(1.571)	(1.364)	(1.740)	(1.509)	(1.492)	(1.418)
θ	-0.1698	-0.1599	-0.0008	0.0184	0.0045	0.0082
	(-1.231)	(-0.993)	(-0.030)	(0.703)	(0.174)	(0.274)
φ_0	-0.1821	-0.1723	-0.1204	-0.1351 **	-0.1208	-0.1194
	(-1.415)	(-1.117)	(-1.225)	(-2.171)	(-1.291)	(-1.255)
φ_1	-0.0045	-0.0050	0.0013	0.0022	0.0028	0.0027
	(-1.206)	(-0.917)	(0.445)	(0.657)	(0.988)	(0.942)
γ	0.0060 **		0.0049 ***		0.0038 *	
	(2.200)		(2.904)		(1.908)	
γ^+		0.0024		0.0023		0.0030
		(0.367)		(1.042)		(0.676)
γ^-		0.0088 **		0.0071 ***		0.0043 *
		(2.149)		(3.996)		(1.840)
Panel B : Variance equation						
α_0	2.9895 ***	2.9677 ***	0.1143 *	0.1153	0.1257 *	0.1203 *
	(6.565)	(7.443)	(1.828)	(1.309)	(1.892)	(1.823)
α_1	0.0198 ***	0.0085	0.2456 ***	0.2433 ***	0.2413 ***	0.2416 ***
	(5.308)	(0.118)	(3.595)	(8.334)	(3.411)	(3.380)
β	-0.0251	-0.0188	0.9629 ***	0.9624 ***	0.9594 ***	0.9617 ***
	(-0.163)	(-0.139)	(45.576)	(28.251)	(42.610)	(43.057)
δ	-15.9119 ***	-36.7798	-0.1516	-0.1634	-0.1554	-0.1357
	(-5.697)	(-0.118)	(-0.925)	(-0.614)	(-0.923)	(-0.782)

Notes: This table reports robustness tests for our two augmented models (i.e. symmetric effects model given by equation (7) and asymmetric effects model given by equation (10)) when we use an alternative stock market index (DJIA), a different calculation method for sentiment change indicator ($\Delta IS'_{t-1}$), and the orthogonalized CCI sentiment measure using the residual from a regression of CCI on a constant and the rolling three-month average value of Chicago Fed National Activity Index (CFNAI) in order to remove the influence of macroeconomic factors on investor sentiment. The variance equation is given by equation (11). The heteroskedasticity-consistent t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.