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Abstract

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JEL Classification: G12, G14

Keywords: sentiment, emotional bias, cognitive error, preservers, accumulators, Momentum, return predictability

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Relative Investor Sentiment Measurement

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Abstract: This paper proposes a new metric to gauge investor sentiment using a relative valuation method. We combine investor behavioral finance traits and option-implied standard deviations under both the real-world probability (P) valued most in the view of uninformed investors and the risk-neutral space (Q) adopted when there exists no cognitive error. Given that investor sentiment can be thought of as risk-taking by the uninformed exceeding their informed peers, we postulate that the differences between the variance, skewness, and kurtosis of P and Q measures for investors with various behavioral traits matter. We hence construct our investor sentiment proxy by summing these differentials of variance, skewness, and kurtosis in weighted forms. It is documented that such relative investor sentiment metric exhibits economically and statistically strong return predictability for momentum portfolios. Our findings contribute to the extant literature by (1) complementing the Baker-Wurgler market-based investor sentiment index from the theoretical perspective, (2) modeling investor sentiment via utilizing the informational content of options prices, and (3) supporting the Barberis-Shleifer-Vishny definition of investor sentiment to be differences in financial market participant behavior.

Keywords: sentiment, emotional bias, cognitive error, bounded rationality, preservers, accumulators, momentum, return predictability

JEL Classification: G12, G14, G58

1. Introduction

It has been well established that investor sentiment drives share price deviations from their fundamental values (Brown and Cliff, 2004; Baker and Wurgler, 2006). Investor sentiment is the emotion that reflects investors' actions in the marketplace. According to the classical theory, under normal market conditions or equivalently during low investor sentiment periods, even if irrational investors cause asset mispricing, the consequences of their actions will be offset by the responses of arbitrageurs and, therefore, they should exert insignificant influences on asset returns. However, high investor sentiment leads to increased market volatility. Consequently, arbitraging activities become riskier. Thus, mispricing significantly affects asset returns.

As investor sentiment is unobservable, the literature develops two common types of investor sentiment measures: survey index and empirical index. The survey index developed from quasi-experimental results, such as surveys on consumer confidence and analysis of relevant text and media content. Tetlock (2007) shows that the number of negative words in the *Wall Street Journal* can predict stock returns. Garcia (2013) examines investor sentiment effects using a survey for the *New York Times* on the choice of words. He finds that investor sentiment possesses better predictability in recessions. Antoniou, Doukas, and Subrahmanyam (2013) measure investor sentiment by the Consumer Confidence Index (CCI)[1] and demonstrate that variations in investor sentiment primarily drive momentum profits. They suggest that loser (winner) stocks become underpriced under optimism (pessimism) because news contradicting investor sentiment induces cognitive dissonance, which slows down the diffusion of such news.

The empirical index is established based on combining selected critical financial and economic variables. Studies employ statistical techniques to determine the weights of different financial and economic variables starting from Zweig (1973). Baker and Wurgler (2006) develop the most widely-accepted empirical sentiment index in terms of financial variables. They put forward a composite index comprising six underlying proxies: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. Using the Baker-Wurgler (BW) index, Yu and Yuan (2011) and Stambaugh, Yu, and Yuan (2012) examine the role of investor sentiment in explaining the anomalies of stock returns. They conclude that the short leg in long-short strategies delivers more significant profits and hence the anomaly being exploited is stronger during periods of high investor sentiment levels. Zhou (2018) compares different sentiment measurement approaches and provides evidence that sentiment indeed captures important information about stock returns.

Moreover, the VIX index published by the Chicago Board Options Exchange (CBOE) has also been adopted to capture the market mood, especially fear, by using the ex-ante volatility

[1] The Conference Board administers the CCI, which is created based on a survey that measures how optimistic or pessimistic consumers attitudes about their expected financial situation.

estimation from option prices to gauge investor sentiment. While VIX purports to assess market disorder during extreme conditions, it is not usually regarded as an investor sentiment indicator.

Although the empirical studies generally find that investor sentiment can explain cross-sectional variations of returns on stocks that are hard to value or arbitrage and predict the aggregate stock market, it is not clear if other metrics for investor sentiment, especially those of an integrative relative and theoretical-based investor sentiment is predictive of cross-sectional stock return variation. Hence, our article aims to take one step further to develop an ex-ante and relative sentiment measurement based on different investor personality traits, behavioral finance models and factors, as well as more comprehensive financial market (stock and options) data.

Our sentiment measuring approach follows Barberis, Shleifer, and Vishny's (1998) theoretical setup that market sentiment should capture the differences in behaviors between risk-neutral investors (who are considered informed) and other uninformed retail investors. These differences are prominent for behavioral biases that are hard to predict, such as the underreaction of stock prices to news such as earnings announcements and the overreaction of stock prices to good or bad news. Since irrational behaviors cannot be perfectly forecasted, arbitrageurs cannot eliminate asset mispricing in the short run, and thus investor sentiment matters in equilibrium. To solve this problem, we consider the information differences of investors, in which informed investors could perform a risk-neutral estimation based on market information and uninformed investors could only make a forecast based on realized values. Therefore, we develop an option-implied sentiment index to measure the behavioral differences between informed and uninformed investors. It has essentially three merits. First, our index contains both forward-looking information implied from options data and contemporaneous information associated market trading activities. Second, the differences in our index have relative over- and under-reaction, together with its data availability advantage, that can overcome the usual survey-based shortcomings pointed out by Zhou (2018). Third, this new index retains the possibility to increase sentiment measure frequency to daily basis from BW's six monthly proxies and also the possibility to narrow sentiment measure granularity down to firm level.

Guided by the Black-Scholes Option Pricing Theory, Latané and Rendleman (1976) developed an option-implied method to estimate volatilities, which later becomes a mainstream approach to revealing any underlying asset's return distribution. Since then, many numerical studies have emerged to enhance their approaches to obtaining model-free implied return moments. Britten-Jones and Neuberger (2000) derive a nonparametric volatility measure under the diffusion process and forecast the implied volatilities relying only on the option prices. Jiang and Tian (2005) further extend the model-free approach to incorporate jump components in the price diffusion. Bakshi, Kapadia, and Madan (2003) relate the pricing of equity options with their return skewness and discover the skewness-dependent risk aversion in the risk-neutral probability density. As a representative of recent papers, Neuberger (2012) provides an unbiased estimate of the third moment using high-frequency returns. The tools developed by the above scholars form the basis of our relative evaluation framework for investor sentiment.

Our study is also complementary to this strand of literature by discovering the functionary channel of how options-pricing-derived volatility could have a direct bearing on investor sentiment. The option-implied return variations have already been applied to various finance research topics, such as forecasting, risk management, and portfolio selection. Poon and Granger (2003) investigate the forecasting techniques in 93 studies and point out the option-implied standard deviation to be the best forecast for return volatilities. Han (2008) reveals that the index options volatility smile is steeper and the risk-neutral skewness of monthly index return is more negative when market sentiment becomes more bearish, which supports that option-implied variations have influences on investor sentiment. Kostakis, Panigirtzoglou, and Skiadopoulos (2011) form portfolios following the two-fund separation theorem by leveraging market price information of options. These portfolios perform much better than the optimal strategies constructed from historical return series. Buss and Vilkov (2012) create an implied predictor of the beta factor using option prices and develop a risk-return relationship that is consistent with linear factor models. Chang et al. (2012) find that option-implied volatility and skewness are equally good predictors of future beta. Their finding suggests that option-implied betas are higher if the underlying risk-neutral distribution is more negatively skewed. Baule, Korn, and Saßning (2013) compare the performances of six implied beta estimators in the literature and reveal useful patterns in the term structure of implied betas. DeMiguel et al. (2013) empirically show that option-implied portfolio strategies could reduce portfolio volatility and substantially improve the Sharpe ratio. Seo and Kim (2015) suggest that option-implied return variations vary over time with the level of investor sentiment, and the results are strong both from in-sample and out-of-sample analyses.

Summing up, our paper makes three contributions. First, we develop a new relative measure of market sentiment based on a well-accepted definition of sentiment, which fills the gap between theoretical theory and quantitative tools on market sentiment. Second, we establish the connection between our approach with the BW index, complementing the BW approach from both the behavioral finance model and momentum portfolio application perspective. Third, we devise an ex-ante sentiment measure that takes good advantage of options data, which have long been proven to display powerful return predictability for the equity market.

2. Construction of Option-Implied Sentiment Index

In behavioral finance theory, investors often make irrational decisions due to cognitive error and emotional bias. This observation is contrary to the traditional assumption that investors are perfectly rational.[2] Thus, the irrational investors' decision-making processes and

[2] Cognitive errors indicate problems caused by faulty cognitive reasoning. Examples include conservatism bias, which occurs when people cling to prior viewpoints at the expense of acknowledging new information, and availability bias, which occurs when people estimate the probability of an outcome based on how prevalent that outcome appears in their lives. Emotional bias

the resulting market activities should also differ from traditional theory. It is evident as early as in Wärneryd (1996), who examines investors' risk attitudes and behaviors using survey data. In attempting to explain the paradoxical phenomena that "people pay more than the expected value for insurance, but they also do so for lottery tickets," Wärneryd (1996) documents that mutual funds and individuals with low-risk aversion pay more attention to obtaining capital gains. They tend to take positions in high-risk assets with significant growth potential. In contrast, other institutional investors and retail investors with high-risk aversion worry more about extreme events and prefer low-risk assets or buy insurance. Pompian (2012) formally introduces several behavioral biases and defines the various investor types based on the cognitive errors and emotional biases found in financial markets. According to his denotation, we classify all market participants into six types along two dimensions—informed and uninformed based on cognitive error, and three criteria—accumulators, normal, and preservers based on emotional bias. Namely, these six types are perfectly informed investors, informed accumulators, informed preservers, bounded rational investors, uninformed accumulators, and uninformed preservers.

Let us first consider cognitive error as the classification criterion for informativeness level. Under our framework, cognitively-biased investors tend to ignore new information arriving at the market; thus, we refer to them as uninformed investors. The uninformed investors compute return variations according to historical information only regarding risk quantification. These uninformed investors resort to realized variations. In contrast, informed investors who make no cognitive mistake have enough information to forecast future return variations. As a result, they adopt ex-ante variations implied by options pricing to measure risk.

The second classification criterion is emotional bias. Under our framework, unlike non-emotional investors who only care about the variance, moody investors are also affected by a higher order of moments of returns beyond the second-order variance, such as the third-order moment proxied by skewness and the fourth-order moment proxied by kurtosis. To further distinguish between the effect of skewness and kurtosis, we refer to investors responding to both variance and skewness as accumulators and those being affected by all three risk measures (variance, skewness, and kurtosis) as preservers, respectively. Intuitively, we follow Bailard, Biehl, and Kaiser (1986) and Barnewall (1987) by defining accumulators as active investors dedicated to creating more wealth, and defining preservers as passive investors who place a great deal of emphasis on financial security and preserving wealth rather than taking the risk to grow wealth. Such investment goal differences constitute our third criterion.

In short, both perfectly rational investors (i.e., informed investors) and boundary-rational investors (i.e., uninformed investors) measure their risks only by return variance, as they

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is a mental state that arises spontaneously rather than through conscious effort. For instance, with loss aversion bias, people strongly prefer avoiding a loss to capturing a gain. Overconfidence bias occurs when people demonstrate unwarranted faith in their judgment or abilities. Regret-aversion bias means that people tend to avoid the fear of and the pain from poor decisions (Kahneman and Riepe, 1998; Pompian, 2012).

behave rationally rather than emotionally. Beyond the variance measure, we can further divide emotionally-biased investors (irrespective of informativeness) into two sub-groups. Accumulators consider return skewness because of their need for wealth creation, while preservers extend the attention span to include return kurtosis due to their principal security requirement. Table 1 illustrates different investor types obtained by implementing the above three classification criteria in classifying all market participants.

[*Insert Table 1 Here*]

To quantify the behavioral difference between the uninformed and informed, we specify and compare their respective expected utilities. As previously discussed, the uninformed investors fail to collect amply contemporaneous information to make rational expectations; thus, they just evaluate the performance of market security based on ex-post parameters of its distribution. Hence, the aggregate expected utility of the uninformed investors in linear expansion is:

$$\begin{aligned} EU_{UN,t}(p_{t+1}) = U_{UN}(p_t) + \frac{1}{2}U''_{UN}(p_t)VAR^{\mathbb{P}} + \frac{1}{6}U'''_{UN}(p_t)SKEW^{\mathbb{P}} \\ + \frac{1}{24}U''''_{UN}(p_t)KURT^{\mathbb{P}} + REM_{UN}, \end{aligned} \tag{1}$$

where p_t and p_{t+1} are the natural logarithm values of the security at time *t* and *t+1*, respectively; $VAR^{\mathbb{P}} = E(p_{t+1} - p_t)^2$, $SKEW^{\mathbb{P}} = E(p_{t+1} - p_t)^3$, and $KURT^{\mathbb{P}} = E(p_{t+1} - p_t)^4$ indicate the variance, skewness, and kurtosis of the security's return distribution in the P space. At last, REM represents the summation of all remaining elements of Taylor's series beyond the fourth moment, with the fourth moment excluded.

On the other side, informed investors can exploit available information and form their rational expectations. Therefore, they evaluate the performance of a security based on its ex-ante return distribution parameters. Similarly, the aggregate expected utility of the informed investors can be written as:

$$\begin{aligned} EU_{IN,t}(p_{t+1}) = U_{IN}(p_t) + \frac{1}{2}U''_{IN}(p_t)VAR^{\mathbb{Q}} + \frac{1}{6}U'''_{IN}(p_t)SKEW^{\mathbb{Q}} \\ + \frac{1}{24}U''''_{IN}(p_t)KURT^{\mathbb{Q}} + REM_{IN}. \end{aligned} \tag{2}$$

Here, the $VAR^{\mathbb{Q}}$, $SKEW^{\mathbb{Q}}$, and $KURT^{\mathbb{Q}}$ are the Q-space option-implied estimators corresponding to the real-world P-space variables specified in equation (1). As a result, the difference between the expected utilities of the above two types of investors is given by:

$$
\begin{aligned}
EU_{UN,t}(p_{t+1}) - EU_{IN,t}(p_{t+1}) \\
&= [U_{UN}(p_t) - U_{IN}(p_t)] \\
&+ \frac{1}{2}[U''_{UN}(p_t)VAR^{\mathbb{P}} - U''_{IN}(p_t)VAR^{\mathbb{Q}}] \\
&+ \frac{1}{6}[U'''_{UN}(p_t)SKEW^{\mathbb{P}} - U'''_{IN}(p_t)SKEW^{\mathbb{Q}}] \\
&+ \frac{1}{24}[U''''_{UN}(p_t)KURT^{\mathbb{P}} - U''''_{IN}(p_t)KURT^{\mathbb{Q}}] \\
&+ [REM_{UN} - REM_{IN}].
\end{aligned}
\tag{3}
$$

In equation (3), since p_t has already been observed by the market, the first component $[U_{UN}(p_t) - U_{IN}(p_t)]$ is a constant, which is irrelevant to the return distribution. Thus, this utility difference between informed and uninformed investors can be denoted as the base value of the sentiment. Furthermore, since the remaining elements of return distribution beyond the fourth moment lack economic intuition and are always neglected in linear expansion, we assume that the informed and uninformed utility over the remainder elements, on average, do not give significant differences. As a result, the last component $[REM_{UN} - REM_{IN}]$ should approximately be close to zero.

According to the notion of considering investor sentiment as capturing the behavioral differences between the informed and uninformed investors, we define the above expected utility difference as our sentiment proxy. Next, we apply the Mean-Value Theory to the remaining components in equation (3) related to the variance, skewness, and kurtosis differentials. More concisely, the proposed investor sentiment metric can be written as:

$$
\begin{aligned}
Sentiment_t &= EU_{UN,t}(p_{t+1}) - EU_{IN,t}(p_{t+1}) \\
&= \mathrm{A} + \mathrm{B}\left(VAR_t^{\mathbb{P}} - VAR_t^{\mathbb{Q}}\right) + \Gamma\left(SKEW_t^{\mathbb{P}} - SKEW_t^{\mathbb{Q}}\right) \\
&+ \Delta\left(KURT_t^{\mathbb{P}} - KURT_t^{\mathbb{Q}}\right),
\end{aligned}
\tag{4}
$$

where $\mathrm{A} = [U_{UN}(p_t) - U_{IN}(p_t)]$ denotes the base value of investor sentiment. B, Γ, and Δ are the weights derived after applying the Mean-Value Theorem.[3]

Now we define investor sentiment as the risk differential between risk-neutral investors who are informed and real-world retail investors who are uninformed. To make this idea quantifiable, we consider risk measures ranging from the second moment (i.e., variance) to the third moment (i.e., skewness) until the fourth moment (i.e., kurtosis) of stock return distributions. Besides, we use option-implied moments to proxy for risks perceived by the informed and use realized moments of stock returns to measure risks perceived by the uninformed. Table 2 describes how various risk measures are assigned among different investors. Therefore, theoretically speaking, the aggregate investor sentiment should be

[3] According to the mean-value theorem, we can always find a m^*, which satisfies $m^*(n_1 - n_2) = m_1 n_1 - m_2 n_2$, for any m_1, m_2, n_1, and n_2.

captured by the weighted sum of differences between the realized and option-implied value for the variance, skewness, and kurtosis, with the market portfolio being the underlying asset. The weighting coefficients can be found through regressing traditional sentiment proxies on our risk differentials as new potential investor sentiment determinants.

[*Insert Table 2 Here*]

A central question concerning the validity of our approach is whether the weights of three types of investors are appropriate. To address the concern, we summarize the weighting coefficients obtained by regressing all well-accepted investor sentiment indicators on the differences of variance, skewness, and kurtosis in our first robustness test. We complement existing investor sentiment measures in several aspects. First, we advance the literature on investor sentiment metrics by proposing a new sentiment metric that is based on classic theories and empirical findings in the fields of sentiment. Second, by attributing the sources of investor sentiment to different behavioral types of investors, our approach can be extended to examine the sentiment effect under different conditions. Third, this investor sentiment approach is computed by the combination of return distributions; thus, it has a superior ability to explain the link between investor sentiment and risk, especially during extreme events or the tail risk.

3. Validation of Option-Implied Sentiment Index

3.1 Preliminary Estimation

In this section, we validate our results with two alternative methods to determine the weights used in the theoretical definition of sentiment in equation (4).

Firstly, we propose the following specification so that those weights can be estimated as coefficients and our generalized concept of investor sentiment is being proxied by a chosen empirical measure of investor sentiment:

$$\begin{aligned} Sentiment_t = \alpha &+ \beta\left(VAR_t^{\mathbb{P}} - VAR_t^{\mathbb{Q}}\right) + \gamma\left(SKEW_t^{\mathbb{P}} - SKEW_t^{\mathbb{Q}}\right) \\ &+ \delta\left(KURT_t^{\mathbb{P}} - KURT_t^{\mathbb{Q}}\right) + \varepsilon_t, \end{aligned} \tag{5}$$

where α is coefficient corresponding to the base value of the investor sentiment in theory, and β, γ, and δ measure the investor sentiment effects valued by the six types of investors categorized in Table 2. The last symbol ε is a random error term.

We obtain daily data for options on the S&P 500 index from the Option Matrix Database, which contains the strike prices, highest bids, and lowest asks of all out-of-money calls and puts but excludes options with zero bid prices. We also follow the CBOE procedure in using nearand next-term put and call options with maturities between 23 and 37 days.[4] The option price is set to be the average of the highest bid and the lowest ask. To compute the option-implied or Q-space values of moments of the stock return distribution, we adopt the quantitative finance tools introduced by Bakshi, Kapadia, and Madan (2003). Column (1) of Table 3 lists the exact formulas used to calculate these risk metrics at a monthly frequency, i.e., Q-space values of the variance, skewness, and kurtosis for the S&P 500 index option.

[*Insert Table 3 Here*]

The daily price and return information for the S&P 500 index are sourced from the Center for Research in Security Prices (CRSP) database. We use the S&P 500 daily prices to construct the P-measures of variance, skewness and kurtosis following equations in column (2) of Table 3 for each month.[5] Then we proceed to derive variance difference (*VD*), skewness difference (*SD*), and kurtosis difference (*KD*) by deducting Q-space values from P-space values.

We rely on the monthly Baker-Wurgler sentiment index (*BW*) as a benchmark, which is taken from the website of Jeffrey Wurgler.[6] Moreover, we also compare our option-based index with the U.S. CCI and the VIX index, which are taken from the OECD database[7] and the website of CBOE[8], respectively. The sample period spans from 2001 to 2018. Table 4 summarizes the mean values and standard deviations of the *BW* index, *VD*, *SD*, and *KD*. For all the three differential components of our proposed sentiment index, only the average of *SD* is positive, and the absolute magnitude of its average is the greatest. The averages for the other two component indicators, namely *VD* and *KD*, are negative. The standard deviation grows larger in the order of *VD*, *SD*, and *KD*. The realized or P-space moments are calculated with historical return data.

[*Insert Table 4 Here*]

In line with the *BW* approach, we use the first components estimated by Principal Component Analysis (PCA) to proxy the weights of *VD*, *SD*, and *KD* in our option-implied sentiment index. The eigenvectors from PCA are 0.292, 0.798, and 0.527, respectively. Furthermore, we rescale our index by multiplying it by 400 to make it easy to compare with other sentiment indices. As a result, our sentiment index can be empirically estimated to be:

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[4] Before October 6th, 2014, we use near- and next-term options with maturities of more than seven days.

[5] Alternatively, one can use the daily prices of the S&P 500 constituents in each month to calculate the p-measures following Table 3 for each constituent and take the unweighted or market-value weighted average. However, the corresponding Q-measures would not be reliable as the options written on individual stocks are far less liquid than the options written on the stock index. As a result, our sentiment index is developed based on the S&P 500 index level.

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

[7] https://data.oecd.org/

[8] https://www.cboe.com/tradable_products/vix/vix_historical_data/

$$\widehat{Sentiment}_t = 116.89(VAR_t^{\mathbb{P}} - VAR_t^{\mathbb{Q}}) + 319.33(SKEW_t^{\mathbb{P}} - SKEW_t^{\mathbb{Q}}) + 210.63(KURT_t^{\mathbb{P}} - KURT_t^{\mathbb{Q}}). \tag{6}$$

Turning to graphical representation, Figure 1 plots the 24-month rolling average of the BW index and our option-based sentiment estimate from 2004 to 2018. To make a complete comparison, we plot the 24-month rolling average of the VIX, and the U.S. CCI normalized to the same VIX range. The reason why we use 24 months as the rolling window is that the sentiment indices display high volatility and are not comparable to each other in the short run due to heavily noisy fluctuations. As can be seen, our proposed sentiment index leads the up and down trends of the BW index, especially after the 2008 financial crisis. Furthermore, our sentiment index captures the hump shape of sentiment missed by Baker and Wurgler and the CCI but recorded by the VIX and retains significant short-term fluctuations. The possible reason is that our method uses the same option information as the VIX. This information covers more content about market microstructure than the BW index and survey methods. As our approach also highlights individual stock option transactions, it reflects short-term variations in investor sentiment.

[*Insert Figure 1 Here*]

The second approach to determining the weights of each component in our proposed sentiment index follows the experimental results of Noussair, Trautmann, and Van De Kuilen (2014). In their paper, the average levels of an investor's prudence and temperance are set at 3.43 and 2.96, respectively. In particular, prudence is defined as the third-order derivative of utility function over risk aversion, and temperance stands for the fourth-order derivative. Therefore, we adopt {1, 3.43, 2.96} as the coefficients of Q-P variation differences as a robustness check, and also rescale them by multiplying 100 for all coefficients:

$$\widehat{Sentiment}_t = 100(VAR_t^{\mathbb{P}} - VAR_t^{\mathbb{Q}}) + 343(SKEW_t^{\mathbb{P}} - SKEW_t^{\mathbb{Q}}) + 296(KURT_t^{\mathbb{P}} - KURT_t^{\mathbb{Q}}). \tag{7}$$

We then compute the sequence of 24-month rolling averages of our option-based sentiment estimate and compare it with the 24-month-rolling-averaged BW index, CCI index, and VIX index. As can be seen in figure 2, the trend and kinks of the new option-implied sentiment index stay similar to the original one. As a result, weights are not the factors driving our proposed relative sentiment metric—moment differentials are key.

[*Insert Figure 2 Here*]

3.2 Explanatory Power for Market Anomalies

To understand the usefulness of the newly-constructed metric, we investigate its capability in explaining return variations. In this subsection, we begin by examining the relationships between this option-implied sentiment index and several commonly-seen market anomalies, such as those represented by the Fama-French SMB, HML, RMW, CMA, and MOM portfolios. Table 5 shows the pair-wise correlations between our metric and these portfolios.

[*Insert Table 5 Here*]

The statistics in Table 5 tell that the option-implied sentiment index has a significant positive association with the *BW* index, indicating that it contains most information that the *BW* index conveys. Furthermore, the correlation coefficients between our option-implied sentiment metric and the size and momentum factors are quite significant, which is consistent with the view that investor sentiment is highly correlated with momentum (Antoniou, Doukas, and Subrahmanyam, 2013). This indicates that our option-implied sentiment index conveys forward-looking information that might be ignored by the *BW* index. To further detect possible causal flows uncaptured by these correlations, we regress our sentiment index on three usual combinations of these anomalies.

[*Insert Table 6 Here*]

As can be seen from Table 6, all the coefficients are insignificant except for the ones associated with the MOM portfolio in the Fama-French-4-factor model and the ones associated with the CMA portfolio in the Fama-French-5-factor model. Besides, the adjusted R-squared of the three regressions can go as low as 5%. Therefore, we believe that the option-implied sentiment index is statistically unrelated to these market anomalies, indicating its potential to act as a good complementary for the existing asset pricing anomalies.

3.3 Market Return Predictability

Given the above said, a natural question would be whether the new information contained in our sentiment metric can predict portfolio returns and, most importantly, which portfolio or market effect is most closely associated with options-implied sentiment information. In this section, we demonstrate that our metric foreshadows the momentum effect well, one of the most significant consequences investor sentiment has on the financial market. Johnson and Tversky (1983) show that investors with high sentiment make over-optimistic choices and low sentiment investors behave over-pessimistically. Hong and Stein (1999) argue that good news about winner stocks diffuses faster if high investor sentiment prevails; thus, the momentum effect matters more in return generating and vice versa. Antoniou, Doukas, and Subrahmanyam (2013) examine the momentum trading strategies under different investor sentiment conditions. They find that investor sentiment heavily affects investors' cognition and, in turn, their momentum investing strategies. In line with this body of research, we begin by validating our sentiment proxy by establishing its linkages with momentum effects.

We construct momentum portfolios following Antoniou, Doukas, and Subrahmanyam (2013). Specifically, at the end of each month in the sample, we sort all stocks according to their average returns for the past six months. Based on this ranking, all investable stocks are then categorized into ten deciles monthly. Each month, we form a momentum portfolio by simultaneously longing stocks in the top decile and shorting those in the bottom decile. To isolate our concerned effect from the potential disturbances from market microstructure, we set up three criteria for developing the momentum investment strategy. First, we hold the momentum portfolio just formed for two, four, or six months; second, we gap one month between the portfolio-formation month and the starting month of the holding period; third, we exclude stocks that are trading at prices below $5 in each month.

To determine the state of sentiment for any holding period, we again follow the approach documented in Antoniou, Doukas, and Subrahmanyam (2013) by computing a series of weighted rolling averages of our proposed option-based sentiment index.[9] Then, a sample month will be labeled as optimistic (pessimistic) as long as the computed average sentiment for this current month falls into the top (bottom) one-third section of the average sentiment sequence.[10] At last, if all the months during which we hold the long-short portfolio are classified as optimistic (pessimistic), then the entire holding period will be identified as one with the optimistic (pessimistic) investor sentiment. All other scenarios are referred to as mild periods.

[*Insert Table 7 Here*]

Without loss of generality, we only use the option-implied sentiment index from the Principal Component Approach to conduct the following tests. The alternative sentiment indices constructed based on the survey weights produce similar results that are not shown here. Table 7 presents the relationship between the return of momentum portfolio and investor sentiment. In all three sentiment scenarios, the two-month, four-month, and six-month holding period portfolios exhibit equivalently significant momentum effects. However, the long-short momentum strategies produce significantly higher returns during high-sentiment or optimistic periods than in the other two scenarios. To get a sense of the magnitude, the average monthly differences in portfolio return between the optimistic and pessimistic states are 2.72%, 3.18%, and 2.57% for two, four, and six months of holding, respectively.

To further investigate how the momentum effect is associated with our proposed option-based sentiment metric, we directly run OLS regressions of the return earned by forming momentum portfolios on the levels of the option-based sentiment metric, controlling for market returns and risks. The regression model is specified as follows:

[9] We use the weighted average of the index level as follows: $\frac{3}{6} \times \widehat{Sentiment}_t + \frac{2}{6} \times \widehat{Sentiment}_{t-1} + \frac{1}{6} \times \widehat{Sentiment}_{t-2}$. This approach assigns more weight to the current observation than faraway ones. Moreover, our main results are robust even when we use other average methods.

[10] We also use 1/4 and 1/5 as our thresholds, and the results remain unchanged.

$$Return_t = \mu + \rho_1 \widetilde{Sentiment}_t + \rho_2 Market_t + \rho_3 Market_t^2 + \rho_4 Market_t^3 + \epsilon_t, \qquad (8)$$

where the dependent variable $Return$ is the time series of monthly returns from the momentum portfolio, $\widetilde{Sentiment}$ denotes the estimated and rolling-averaged statistics of option-based investor sentiment metric, and $Market$ represents the time series of monthly returns of the market portfolio. We also include the quadratic and cubic terms in equation (8) to account for market return nonlinearities. Table 9 reports the corresponding regression results.

[*Insert Table 8 Here*]

The patterns shown in Table 8 imply that the returns from the momentum portfolio and the investor sentiment measured by our proxy have a stable correlation. The coefficients of sentiment in all specifications are significantly positive. The magnitudes of these coefficients are all close to 0.4. The results indicate that the option-based investor sentiment metric captures material variation in the returns of momentum investment strategies, even after considering market returns and risks. All in all, cognitive and emotional biases cause behavioral differences among different types of investors. For this reason, investor sentiment emerges and becomes observable via market trading activities.

At last, we repeat the above exercise for other alternative sentiment proxies, including the Baker-Wurgler index, VIX, and CCI; no such strong relationship has been found. The findings confirm the conjecture that our proposed option-based investor sentiment metric is a viable alternative to other investor sentiment metrics.

4. Conclusion

The present article provides evidence for the Barberis-Shleifer-Vishny definition of investor sentiment. Investor sentiment can essentially be considered differences in risk behaviors between the informed rational investors and the uninformed emotional market participants. By resorting to mathematical measurements of risk metrics, which describe a portfolio return's distribution using real-world probabilities, we subtract from them the corresponding option-implied risk metrics and obtain a new proxy to estimate investor sentiment under a setup analogous to the relative valuation framework. We first run preliminary tests to demonstrate the validity of the new option-based investor sentiment metric. Then, we show that this new proxy can significantly foreshadow future stock returns economically and statistically with momentum portfolio investment strategies. We demonstrate that our proposed metric complements the Baker-Wurgler market-based sentiment measure in terms of its forward-looking nature inherited from the options data.

Table 1: Type of investors

	Emotional biases? No	Emotional biases? Yes	
		Emotional accumulators	**Emotional preservers**
Cognitive errors? No	Perfectly rational investors who are both informed (have no cognitive errors) and emotionally unbiased	Informed accumulators who are informed and active investors with the aim of creating wealth	Informed preservers who are informed but obsessed with financial security
Cognitive errors? Yes	Bounded rational investors who ignore or wrongly process information (suffer from cognitive errors) but are emotionally unbiased	Uninformed accumulators who ignore or wrongly process information and actively seek for financial wealth creation	Uninformed preservers who ignore or wrongly process information and value most wealth preservation

Table 2: Theory-based empirical measures of investor sentiment for different types of investors

	Rational investors	Accumulators	Preservers
Behaviors of informed investors +	Perfectly rational investors who only compute $VAR^{\mathbb{Q}}$ as their measurement of return risk	Informed accumulators who also highlight $SKEW^{\mathbb{Q}}$ in addition to $VAR^{\mathbb{Q}}$ as their measurement of return risk	Informed preservers who also highlight $KURT^{\mathbb{Q}}$ in addition to $VAR^{\mathbb{Q}}$ as their measurement of return risk
Theoretical definition of investor sentiment by Barberis, Shleifer, and Vishny (1998) =	● Sentiment is the “difference” between behaviors of informed risk-neutral informed investors and behaviors of non-informed retail investors ● This paper proxies such behaviors by different types of investors’ computed risk statistics		
Behaviors of uninformed investors	Bounded rational investors who only compute $VAR^{\mathbb{P}}$ as their measure of return risk	Uninformed accumulators who also highlight $SKEW^{\mathbb{P}}$ in addition to $VAR^{\mathbb{P}}$ as their measurement of return risk	Uninformed preservers who also highlight $KURT^{\mathbb{P}}$ in addition to $VAR^{\mathbb{P}}$ as their measurement of return risk

Table 3: Formulas of returns moments in P and Q spaces

	(1) Option-implied moments of stock return (Q Space)	(2) Realized moments of stock return (P Space) computed by uninformed investors
Second Moment **Variance**	$VAR^{\mathbb{Q}} = e^{r}\left\{\int_{S_t}^{\infty}\frac{2-2\left(ln\frac{K}{S_t}\right)}{K^2}C(t,K)dK + \int_{0}^{S_t}\frac{2-2\left(ln\frac{K}{S_t}\right)}{K^2}P(t,K)dK\right\}$	$VAR^{\mathbb{P}} = \left(ln\frac{S_{t+1}}{S_t}\right)^2$
Third Moment **Skewness**	$SKEW^{\mathbb{Q}} = e^{r}\left\{\int_{S_t}^{\infty}\frac{6\left(ln\frac{K}{S_t}\right)-3\left(ln\frac{K}{S_t}\right)^2}{K^2}C(t,K)dK + \int_{0}^{S_t}\frac{6\left(ln\frac{K}{S_t}\right)-3\left(ln\frac{K}{S_t}\right)^2}{K^2}P(t,K)dK\right\}$	$SKEW^{\mathbb{P}} = \left(ln\frac{S_{t+1}}{S_t}\right)^3$
Fourth Moment **Kurtosis**	$KURT^{\mathbb{Q}} = e^{r}\left\{\int_{S_t}^{\infty}\frac{12\left(ln\frac{K}{S_t}\right)^2-4\left(ln\frac{K}{S_t}\right)^3}{K^2}C(t,K)dK + \int_{0}^{S_t}\frac{12\left(ln\frac{K}{S_t}\right)^2-4\left(ln\frac{K}{S_t}\right)^3}{K^2}P(t,K)dK\right\}$	$KURT^{\mathbb{P}} = \left(ln\frac{S_{t+1}}{S_t}\right)^4$

Note: K denotes the strike price of the S&P index option under concern. S_t and S_{t+1} are the spot S&P 500 price in day t and t+1, respectively. $C(t,K)$ and $P(t,K)$ are the premium of out-of-money call and put option written on the S&P 500 index. r is a proxy for the risk-free rate.

Table 4: Summary statistics

	the BW Index	$VD\ (\times 10^{-2})$	$SD\ (\times 10^{-3})$	$KD\ (\times 10^{-3})$
Average	-0.223	-0.390	0.949	-0.732
Standard Deviation	0.286	0.494	2.214	2.569

Note: This table reports the average and the standard deviation of the Baker-Wurgler Index, the Variance Difference (VD), the Skewness Difference (SD), and the Kurtosis Difference (KD).

Table 5: Correlation between sentiment index and market anomies

Sentiment		Fama-French Portfolios					
	BW	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**MOM**
Option-Implied	**0.173****	-0.093	**-0.155****	-0.007	0.028	-0.124	**0.207*****
(FPC)	**[2.42]**	[-1.29]	**[-2.17]**	[-0.10]	[0.38]	[-1.73]	**[2.91]**
Option-Implied	**0.188****	-0.092	**-0.143****	0.006	0.021	-0.111	**0.211*****
(Survey)	**[2.64]**	[-1.27]	**[-2.00]**	[0.09]	[0.28]	[-1.53]	**[2.97]**
BW		-0.076	0.046	-0.058	-0.089	-0.082	0.066
		[-1.51]	[0.81]	[-0.97]	[-0.72]	[-1.04]	[0.77]

Note: This table reports the Pearson correlation of the two sentiment indices based on the First Principal Component (FPC) and survey data for the weightings of the individual components against the Baker-Wurgler investor sentiment index (BW) and the Fama-French portfolios for market (MKT), size (SMB), value (HML), profitability (RMW), investment style (CMA), and momentum (MOM) factors. The respective t-statistics are reported below in brackets.

Table 6: Regressions of option-implied sentiment index on market anomalies

	Option-Implied (FPC)			Option-Implied (Survey)		
	[1]	[2]	[3]	[4]	[5]	[6]
Constant	**-0.323*** **	**-0.316*** **	**-0.326*** **	**-0.293*** **	**-0.285*** **	**-0.296*** **
	[-18.13]	**[-17.40]**	**[-18.65]**	**[-15.27]**	**[-14.58]**	**[-15.77]**
MKT	-0.256	-0.603	0.112	-0.315	-0.685	0.099
	[-0.52]	[-1.16]	[0.49]	[-0.60]	[-1.22]	[0.19]
SMB	-1.503	-1.631	-1.610	-1.490	-1.644	-1.611
	[-1.85]	[-1.94]	[-2.02]	[-1.71]	[-1.81]	[-1.89]
HML	0.419	1.314	1.232	0.583	1.510	1.497
	[0.55]	[1.53]	[1.56]	[0.72]	[1.62]	[1.76]
RMW		-1.200			-1.332	
		[-1.03]			[-1.06]	
CMA		**-3.073** **			**-3.149** **	
		[-2.16]			**[-2.06]**	
MOM			**1.319*** **			**1.483*** **
			[2.99]			**[3.14]**
Obs.	192	192	192	192	192	192
Adj. R^2	0.011	0.028	0.051	0.009	0.024	0.053

Note: This table reports the estimation results of regressing the two sentiment indices constructed based on the First Principal Component (FPC) and survey data for the weightings of the individual components on the Fama-French portfolios for market (MKT), size (SMB), value (HML), profitability (RMW), investment style (CMA), and momentum (MOM) factors. The respective t-statistics are reported below in brackets.

Table 7: Momentum portfolio returns under different states of option-based sentiment

Sentiment State	1 (Sell)	2	3	4	5	6	7	8	9	10 (Buy)	Buy-Sell	[t-Stat.]
Holding 2 months												
Optimistic	-8.11	-4.48	-2.96	-1.83	-1.01	-0.25	0.56	1.60	3.03	6.99	15.11	[19.31]
Mild	-5.03	-1.50	-0.24	0.50	1.04	1.57	2.13	2.85	4.16	7.71	12.74	[25.33]
Pessimistic	-5.39	-2.35	-1.00	-0.18	0.48	1.13	1.89	2.68	3.94	7.00	12.38	[44.94]
										Opt.-Pes.	2.72	[3.06]
Holding 4 months												
Optimistic	-8.02	-4.33	-2.78	-1.64	-0.85	-0.09	0.77	1.78	3.24	7.36	15.38	[30.64]
Mild	-5.09	-1.60	-0.35	0.36	0.92	1.39	1.97	2.71	3.94	7.56	12.65	[50.66]
Pessimistic	-5.09	-2.04	-0.83	0.00	0.67	1.27	1.96	2.74	3.94	7.11	12.20	[73.96]
										Opt.-Pes.	3.18	[4.56]
Holding 6 months												
Optimistic	-6.66	-3.61	-2.25	-1.32	-0.67	-0.02	0.68	1.50	2.76	6.17	12.84	[23.74]
Mild	-4.24	-1.24	-0.23	0.38	0.85	1.27	1.72	2.37	3.40	6.40	10.64	[41.69]
Pessimistic	-3.98	-1.37	-0.40	0.29	0.86	1.37	1.89	2.54	3.60	6.29	10.27	[59.52]
										Opt.-Pes.	2.57	[4.55]

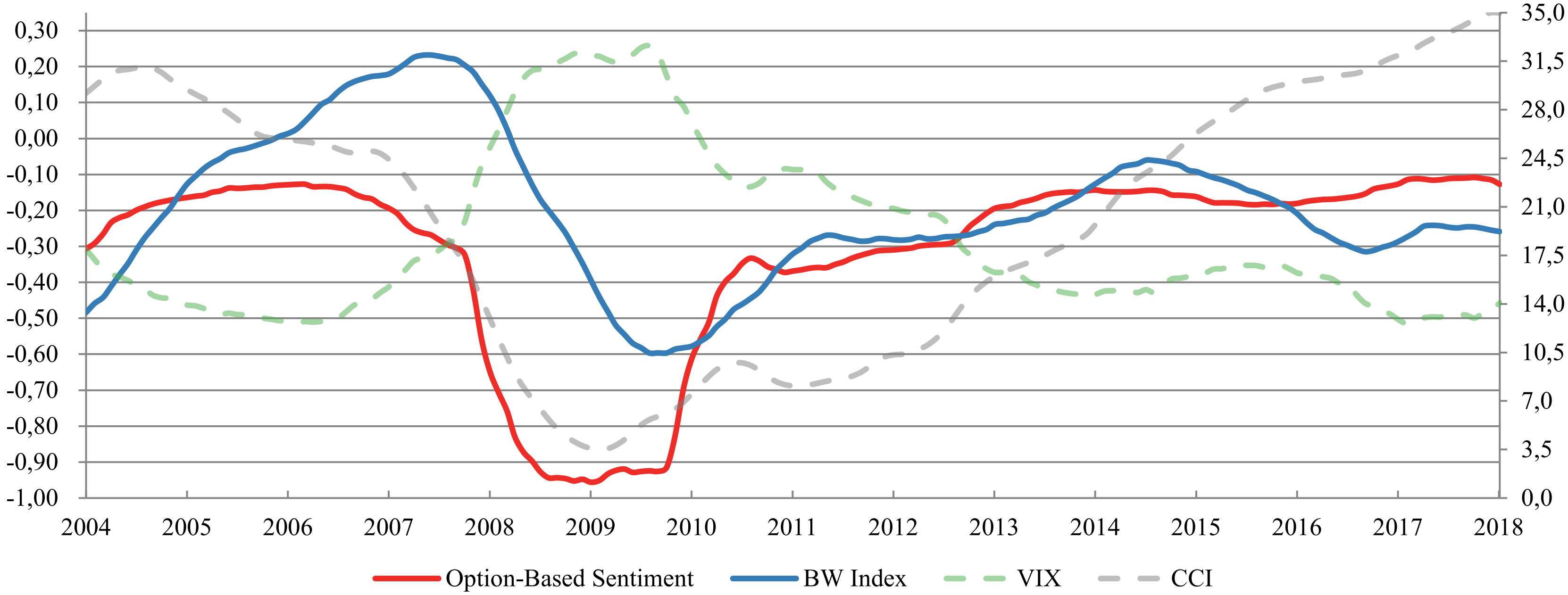
Note: This table reports the average monthly returns in percentages for price momentum strategies involving all CRSP stocks for the period 2001-2018. At the end of each month in the sample, we sort all stocks according to their average returns for the past six months. Based on this ranking, all investable stocks are then categorized into ten deciles monthly. Each month, we form a momentum portfolio by simultaneously longing stocks in the top decile and shorting those in the bottom decile. To determine the state of sentiment for any holding period, we compute a series of weighted rolling averages of our proposed option-based sentiment index. Then, a sample month will be labeled as optimistic (pessimistic) if the computed average sentiment for this current month falls into the top (bottom) one-third section of the average sentiment sequence. At last, if all the months during which we hold the long-short portfolio are classified as optimistic (pessimistic), then the entire holding period will be identified as one with the optimistic (pessimistic) investor sentiment. All other scenarios are referred to as mild periods.

Table 8: Regressions of momentum portfolio returns on option-based investor sentiment

		2-Month Holding Period			4-Month Holding Period			6-Month Holding Period		
	Parameter	**Est.**	**t-Stat.**	**Adj. R^2**	**Est.**	**t-Stat.**	**Adj. R^2**	**Est.**	**t-Stat.**	**Adj. R^2**
$Return_t = \mu + \rho_1 Senti_t + \rho_2 Market_t + \epsilon$										
Constant	μ	0.142	36.22	9.80%	0.143	48.98	17.38%	0.119	49.59	12.42%
Sentiment	ρ_1	**0.035**	**2.85**		**0.039**	**4.24**		**0.035**	**4.56**	
Market	ρ_2	-0.188	-2.58		-0.165	-3.05		-0.024	-0.53	
$Return_t = \mu + \rho_1 Senti_t + \rho_2 Market_t + \rho_3 Market_t^2 + \epsilon$										
Constant	μ	0.138	33.64	13.08%	0.139	46.46	23.79%	0.118	46.06	12.84%
Sentiment	ρ_1	**0.040**	**3.23**		**0.044**	**4.88**		**0.036**	**4.71**	
Market	ρ_2	-0.148	-2.02		-0.123	-2.32		-0.011	-0.24	
$Market^2$	ρ_3	2.343	2.52		2.430	3.60		0.751	1.30	
$Return_t = \mu + \rho_1 Senti_t + \rho_2 Market_t + \rho_3 Market_t^2 + \rho_4 Market_t^3 + \epsilon$										
Constant	μ	0.138	33.54	12.90%	0.139	46.55	24.43%	0.118	45.91	12.50%
Sentiment	ρ_1	**0.041**	**3.31**		**0.045**	**5.04**		**0.037**	**4.74**	
Market	ρ_2	-0.209	-2.04		-0.200	-2.70		-0.041	-0.64	
$Market^2$	ρ_3	2.878	2.56		3.105	3.82		1.017	1.45	
$Market^3$	ρ_4	8.670	0.85		10.944	1.48		4.310	0.67	

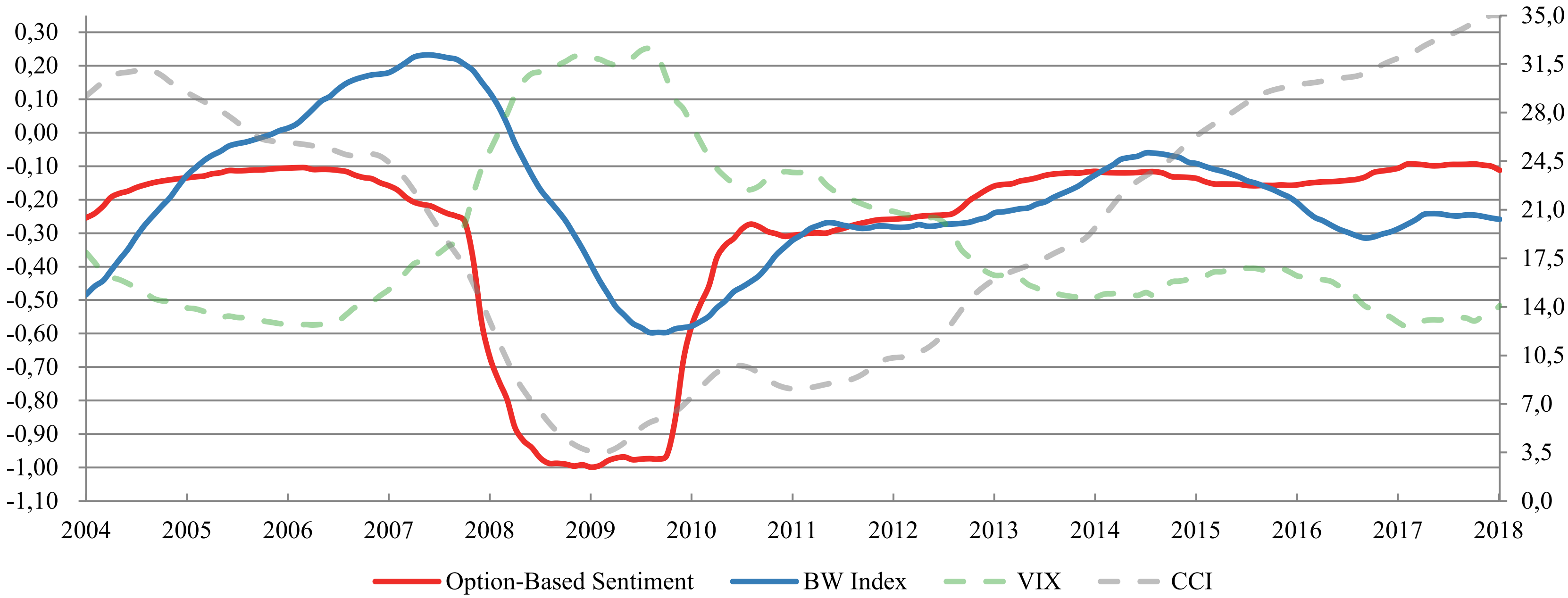
Note: This table reports regression results monthly returns on momentum portfolio over the sentiment index based on the First Principal Component (FPC), controlling the effects of market return, quadratic market return and cubic market return. The respective t-statistics are reported below in brackets.

Figure 1: Monthly time-series of the option-based sentiment proxy (FPC-based weight) in comparison to the BW Index, VIX, and CCI



Note: This figure plots the 24-month rolling average of our option-based sentiment proxy computed by the first principal component approach, the BW index, VIX index and CCI index. To make clear comparison, VIX is presented in percentage and shown in the right axis.

Figure 2: Monthly time-series of the option-based sentiment proxy (survey-based weights) in comparison to the BW index, VIX, and CCI



Note: This figure plots the 24-month rolling average of our option-based sentiment proxy computed by the survey weights, the BW index, VIX index and CCI index. To make clear comparison, VIX is presented in percentage and shown in the right axis.

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