The Information Value of Media Coverage of Market Volatility: A Textual Analysis

Ming-Hung Wu, **Wei-Che Tsai**, **Nai-Wen Cheng** and **Yi-Wei Chuang***

ABSTRACT

Our primary aim in this study is to measure media sentiment using textual analysis of news stories, blog posts, and discussion messages, before going on to explore the links with market sentiment based upon large-scale web data feeds and VIX futures returns. Our results reveal that whilst the sentiment index (calculated overnight) can indeed predict daily VIX futures returns, its predictive power is weakened by macroeconomic announcements. The sentiment effect is also found to be more pronounced on days with high numbers of postings, trading volume, volatility, and illiquidity. Following the strategies highlighted by the media sentiment index, our portfolio exhibits high performance, particularly when the analysis relates to news articles. These findings suggest that media sentiment contains the economic value in volatility trading.

Keywords: Text mining; Information flow; Investor sentiment; Media; VIX futures.

JEL Classifications: G12, G13, G14.

* Ming-Hung Wu is an assistant professor of finance at Beijing Normal University, Zhuhai (No 18 Jinfeng Road, Tangjiawan, Zhuhai City, Guangdong Province, China. E-mail: hung770416@gmail.com; Tel: +886-919394209); Wei-Che Tsai is a Distinguished Professor of Finance at the National Sun Yat-sen University (No. 70, Lienhai Road, Kaohsiung 80424, Taiwan. E-mail: weiche@mail.nsysu.edu.tw; Tel: +886-7-525-2000 ext. 4814) and a Research Fellow at the Risk and Insurance Research Center, National Chengchi University; Nai-Wen Cheng is affiliated with The Taiwan Futures Exchange (4th. FL., 100, Roosevelt rd, Sec.2, Taipei City, 10084, Taiwan. E-mail: y01371c@gmail.com; Tel: +886-2-2369-5678); and Yi-Wei Chuang is an assistant professor at the Department of Shipping and Transportation Management, National Kaohsiung University of Science and Technology (No.142, Haijhuan Rd., Nanzih Dist., Kaohsiung City 81157, Taiwan. E-mail: ywchuang@nkust.edu.tw; Tel: +886-7-361-7141 ext. 23170).

1. INTRODUCTION

In an efficient market, new information, which is immediately reflected in asset prices, is freely available to all participants at zero cost; however, in real-world financial markets, the speed and cost of acquiring information are factors crucially affecting the asset allocation decisions to be taken by investors. Investors are therefore compensated for the effort that they place into obtaining information (Sherman and Titman, 2002), with media coverage being a major intermediary enabling market participants to access such information, and indeed, numerous prior related studies have shown that media coverage can predict future price movements at both the individual firm level and the aggregate market level.[1]

Our primary aim in this study is to carry out textual analysis using the Loughran-McDonald dictionary (2011) to analyze media coverage of market volatility, and to then assess its informational content relating to the Chicago Board Options Exchange (CBOE) volatility index (VIX). Specifically, we examine the ways in which media sentiment affects the VIX futures market, a market which provides investors with a simple and direct way of trading volatility without complex strategies or risks.[2]

Studying the VIX futures market and social media coverage of market volatility offers

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1 See Tetlock (2007), Bollen, Mao and Zeng (2011), Loughran and McDonald (2011), Dougal, Engelberg, Garcia and Parsons (2012), Garcia (2013), Dzielinski and Hasseltoft (2013), Riordan, Storkenmaier, Wagener and Zhang (2013), Chen, De, Hu and Hwang (2014), Heston and Sinha (2015) and Sinha (2016).

2 The implied volatility index (VIX) was introduced by the Chicago Board Options Exchange (CBOE) in 1993, with VIX futures being launched in 2004 to fulfill the need for trading in volatility-related assets. The average daily volume of VIX futures grew from 5,000 contracts in 2009, to 207,700 contracts by Q3 of 2020, indicating a growth rate of roughly 41.54 times over one decade. This substantial increase in demand for direct volatility trading is noteworthy.

several advantages. Firstly, the growing daily trading volume and open interest in VIX futures contracts provides investors with a more accessible means of acting on market information relating to volatility, as compared to engaging in complex volatility trading strategies. Secondly, numerous prior related studies have explored the connection between news media, financial reports and the first moment of asset returns, as well as the relationship between social network sites and the second moment of asset returns.

For example, Antweiler and Frank (2004) found that analyzing internet stock message boards could help to predict market volatility, with Sprenger et al. (2014) subsequently demonstrating that by analyzing Twitter using high-frequency frameworks, correlations could be found with the trading volume, returns and volatility of individual stocks. Behrendt and Schmidt (2018) later discovered that Twitter sentiment and counts could have specific impacts on the volatility of individual stocks. All of these studies suggest that social media provides valuable information potentially affecting market volatility, which can cause asset prices to fluctuate through the incorporation of such information into the price. This clearly presents an opportunity for us to explore the information value of media coverage on market volatility and its potential impacts on future price movements in CBOE volatility futures.[3]

VIX futures contracts can also serve as a direct channel for investors wishing to trade in volatility-related information, and indeed, these instruments act as a price discovery function

[3] Bollen, O'Neill and Whaley (2017) and Chen and Tsai (2017) further demonstrated that VIX futures provided a price discovery function in intraday trading activity.

for the VIX spot index, with the VIX futures dominating the VIX spot index during periods of high volatility. As a result, we concentrate on the VIX futures market, since it has the greatest demand for hedging volatility and more trading activity in volatility information. Furthermore, VIX futures, as a risk management tool, have contributed to a significant increase in trading activity, and as a result, there are fewer missing values when investigating the connection between media coverage and the VIX market using high-frequency frameworks.

Finally, in the examination of trading activity in VIX futures trading, the growing demand for direct trading of VIX futures has led investors to seek new information on volatility from news media and online discussion forums. As a result, media outlets are now providing more coverage of market volatility, resulting in the availability of a wealth of data through media sources, such as news articles, blog posts and online discussions. This presents an opportunity to investigate the information content of social media coverage on market volatility by extracting the volatility index.

In the present study, we extend the scope of the extant research on the potential information value of media coverage relating to market volatility by constructing three sentiment indices from three different types of social media sources (news feeds, blog datasets and online discussions) based upon 523,456 postings published on the webhose.io platform, as well as feeds relating to the ‘volatility index’. Our aim is to attempt to investigate whether volatility information contained in social media provides significant predictive ability on price movements in VIX futures contracts on a daily-frequency framework. Our empirical analysis and corresponding findings in this study comprise of the following three elements.

Firstly, we used the Loughran-McDonald dictionary (2011) for textual analysis to measure the media sentiment index in the overnight hours, and found a significant predictive relationship between VIX futures returns and the three sentiment indices constructed from web postings during the overnight hours. Our findings reveal that the positive (negative) sentiment index is significantly and negatively (positively) correlated with VIX futures returns, particularly for news articles, and that negative sentiment is a stronger predictor than positive sentiment, which implies that the VIX futures market attracts more investors wishing to trade on negative information. Furthermore, the sentiment effect is found to be more pronounced on Mondays, thereby indicating that a greater information flow leads to a greater reaction in VIX futures prices. Our evidence supports the findings of Da et al. (2015), that market volatility effectively captures negative information, as their fear index based on the thirty most negatively correlated words is found to be positively correlated with VIX futures returns and realized volatility on the SPY.

Secondly, we examined the predictive power of the sentiment indices on VIX futures returns under different conditions in an effort to provide further evidence of these indices validly capturing volatility information. Our empirical results indicate that the predictive ability of returns based on sentiment is more significant during periods of greater amounts of released postings, high trading volume and realized volatility in the VIX futures market. The theoretical study of Kim and Verrecchia (1994) suggested that greater levels of trading volume and high uncertainty tend to be initiated by information, followed by a period of cooling off until the traders reach a consensus on the consequences of the information through the trading process. These results again echo our prior evidence on Mondays, that the greater the accumulated information flow, the greater the reaction of the VIX futures prices.

Thirdly, we reveal the predictive ability of the sentiment index through simulated trading strategies. Using the news, blogs and discussion boards as indicators, we achieve respective annualized returns of 88.58%, 23.31% and 74.12%, even after factoring in transaction costs. Surprisingly, a shorting strategy based upon positive sentiment dominates most trading profits, which indicates a bullish market during our sample periods. Our results also reveal that news-based sentiment predictive ability and trading strategy outperform other sentiment indices, which clearly indicates that news-based volatility and investor sentiment are essential factors in the VIX futures market. News content is found to have broader coverage and more timely dissemination, leading to increased investor attention and trading on news information, thereby improving market efficiency and accelerating the speed of incorporation of the information into prices.

Our empirical findings reveal that sentiment constructed through textual analysis of social media coverage of market volatility has statistically significant predictive ability on returns, and economic value through trading strategies in the VIX futures market. We contribute to the extant literature in the present study by establishing a connection between social media sentiment and the VIX futures market, thereby providing a direct channel for trading volatility information. Our approach improves the objectivity and accuracy of the media-based sentiment indices by utilizing huge, timely amounts of information from diverse social media sources. We also offer new insights by examining the relationship between sentiment and market reaction at a higher frequency and short-term advantage, constructing sentiment indices from the overnight hours after the market close through to the market open, and examining whether the daily return in the VIX futures market reflects all published and accumulated information prior to the market open.

The remainder of this paper is organized as follows. Section 2 provides a review of the extant literature on information content and media sentiment, followed in Section 3 by a description of the data and construction of the sentiment index. Section 4 presents the results on the relationship between the sentiment indices and VIX futures, including those under different market conditions. Discussions of our methodology and the results of simulated VIX futures trading strategies based upon the sentiment indices are provided in Section 5. Finally, Section 6 concludes our study with suggestions for possible avenues for future research.

2. LITERATURE REVIEW

Media coverage plays a pivotal role in disseminating information to facilitate the price formation process, and indeed, Engelberg (2008) recognized that qualitative information embedded in the news has higher predictive power on stock returns over longer horizons, whilst quantitative information reported in the news is more rapidly incorporated into stock prices. Fedyk (2017) further documented the importance of the 'front page' positioning of news on the Bloomberg Terminal, since such positioning was found to be capable of prompting 280% trading volume and 180% absolute price changes during the first ten minutes after a news release; this was then found to be followed by substantially higher short-term returns for around 30-45 minutes. In other words, different ways of presenting the news can directly affect the speed of dissemination of the information conveyed.

The 'investor recognition' hypothesis, developed by Merton (1987), provides a potential explanation for why media coverage has such a crucial impact on the value of a firm, with the intuition being that a stock with lower investor recognition should have higher expected returns in order to compensate investors for trading in an incomplete information market. Fang and Peress (2009) provided evidence of a cross-sectional relationship between expected stock returns and media coverage, thereby providing further support for the Merton (1987) hypothesis.

An additional argument relating to the impacts of media coverage on stock prices is the 'attention' theory of Barber and Odean (2008), which posits that individuals are likely to buy stocks referred to in media coverage, thereby resulting in an increase in trading activity in those particular stocks. Using the 'search volume index' (SVI) as a proxy for investor attention, Da, Engelberg and Gao (2011) demonstrated that a higher SVI was associated with higher stock prices in the subsequent two-week period, then turning into a price reversal within a year. Kaniel and Parham (2017) noted that the investor attention effect also occurs in capital flows of mutual funds after press releases.[4] Erdemlioglu, Gillet and Renault (2017) combined the information flows from traditional media sources with the 'tweet' flows of investors and financial experts to demonstrate that the level of attention on Twitter relating to certain types of news was associated with stock trading activity.

Several prior related studies have clearly documented the over-reaction or under-reaction of stock prices to media coverage; for example, using a rational equilibrium model, Veronesi (1999) showed that stock prices underreacted to favorable news in bad times and overreacted to bad news in good times. Chan (2003) subsequently demonstrated that stocks associated with good public news exhibited less price drift, whereas those associated with bad news exhibited a negative price drift which was found to last for up to a year.

The extant related literature reveals an obvious asymmetric response to media coverage, such that negative (positive) information flows are found to have a greater (lesser) influence on stock returns and volatility; indeed, both Leinweber and Sisk (2011) and Groß-Klußmann

[4] Kaniel and Parham (2017) demonstrated a 31% local average increase in quarterly capital flows into the mutual funds mentioned in the prominent 'Category Kings' ranking list of the *Wall Street Journal*.

and Hautsch (2011) showed that the responses to negative news were much stronger. Smales (2014) also confirmed that negative news generated greater influences on returns, volatility and spreads.

There is also a rapidly growing body of literature within which textual analysis is being increasingly used to extract useful information from media coverage of 10-k financial reports. Tetlock (2007), for example, carried out a classification of various words in the ‘Abreast of the Market’ column of the *Wall Street Journal*, based upon the General Inquirer along with the Harvard-IV-4 dictionary, and revealed that high levels of media pessimism effectively predicted the downward pressure on market prices, which was then quickly followed by a reversal to fundamentals.

Basing their measure of sentiment on the Harvard psychosocial dictionary, Tetlock, Saar-Tsechansky and Macskassy (2008) discovered that the proportion of negative words appearing in company-specific news articles predicted both lower earnings and lower stock prices. Loughran and McDonald (2011) further refined the Harvard-IV-4 dictionary to create six lists of words that were capable of more accurately capturing the tone of financial documents, and subsequently identified a positive relationship between stock return volatility and the use of uncertain and weak modal words in 10-K filings. Boudoukh, Feldman, Kogan and Richardson (2013) also used textual analysis to examine all news items and documents in the Dow Jones Newswire and showed that confirmed-source news had a stronger impact on stock prices than unidentified news.

There are several other related studies (such as Da, Engelberg and Gao, 2015), within which a ‘financial and economic attitudes revealed by search’ (FEARS) sentiment index is constructed based upon daily Google search volume of queries associated with household concerns. Baker, Bloom and Davis (2016) went on to use textual analysis to construct an economic policy uncertainty index based upon the frequency of newspaper articles containing specific terms relating to the economy, policy matters and uncertainty. Focusing on front-page articles in the *Wall Street Journal*, Manela and Moreira (2017) combined textual analysis with machine learning to establish a ‘news-based measure of implied volatility’ (NVIX).

In addition to media coverage, due to the popularity of the Internet and the widespread use of social media over recent years, the forum discussions and messages posted on social media can also reflect the thoughts and sentiments of market participants, which may of course help to predict future price movements. Antweiler and Frank (2005) analyzed more than 1.5 million messages posted on Yahoo! Finance and Raging Bull, and demonstrated that these messages were not just noise, but that they also helped to predict market volatility. In their textual analysis of Twitter, which is one of the most popular social websites, Sprenger et al. (2014) analyzed approximately 250,000 stock-related tweets and demonstrated that the trading volume, returns and volatility of stocks were significantly correlated with the features of these tweets, such as sentiment, volume and disagreement.[5]

Motivated by the above studies, our primary aim in the present study is to investigate the information value of media coverage on market volatility by examining the relationship between the VIX futures market and the sentiment index, which applies textual analysis to extract market-volatility-related information. Our analysis in this study provides new insights into the extant literature on VIX futures and extends the scope of the extant studies to include media sentiment. To the best of our knowledge, this link between the information content of media coverage of market volatility and VIX futures has not previously been explored within the literature.

3. DATA ND METHODOLOGY

3.1 Volatility Index Futures

The VIX was introduced by the CBOE in 1993 as a benchmark of stock market volatility (conveyed by S&P 500 index option prices) providing the means of measuring investor sentiment, and ever since its debut, has attracted the rapidly growing attention and interest of investors; the VIX is also referred to as an 'investor fear' gauge (Whaley, 2000, 2009). In 2004, the CBOE introduced VIX futures as the first listed futures contracts (Zhang and Zhu, 2006),

[5] Other examples include Chen, Prabuddha, Hu and Hwang (2014), Sul, Dennis and Yuan (2014), Avery, Chevalier and Zeckhauser (2016) and Crawford, Wesley and Kern (2017). However, it is argued in other related studies that no predictive relationship is found to exist between future returns and opinions posted in online communities (see, for example, Tumarkin and Whitelaw, 2001; Dewally, 2003; Das and Chen, 2007; and Kim and Kim, 2014. Tumarkin and Whitelaw (2001) demonstrated that Internet message board activity had no significant forecasting power on either abnormal trading volume or industry-adjusted returns, whilst from their analyses of the messages downloaded from Yahoo! Finance message board, both Das and Chen (2007) and Kim and Kim (2014) provided evidence showing no strong relationship between investor sentiment and stock returns.

with these contracts having become a popular and growing asset class among investors. Frijns, Tourani-Rad and Webb (2016) found that the causal relationship, running from VIX futures to the VIX, had increased, whereas reverse causality had been reduced, thereby suggesting that investors were now using VIX futures for hedging, as opposed to engaging in the trading of S&P 500 index options.

Our VIX futures data in the present study were obtained from the CBOE, with the sample period running from December 2014 to the end of September 2017. We use front VIX futures contracts which have at least seven days to the settlement date, essentially because, beyond the front contracts, quoted bid-ask spreads are found to rise substantially whilst liquidity drops off. We use bid-ask spreads to measure the transaction costs, which are estimated based upon daily high and low prices (Simon and Campasano, 2014). Due to the fact that daily low prices are nearly always buyer-initiated trades, and the daily high prices are, in practice, seller-initiated trades, the ratio of daily high-to-low prices reflects both bid-ask spreads and stock volatility. The front S&P 500 futures data with at least seven days to the settlement date were obtained from Investing.com, with the data including daily open, high, low and close throughout the sample period.[6] Table 1 reports the summary statistics of all of the variables used in this study.

<Table 1 is inserted about here>

The average VIX index return is -0.58%, whilst the mean of the front VIX futures return

[6] The data are available from https://www.investing.com/

(S&P 500 return) is -0.33% (0.04%). Unsurprisingly, the S&P 500 index grew by 22.69% during our bullish sample period, whilst the VIX index fell by 32.84%. The range of VIX index returns is found to have expanded, relative to the front VIX futures contracts, essentially because, when the VIX is at extremely high (low) levels, the VIX index is often found to be higher (lower) than the VIX futures prices.

The basis of front VIX futures contracts, which are defined as each front VIX futures contract price minus the VIX price, averages out at 108.9 basis points (bps), with the cut-offs for the 25^{th} and 75^{th} quantiles being 66bps and 190bps, and the VIX term structure generally being found to be upwardly sloped. The volatility of front VIX futures contracts is defined as the difference between the daily high prices and low prices of the front VIX futures contracts divided by the daily closing prices of the front VIX futures contracts. The mean of the front VIX futures volatility is 6.64%, with a 25^{th} and (75^{th}) quantile of 3.9% (8.0%).

The average turnover of front VIX futures contracts is roughly 69%, defined as daily trading volume of front VIX futures contracts divided by the daily open interest of front VIX futures contracts, indicating that the VIX futures market is liquid. The standard deviation of front VIX futures turnover is 36.88%, which indicates high variations in the liquidity of the front VIX futures contracts. Finally, the mean of the news-based index of 'economic policy uncertainty' (EPU), which was proposed in Baker et al. (2016), is 83.06, with a large standard deviation and a wide maximum and minimum range.

3.2 Media Data

Our media coverage data were obtained from the Webhose Ltd., which provides up-to-the-minute structured web data coverage of various content domains from global websites, such as news media articles, self-published blog posts obtained from public platforms and personal websites, and online discussions sourced from forums, message boards and online review sites.[7] In order to estimate the relationship between the coverage of these posts and the returns of the front VIX futures contracts, we use textual analysis to capture the tone and sentiment of these posts. The query keywords to gain access to the related archive web data via an API are ‘volatility index’. The total number of posts downloaded between December 2014 and September 2017 was 523,456, comprising of 380,179 news articles, 128,707 blog posts, and 14,570 online discussions.

Figure 1 shows the content of words appearing in the data, including inflation, gold, etf, brexit, trump and others. The major events occurring during the sample period were the election of Donald Trump as the United States president and the exit of the UK from the European Union in 2016. The larger the word count, the more frequently they appeared. Appendix C lists the top 20 words appearing most frequently for all kinds of sentiments in the news, blogs and discussions.

<Figure 1 is inserted about here>

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[7] Webhose was chosen because they had the largest historical (i.e., oldest) dataset and provided article text along with metadata. The data are available from https://webhose.io/

The posts data contain several items, such as the country in which the site is based, the site types (news/blogs/forums), the title of the post, the text of the post and the date/time that the post was published, with the latter being converted to GMT-6 (daylight saving time is GMT-5). Figure 2 shows the top ten countries of the sites providing the news articles, blog posts and online discussions, with most of the web data being US based. Appendix B shows the top ten sources of the websites for the different types of posts. The No. 1 sources for the respective postings of news media, self-published blogs and posts on message boards, forums and review sites were 22,539, 7,622 and 1,068.

<Figure 2 is inserted about here>

Figure 3 illustrates the number of posts published over the sample period, with the number of released-news postings being far higher than the other types. On average, the frequency of posts released among the three types of sites were more intensive between December 2015 and June 2016, and between March 2017 and September 2017.

<Figure 3 is inserted about here>

3.3 Sentiment Index of Media Data Feed

This study applies the Loughran-McDonald 2014 Financial Sentiment Dictionary to quantify the text content of media data. The sentiment dictionary was created by Loughran and McDonald (2011) with a new-negative word list and six other word lists, all of which more accurately reflect sentiment in financial texts. For our construction of the media-based sentiment index, we used textual analysis to quantify the qualitative information, a process following the dictionary methods proposed so far, which measure the tone of a large-scale of corpus by counting and averaging the number of words that have a specific sentiment connotation, such as “negative” or “positive”.

4. EMPIRICAL ANALYSIS

In this section, we present our empirical results on the relationship between the media-based sentiment index and the VIX futures returns, which is subsequently followed by our cross-sectional analyses. We then go on to investigate whether this relationship is found to persist in the long run.

4.1 Return Predictive Ability of the Sentiment Index on VIX Futures

To examine the validity of the predictive ability of the media-based sentiment index on the front VIX futures returns, we use real information to test whether or not the posts published after overnight hours, the close of the previous day and before the open of the next day, could have direct influences on the VIX futures price daily movements. The sentiment index from Tuesdays to Fridays is measured by the postings published after the close of the previous day and before the open of the next day. For Mondays, the sentiment index is measured from postings released after the market close on Friday and before the market open on Monday. Our model specification is shown in Equation (1).

$$Return_t = \beta_0 + \sum_m \beta_m \, Sentiment^m + + \sum_n \beta_n \, Controls^n + \varepsilon_t \qquad (1)$$

where $Return_t$ denotes the front VIX futures returns and $Sentiment^m$ is the index (scores) for the seven types of sentiment. The control variables ($Controls^n$) include lagged VIX futures returns (up to two lags), lagged turnover of the front VIX futures and the lagged news-based measure of 'economic policy uncertainty' (EPU). Table 2 reports the estimation results of Equation (1). It should be noted that we count only posts published during the overnight hours after the market close of the previous day and before the open of the next day.

<Table 2 is inserted about here>

The significantly positive coefficient on the negative sentiment index for all three different types of posts suggests that an increase in the magnitude of negative words predicts higher VIX futures returns. Conversely, the coefficient on the positive sentiment index is found to be negative and highly statistically significant for news and blogs, thereby implying that when the market is more optimistic, the returns of the VIX futures are lower. Both the negative and positive sentiment effects on VIX futures returns are found to be relatively stronger for news; however, the effect of positive sentiment for discussions is not found to be significant. This evidence is consistent with the negative correlation found between market returns and implied volatility.

We further explore the strength of the predictive power of negative and positive sentiment on VIX futures by running the following regression.

$$Return_{t+k} = \beta_0 + \beta_1 Negative_{close_{t-1}}^{open_t} + \beta_2 Positive_{close_{t-1}}^{open_t} \tag{2}$$

$$+\sum_{n}\beta_n\,Controls^n+\varepsilon_{t+k}$$

where $Return_{t+k}$ are the VIX futures returns on day $t+k$, and the control variables ($Controls^n$) include lagged VIX futures returns (up to two lags), lagged turnover of the front VIX futures and the lagged news-based measure of 'economic policy uncertainty' (EPU). $Negative_{close_{t-1}}^{open_t}$ ($Positive_{close_{t-1}}^{open_t}$) refers to the negative (positive) sentiment index extracted from the information published during the overnight hours after the close of the previous day and prior to the open of the current day. The results are reported in Table 3.

As shown in columns (1) and (2) in Panels A and B of Table 3, negative (positive) sentiment for news and blogs is found to have significantly positive (negative) effects on the VIX futures returns for the first two days (t+1, t+2). As regards the effects over longer horizons (ranging from k=3 to 5), column 3 (k=3) of Panel A shows that the positive sentiment of news has a significantly negative impact on VIX futures returns, whilst column (4) (k=4) shows that the negative sentiment of news has a significantly positive association with VIX futures returns, although the effect disappears on day t+5. For blogs, the positive effect of negative sentiment over longer horizons is only found to be significant on day t+5, as shown in column (5) in Panel B. Turning to discussions, Panel C shows that with the exceptions of the significantly positive coefficients on negative sentiment on days t+1 and t+5, none of the other coefficients on the positive and negative sentiment are found to be statistically significant.

<Table 3 is inserted about here>

In summary, two important findings are revealed in this section; firstly, the negative sentiment of news is found to predict VIX futures for up to four days; and secondly, the predictive ability of both negative and positive sentiments for VIX futures by news and blogs are stronger than that provided by discussions, thereby suggesting that news media articles from niche websites contain more relevant information.

4.2 The Effects of Macroeconomic Announcement Surprises

We set out in this section to investigate the reaction of VIX futures to macroeconomic announcement shocks and the sentiment effects. The macroeconomic announcements in the US – which comprise of 59 released items, including all weekly, biweekly, monthly and quarterly announcements – were obtained from the economic calendar archive at Briefing.com.[8] We focus on released items by following the extant literature (such as Ederington and Lee, 1993; and Chen et al., 2013).

These economic announcements comprise of the following 14 items: Consumer Price Index, Producer Price Index, Gross Domestic Product Advance, Non-farm Payrolls, Unemployment Rate, Retail Sales, Consumer Confidence, Building Permits, Existing Home Sales, Capacity Utilization, Durable Goods Orders, Leading Indicators, Personal Spending and Case-Shiller 20-city Index. We explore the interaction effect between the macroeconomic

[8] The data are available from https://www.briefing.com/

announcements and the sentiment index on VIX futures using the following regression:

$$Return_t = \beta_0 + \beta_1 Negative_{close_{t-1}}^{open_t} + \beta_2 Positive_{close_{t-1}}^{open_t} + \beta_3 Macro_t + \beta_4 Negative_{close_{t-1}}^{open_t} * Macro_t + \beta_5 Positive_{close_{t-1}}^{open_t} * Macro_t + \varepsilon_t \quad (3)$$

where $Macro_t$ is a dummy variable of macroeconomic announcements.

Considering the ex-ante and ex-post effects of the macroeconomic news announcements, the dummy variable takes the value of 1 for the two days before and the two days after the macroeconomic announcement dates, otherwise 0. The results are reported in Panel A of Table 4, where the negative (positive) and strongly significant coefficient on the interactive dummy on GDP Advance and the negative (positive) sentiment indicates that the predictive ability of negative and positive sentiments on VIX futures price movements become worse after GDP announcements. The slight significance (at the 10% level) and negative impact on the interactions between GDP Advance and the negative sentiment of blog posts also suggests the relatively poor forecasting performance of negative sentiment on VIX futures.

<Table 4 is inserted about here>

Panel B of Table 4 reports whether the ‘Federal Open Market Committee’ (FOMC) interest rate decision meetings will affect the predictive ability of the sentiment index on VIX futures. For news and discussions, the coefficient on the interaction term between positive sentiment and the FOMC decision dummy is found to be significantly positive; the sign on the coefficient, which is opposite to that on positive sentiment, implies that FOMC meetings not only weaken the impact of positive sentiment on VIX futures, but also reverse the direction of the influence. In other words, for FOMC meetings, positive sentiment will be significant, and will positively affect the VIX futures. Similarly, the interaction term between negative sentiment and FOMC meetings reduces the predictive ability of negative sentiment on VIX futures.

Panel C of Table 4 explores the predictive power of 'non-farm payrolls' (NFPs) with the sentiment index. In cases where the postings are news and blogs, only the coefficient on the interaction term between NFPs and the negative sentiment index are found to be significantly negative, which indicates that the release of NFP data leads to negative sentiment being less forecastable for VIX futures price fluctuations; in particular, where the postings are in the form of blogs, the effects of the interactive dummy (significant at the 10% level) and negative sentiment almost cancel out to zero. Although the interaction term between NFPs and positive sentiment is not found to have any significant impact on VIX futures returns, the direction of the coefficient is again reversed.

Panel D of Table 4 provides the results of exactly the same type of analysis for the CPI. Based upon both news articles and blog posts, the CPI is found to have a significant impact on price movements in the VIX futures, with the effect for blogs being stronger than that for news. Furthermore, the interaction term between the CPI and negative (positive) sentiment is found to be more significant for news than for blogs; similarly, the opposite direction of the coefficient on the interactive dummy indicates that when CPI data is announced, the trend in the influence of the negative and positive sentiments on VIX futures price will be weaker, or even reversed.

In summary, four out of the total of 14 economic announcements (GDP Advanced, FOMC interest rate decision meetings, NFPs and the CPI) are found to provide poor predictive power for the sentiment index on VIX futures returns. Due to the layout restrictions, the additional explanatory power on VIX futures price movements from unreported macroeconomic announcements is found to be of a significantly greater magnitude. For example, the impact of the interaction term between 'retail sales' and the negative (positive) sentiment based on blog-type postings is found to be significantly positive (negative), whilst for news articles, the dummy variable of 'durable goods' exhibits a significantly positive effect on VIX futures returns. The coefficient on the interaction term for durable goods and negative sentiment is found to be positive and significant for both news and blog type postings. The above results demonstrate that the release of retail sales and durables goods data will increase the predictive value of the sentiment index on VIX futures returns.

4.3 Day of the Week Effects

In this section, we follow an additional strand of literature examining the relationships between stock returns and the weekend effect (French, 1980; Keim and Stambaugh, 1984; Abraham and Ikenberry, 1994) to analyze the impact of sentiment on VIX futures price movements across days of the week by splitting the sentiment index and VIX futures returns into five groups from Monday to Friday. The time series regression is as follows:

$$Return_t = \beta_0 + \beta_1 Negative_{closing_{t-1}}^{opening_t} + \beta_2 Positive_{closing_{t-1}}^{opening_t} + \varepsilon_t \tag{4}$$

where $Return_t$ is the VIX futures return on weekday t, $Negative_{close_{t-1}}^{open_t}$ and $Positive_{clos_{t-1}}^{open_t}$ denote the sentiment scores measured from the market close of the previous day to the market open on weekday t. Table 5 reports the results of the predictive ability of negative and positive sentiments on VIX futures returns sorted by different types of postings and the day of the week.

<Table 5 is inserted about here>

Panel A of Table 5 reports the estimation results of news media articles, where both negative and positive sentiment are found to have significant influences on VIX futures returns, with the exceptions of Tuesdays and Wednesdays. As shown in column (1), an increase in one negative (positive) word leads to an average increase (reduction) of 0.0217 (0.0305) in the VIX futures returns. The regression results based upon blog posts are reported in Panel B of Table 5, where the effects of negative (positive) sentiment on VIX futures are found to be significantly positive (negative) only on Mondays. The results for online discussions are shown in Panel C of Table 5, where the effect is found to be more pronounced on Mondays. On Tuesdays and Fridays, only negative sentiment is found to have any significant impact on VIX futures.

To summarize, among the days of the week, the predictive power of sentiment on VIX futures price movements is found to be relatively strong and significant on Mondays, regardless of the types of postings, a finding which is clearly in line with the Monday effect. In addition, the marginally significant effect of sentiment on Fridays reflects the expectations of investors for the coming week.

4.4 Information Flow and Market Characteristics

In this section, we explore the cross-sectional predictive ability of the sentiment index on VIX futures price movements, based upon information flow and VIX futures characteristics. We divide the full sample into daily numbers of published postings, daily trading volume of VIX futures and daily realized volatility of VIX futures (as in Alizadeh, Brandt and Diebold (2002), which is defined as the ratio of the difference between the intraday highest and lowest prices to the close price.

The sample data are divided into three sub-groups, based upon the value of each characteristic, with the following regression model then being tested:

$$Return_{i,t} = \beta_0 + \beta_1 Negative_{Close_{i,t-1}}^{Open_{i,t}} + \beta_2 Positive_{Close_{i,t-1}}^{Open_{i,t}} + \varepsilon_{i,t} \tag{5}$$

where $Return_{i,t}$ refers to the VIX futures returns on day t of groups of characteristic i, and $Negative_{Close_{i,t-1}}^{Open_{i,t}}$ and $Positive_{Close_{i,t-1}}^{Open_{i,t}}$ are the negative and positive sentiment indices measured after the market close on day t-1, and before the market open on day t, for the i^{th} characteristic group.

The estimated results of the three types of postings subdivided by the three selected characteristics are reported in Table 6, with the effects of sentiment on VIX futures returns based upon numbers of published postings being shown in Panel A. As shown in column (3), the positive (negative) impact on the VIX futures returns of negative (positive) sentiment is found to be more pronounced in the high number of daily postings sub-group; however, no significant sentiment effect is discernible on VIX futures in the high number of daily postings sub-group for online discussions. Overall, the results indicate that the more postings released per day, the more negative and positive words are entrained, leading to a more prominent impact of sentiment on VIX futures price movements.

<Table 6 is inserted about here>

Panel B of Table 6 reports the estimated results for the trading volume sub-groups, with the results being found to be consistent across the three types of postings; the positive (negative) effects of negative (positive) sentiment on VIX futures returns are found to be more pronounced in the high trading volume sub-group, which suggests that the predictive ability is stronger when market liquidity is high. As compared to news articles and blogs, the effects of sentiment on VIX futures are found to be relatively weak for the discussions sub-group.

Panel C of Table 6 reports the effects of sentiment on VIX futures among the low-, median- and high-volatility sub-groups. The positive (negative) effects of negative (positive) sentiment on VIX futures are found to be significant only in the high-volatility group for news articles and blogs posts; however, this is not the case for discussions, where only negative sentiment is found to have any significant and positive effect on VIX futures returns. These results imply that the predictive ability of the sentiment index on VIX futures is relatively stronger when VIX futures are relatively volatile.

4.5 How Persistent is the Predictive Ability?

In this section we shed some light on the long-term effects of sentiment by investigating whether the predictive ability lasts over longer (weekly) horizons. If the financial market is efficient in incorporating new information, then the predictive ability is expected to be less likely to persist over longer periods, and indeed, likely to disappear.

In order to examine the long-term effects, we aggregate the daily negative and positive sentiment indices on a weekly basis, and then investigate whether a weekly sentiment index could predict long-term VIX futures returns using the following regression:

$$\begin{aligned} Return_{w+k} = \beta_0 + \beta_1 Negative_{w-k} + \beta_2 Positive_{w-k} \\ + \sum_n \beta_n \, Controls_{w-1}^n + \varepsilon_{w-k} \end{aligned} \tag{6}$$

where $Return_{w+k}$ refers to the VIX futures return in week w, which is the logarithm of the ratio of the open (close) price on the first (last) day of the week; $Negative_{w\text{-}k}$ ($Positive_{w\text{-}k}$) is defined as the average daily negative (positive) sentiment in week w; and $Controls_{w-k}^n$ include lagged VIX futures returns, lagged turnover of VIX futures and the lagged news-based measure of 'economic policy uncertainty' (EPU), with *k* standing for 0 and 1 week. The results on the long-term effects of sentiment are reported in Table 7.

<Table 7 is inserted about here>

Panel A of Table 7 shows the weekly sentiment index impact on the contemporary weekly VIX futures return (*k*=0). The results of both news media articles and blog postings show significant positive (negative) influences of negative (positive) sentiment on the VIX futures. The sentiment effects are statistically significant at least at the 1% level, with the impact of news type posting being stronger than that of blogs posts; however, no sentiment impact is discernible on VIX futures based upon the discussion messages.

Panel B of Table 7 reports the predictive power of the weekly sentiment index for VIX futures price movements in the subsequent week (*k*=1). Among the three types of postings, the significant predictive ability of the sentiment index on VIX futures returns is found to exist only for news articles, with both the negative and positive sentiments effects being statistically significant at the 5% level. A unitary increase in the negative (positive) sentiment index for news articles leads to a 3.7% (3.75%) increase (reduction) in the VIX futures returns after one week; however, no evidence is discernible of any long-term effects for blogs or discussions. The results reported in Panel B suggest that the reaction to information contained in news media postings is relatively persistent.

5. PROFITABILITY OF TRADING-STRATEGY-BASED SENTIMENT

The previous section revealed that both negative and positive sentiment have substantial forecasting power for subsequent VIX futures price changes, particularly for news articles. In this section, we examine the profitability of shorting or buying VIX futures in accordance with the sentiment index computed during the period from the market close (15:15) on the previous day to the market open (08:30) on a trading day.

5.1 Performance of Unhedged VIX Futures Positions

Our day trading strategy in the VIX futures market is dependent upon the difference between the negative and positive sentiment indices. Once the conditions of the trading strategies are met, we buy or short one VIX futures contract at the open price of the day and offset the VIX futures position at the close price. We establish the benchmark trading strategy which always shorts one VIX futures contract at the open price and short covering at the close price in order to evaluate the performance of our proposed strategies. The conditions for each trading strategy are defined as follows:

Strategy 1: Strategy 1 only takes into consideration the difference between the negative and positive sentiment indices after the close on the previous day and before the open on the next day. This involves shorting one VIX futures contract when the difference between the negative and positive sentiment indices is smaller than zero, and buying one VIX futures contract when the difference between the negative and positive sentiment index is greater than zero.

Strategy 2: As compared to Strategy 1, the additional condition in Strategy 2 is a moving average of the difference between the negative and positive sentiment indices. The conditions are as follows. Short (buy) one VIX futures position when the negative sentiment index is smaller (greater) than the positive sentiment index, and the difference between the negative and positive sentiment indices is smaller (greater) than the past five-day moving average of the negative minus positive sentiment scores.

Strategy 3: Following the conditions of the previous trading strategies, Strategy 3 further considers the changes in the basis to construct more stringent entrance and exit thresholds for the trades; that is, when the following three conditions are simultaneously established, Short (Buy) one VIX futures contract when: (i) the negative sentiment index minus the positive sentiment index is smaller (greater) than zero; (ii) the difference between the negative and positive sentiment scores is smaller (greater) than the five-day moving average of the negative sentiment index minus the positive sentiment index; and (iii), the basis is in contango ('backwardation'), which means that the VIX futures price is higher (lower) than the VIX.

The performance of unhedged VIX futures positions containing both transaction and non-transaction costs for each trading strategy among each type of media, along with the constant short benchmark strategy, are reported in Table 8. In order to simulate the transactions in practice, the trading simulations incorporate the average of the daily bid-ask spread from Aug 2014 to Aug 2015 as the transaction costs.

<Table 8 is inserted about here>

Panel A of Table 8 reports the trading performance for Strategy 1, with the results indicating that, relative to buying VIX futures, shorting VIX futures based upon the sentiment index is highly profitable. The annualized returns for news articles and discussions messages are found to exceed the performance of the constant short strategy, with a win-to-loss ratio of roughly 0.5. Furthermore, the highly positive annualized Sortino ratio indicates that investors will earn greater excess returns per unit of downside risk that they take on, particularly when trading VIX futures according to the sentiment index extracted from news articles and online discussions.[9]

Panel B of Table 8 reports the trading performance for Strategy 2, which contains one more trading condition, a five-day moving average on the sentiment indices. The average performance of Strategy 2 is relatively inferior to that of Strategy 1, with lower volatility in trading returns; however, as compared to Strategy 1, the profits of blog postings and online discussions are both found to decline, with the positive skewness of returns among the three

9 The Sortino ratio penalizes only downside volatility, which is calculated as average annualized P&L divided by the annualized downside deviation in the P&L. The downside deviation, which is essentially the standard deviation of all negative returns, assumes that the minimum acceptable return is equal to 0, with gains set as being equal to 0 and included in the calculations.

types of postings being larger for Strategy 2.

Panel C of Table 8 reports the profits and losses (P&Ls) of Strategy 3, which includes the last added transaction condition, the basis between VIX futures and the VIX. Regardless of the media types, the overall performance of Strategy 3 is found to be relatively worse than the benchmark strategy; for example, the smaller Sharpe and Sortino ratios indicate that lower excess returns are generated by a unitary standard deviation and downside deviation, with the smaller standard deviation implying gentler fluctuations in profits. Among the three types of media, the P&Ls of trades on the news sentiment index are the only ones which beat the performance of the benchmark strategy. The success rate, skewness and kurtosis of returns under Strategy 3 are found to be higher than either Strategy 2 or Strategy 3 without the inclusion of the basis condition.

5.2 Performance of Hedged VIX Futures Positions

These trading strategies are exposed to the potentially substantial risks relating to converse movements in the VIX futures price. For instance, traders who buy VIX futures are confronted with substantial losses if the VIX curve falls; similarly, traders shorting VIX futures face the risk of VIX futures prices going up. Since the price movements of VIX futures are diametrically opposite to those in the equity market, spikes in the VIX futures curve generally stem from stock market sell-offs. Conversely, declines in VIX futures price indicate that the equity markets are relatively bullish. In light of the relationship between VIX futures and the equity markets, most of the risk can be hedged by shorting or buying S&P 500 futures in the same direction as the VIX futures positions.

Our trading simulations examine the profits and losses of hedged VIX futures positions where the size of the S&P 500 futures hedge is in accordance with out-of-sample hedge ratio estimates. The hedge ratios – which refer to the number of S&P 500 futures contracts to short or long per VIX futures contract – are established based upon Simon and Campasano (2014). The daily logarithm returns of the front VIX futures are regressed on a constant, contemporaneous daily logarithm of price changes in the front S&P 500 futures, with the daily logarithm of the price changes in the front S&P 500 futures then being multiplied by the number of business days that the VIX futures contract is from the settlement date, as shown below:

$$VIXRET_t = \beta_0 + \beta_1 SPRET_t + \beta_2 SPRET_t * TTS_t + \varepsilon_t \quad (7)$$

where the hedge ratio is constructed based upon a 250-day rolling window with updated out-of-sample parameter estimates from regression (7), along with data from the beginning of 2013 up to the previous day.

The value of a unitary VIX futures price change is $1,000, whilst a 1% change in S&P 500 futures is equal to 0.01 times the lagged close price of the S&P 500 futures contract multiplied by the value of one S&P futures point ($250). The average hedge ratio equates approximately to a single S&P 500 futures contract per VIX futures contract, with the formula being expressed as follows:

$$HR_t = [\beta_0 * 1000 + \beta_1 * TTS_{t-1} * 1000]/[0.01 * SPF_{t-1} * 250] \quad (8)$$

Table 9 reports the profitability of hedged VIX futures positions, as well as the effectiveness of hedging with S&P 500 futures positions. Consistent with unhedged VIX futures positions, the vast majority of profits come from shorting VIX futures and S&P 500 futures. However, the lower profitability levels of the hedged VIX futures positions under each strategy, such as the annualized returns, annualized Sharpe ratio and annualized Sortino ratio, are found to be below those of the unhedged VIX futures positions, with the reduction in the annualized standard deviation indicating that the overall risk in the trades is on a downward trend. In line with each strategy, the substantial decline in annualized returns and standard deviations based on the different types of media (news articles, blog posts and discussion messages) across each strategy implies that hedging efficiency is relatively remarkable.

<Table 9 is inserted about here>

All in all, the performance of some strategies involving the shorting and buying of VIX futures contracts, and even hedging market risk with S&P 500 futures in accordance with the negative and positive sentiment scores for the different types of data, will generate substantial profits. Furthermore, most of the profits from VIX futures positions are derived from the shorting strategy; given that the overall market was in a bullish mood during our sample period, there was a notable downturn in the VIX market. In addition, most of the extreme profits and losses were attributable to the shocks of 'Black Swan' events on the financial market, such as 'Black Monday' in Asia, with the selloff in Asia triggering significant falls in US stock futures prior to the opening of the US markets; on 24 August 2015, the S&P 500 was down 120 points, whilst VIX futures gained 22.91%. The surprise Brexit vote in the UK led to the S&P 500 losing 3.6% on 24 June 2016, whilst VIX futures gained 30.94%.

For both hedged and unhedged VIX futures positions, the profitability of news sentiment is found to be infinitely superior to the performance of the VIX futures trades based not only on the benchmark strategy, but also on the blog- and discussion-type sentiment indices across all of the strategies, with much greater fluctuations in the profits of VIX futures positions for discussion-type postings. However, when including the bid-ask spread across each strategy, the profits of both hedged and unhedged VIX futures positions fell by about 20% to 50%. For Strategy 1 in particular, a substantial decline of roughly 50% is discernible in annualized returns for the three types of media.

In general, the winning rate of these strategies fell by an average of 2% to 3% for both hedged and unhedged positions, with the Sharpe ratio declining by 0.4% to 0.6% for unhedged positions, and by 0.4% to 0.8% for hedged positions. Similarly, a much larger reduction is discernible in the Sortino ratio for hedged positions, relative to non-hedged positions. In line with our previous results, the profits of the different types of postings are found to be driven by the shorting strategy, with the profitability of news sentiment on VIX futures still being superior to either blog- or discussions-type posts, even beyond the constant short strategy.

6. CONCLUSIONS

In this study, we examine the potential predictive ability of daily VIX futures returns based upon our analysis of changes in sentiment across different types of media, comprising of news, blogs and online discussions. We collect significant amounts of internet postings relating to the 'volatility index', with a sentiment measure then being constructed through dictionary-based textual analysis focusing on overnight investor sentiment, since that was likely to be more accurately reflected in the next day's return.

Our results indicate that both negative and positive media-based sentiment measures during the overnight hours can predict daily VIX futures returns, with negative sentiment being more predictable than positive sentiment across all types of media. This is consistent with the idea of an asymmetric reaction to negative information flow, which has a more substantial and longer-lasting impact on price movements and volatility (Groß-Klußmann and Hautsch, 2011; Smales, 2014a). Our findings also reveal that macroeconomic news announcements do not generally enhance the predictive ability of sentiment, and may even reduce its impact on VIX futures returns, with the notable exceptions of announcements relating to retail sales and durable goods.

We also show that the effects of sentiment on VIX futures returns vary significantly across different types of media and days of the week. Mondays are found to have a significant impact on VIX futures returns, which implies that investor sentiment reflects a three-day outlook influenced by both positive and negative sentiment; however, the effects of sentiment are found to be less pronounced on Fridays, as observed from the news articles and discussion messages, which suggests that VIX futures price movements reflect the expectations of investors for the forthcoming week.

Furthermore, based upon the characteristics of information flow and VIX futures, predictive ability is found to be much improved by greater numbers of published postings, higher trading volume, higher volatility and higher illiquidity days, a finding which is consistent with the well-known argument that noise traders tend to participate in the market when trading volume is high (Barber and Odean, 2000). Slower information diffusion also indicates that, in cases of low liquidity in the VIX futures market, prices may not immediately reflect the available information.

Finally, we explore the profitability of simulated trading strategies based upon the sentiment indices in the VIX futures market, from which we find that shorting and buying VIX futures according to the sentiment index – during the interval between the market close on the previous day and the market open on the current day – is more profitable for both hedged and unhedged positions. Our results suggest that news articles are better at capturing the future price trend in VIX futures due to real-time information flow and more intensive investor attention, particularly from niche websites. We also demonstrate that not only is sentiment a significant predictor of VIX futures returns, but that it also has economic value, as measured by the annualized returns and the Sharpe ratio in trading strategies. Future research could focus on developing more effective measures or proxy variables for investor sentiment and information flow.

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Table 1 Daily summary statistics of the variables

Variables	VIX Returns	VIX Futures Returns	VIX Basis	VIX Volatility	VIX Turnover	S&P Futures Returns	EPU
Mean	-0.0058	-0.0033	1.0890	0.0664	0.6911	0.0004	83.0600
Median	-0.0099	-0.0068	1.2850	0.0555	0.5895	0.0003	73.5400
S.D.	0.0589	0.0481	1.4925	0.0443	0.3688	0.008	48.0970
Max.	0.4126	0.3100	3.7300	0.5824	3.2444	0.0325	586.5500
Min.	-0.3643	-0.2028	-15.5900	0.0162	0.2074	-0.0486	3.3200
1st Quantile	-0.0397	-0.0270	0.6600	0.0391	0.4457	-0.0028	51.6600
3st Quantile	0.0223	0.0188	1.9000	0.0802	0.8149	0.0041	100.6700
Skewness	0.7364	0.7268	-3.5898	4.4908	2.0926	-0.5526	2.7239
Kurtosis	4.4091	4.9430	29.1308	40.1959	6.5855	4.7852	15.8353

Note: This table summarizes the daily descriptive statistics of the variables used in this study, the definitions of which are provided in Appendix A.

Table 2 Sentiment index and VIX futures returns, Dec 2014 to Sep 2017

Variables	News		Blogs		Discussions	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Intercept	0.0121*	1.789	0.0080	1.498	0.0054	0.940
Negative	0.0103***	3.735	0.0074**	2.250	0.0045*	1.863
Positive	-0.0135***	-3.713	-0.0039*	-1.764	-0.0026	-1.131
Uncertainty	0.0015	0.798	0.0010	0.502	-0.0009	-0.358
Litigious	0.0032	0.435	0.0070	1.262	0.0049	1.040
Constraining	0.0064	1.735	-0.0029	-1.220	0.0020	0.845
Superfluous	-0.0042	-0.642	-0.0070	-1.569	-0.0047	-1.459
Interesting	-0.0022	-0.897	-0.0021	-0.856	-0.0007	-0.285
EPU (-1)	0.0001**	-2.120	-0.0001*	-1.914	-0.0001**	-2.051
Turnover (-1)	0.0148	1.234	0.0181	1.485	0.0201	1.531
Return (-1)	-0.1160**	-2.413	-0.1183**	-2.572	-0.1200**	-2.020
Return (-2)	-0.1051**	-2.530	-0.0895*	-1.934	-0.1005**	-2.016
Adj R^2 (%)	6.29		4.52		4.05	
No. of Obs.	704		675		692	

Notes: This table presents the relationships between the VIX futures daily returns and seven categories of the sentiment index. The dependent variable is 'VIX futures daily returns', calculated on a close-to-open basis, whilst the independent variables are the sentiment indices. The set of control variables include lagged returns (up to two lags), lagged volatility of VIX futures (up to five lags), the lagged turnover of VIX futures and the lagged news-based measure of 'economic policy uncertainty' (EPU). $***$ indicates significance at the 1% level; $**$ indicates significance at the 5% level; and $*$ indicates significance at the 10% level.

Table 3 Predictive ability of sentiment on VIX futures, Dec 2014 to Sep 2017

Variables	(1) $Return_{t+1}$ Coeff.	t-stat.	(2) $Return_{t+2}$ Coeff.	t-stat.	(3) $Return_{t+3}$ Coeff.	t-stat.	(4) $Return_{t+4}$ Coeff.	t-stat.	(5) $Return_{t+5}$ Coeff.	t-stat.
Panel A: News										
Intercept	0.0105*	1.769	0.0113**	2.328	0.0104*	2.139	0.0098*	1.798	0.0080*	1.882
Negative	0.0114***	3.289	0.0085***	3.545	0.0040	1.166	0.0062***	2.609	0.0028	1.157
Positive	-0.0102***	-3.558	-0.0094***	-3.188	-0.0049**	-1.964	-0.0035	-1.627	0.0012	0.551
Adj R^2 (%)	5.57		3.21		0.16		1.79		0.46	
Panel B: Blogs										
Intercept	0.0062	1.349	0.0117**	2.271	0.0078*	1.763	0.0076	1.646	0.1100**	2.307
Negative	0.0072**	2.232	0.0077***	2.878	0.0016	0.564	0.0044	1.639	0.0058**	2.228
Positive	-0.0057***	-2.632	-0.0078***	-2.774	-0.0018	-0.862	-0.0022	-0.925	-0.0028	-1.206
Adj R^2 (%)	3.74		2.89		-0.22		0.24		0.92	
Panel C: Discussions										
Intercept	0.0055	0.974	0.0093*	1.714	0.0072	1.424	0.0087*	1.749	0.0090**	2.050
Negative	0.0054**	2.349	0.0018	0.764	0.0011	0.477	0.0009	0.419	0.0049*	1.818
Positive	-0.0022	-1.168	-0.0013	-0.746	-0.0005	-0.281	0.0008	0.470	-0.0014	-0.757
Adj R^2 (%)	3.29		1.77		0.00		0.49		1.20	

Notes: This table reports the predictive ability of the negative and positive sentiment indices on the daily returns of VIX futures by controlling the other control variables. The dependent variables, which are the future daily returns of the VIX futures over the next five days, are respectively reported in columns (1), (2), (3), (4) and (5). The independent variable is the sentiment index, which is constructed from the information published during overnight hours after the close on previous day and before the open of the current day. The set of control variables include lagged returns (up to two lags), lagged volatility of VIX futures (up to five lags), the lagged turnover of VIX futures and the lagged news-based measure of 'economic policy uncertainty' (EPU). $***$ indicates significance at the 1% level; $**$ indicates significance at the 5% level; and $*$ indicates significance at the 10% level.

Table 4 Effects of macroeconomic announcement surprises on VIX futures

Variables	News		Blogs		Discussions	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel A: GDP						
Intercept	0.0104*	1.723	0.0049	1.081	0.0057	0.983
Negative	0.0131***	3.287	0.0080**	2.384	0.0066***	2.680
Positive	-0.0119***	-3.672	-0.0057**	-2.533	-0.0035*	-1.690
GDP	0.0008	0.130	0.0098	1.420	0.0033	0.614
Negative GDP	-0.0101**	-1.988	-0.0111*	-1.757	-0.0195**	-2.522
Positive GDP	0.0115**	2.313	-0.0061	-0.841	0.0189***	2.739
Adj R^2 (%)	5.62		4.06		3.65	
Panel B: Federal Open Market Committee (FOMC)						
Intercept	0.0114*	1.877	0.0063	1.323	0.0065	1.128
Negative	0.0132***	3.376	0.0076**	2.307	0.0059**	2.338
Positive	-0.0126***	-3.922	-0.0066***	-2.728	-0.0037*	-1.662
FOMC	-0.0019	-0.416	-0.0020	-0.399	-0.0006	-0.125
Negative FOMC	-0.0102*	-1.931	-0.0061	-0.675	-0.0026	-0.439
Positive FOMC	0.0142**	2.492	0.0075	1.378	0.0109**	2.280
Adj R^2 (%)	5.89		3.48		3.29	
Panel C: Non-farm payrolls (NFPs)						
Intercept	0.0130**	2.003	0.0074	1.555	0.0064	1.109
Negative	0.0152***	3.320	0.0117**	2.527	0.0075**	2.364
Positive	-0.0116***	-3.074	-0.0078***	-2.612	-0.0027	-1.217
NFPs	-0.0016	-0.388	-0.0008	-0.181	-0.0022	-0.507
Negative NFPs	-0.0144**	-2.253	-0.0118*	-1.959	-0.0055	-1.220
Positive NFPs	0.0054	0.900	0.0049	1.179	0.0001	0.026
Adj R^2 (%)	6.32		4.25		3.2	
Panel D: CPI						
Intercept	0.0107*	1.805	0.0064	1.358	0.0058	1.015
Negative	0.0118***	3.352	0.0074**	2.288	0.0054**	2.290
Positive	-0.0111***	-3.810	-0.0061***	-2.716	-0.0023	-1.166
CPI	-0.0126*	-1.736	-0.0149**	-2.054	-0.0127	-1.722
Negative CPI	-0.0213**	-2.351	-0.0233*	-1.737	0.0020	0.255
Positive CPI	0.0222***	3.333	0.0209*	1.676	0.0012	0.115
Adj R^2 (%)	5.87		3.92		3.19	

Notes: This table reports the regression results of the interaction effect between negative and positive sentiment and the macroeconomic announcements on VIX futures across different types of postings. The independent variables include the negative and positive sentiment index, a macroeconomic announcement dummy and the interaction effect dummy between the sentiment index and the macroeconomic announcements. The macroeconomic announcements dummy takes the value of 1 on the announcement date, two days prior to the announcements and two days after the release of the macroeconomic data, otherwise 0. Unreported control variables include lagged returns (up to two lags), lagged volatility of VIX futures (up to five lags), the lagged turnover of VIX futures and the lagged news-based measure of 'economic policy uncertainty' (EPU). $***$ indicates significance at the 1% level; $**$ indicates significance at the 5% level; and $*$ indicates significance at the 10% level.

Table 5 Predictive ability of the sentiment index across days of the week, Dec 2014 to Sep 2017

Variables	(1) Mon		(2) Tue		(3) Wed		(4) Thu		(5) Fri	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel A: News										
Intercept	0.0230	1.018	0.0073	0.455	0.0080	0.753	0.0103	1.417	0.0051	0.375
Negative	0.0217***	3.011	0.0054	0.798	0.0033	0.716	0.0094***	2.966	0.0185*	1.864
Positive	-0.0305***	-3.840	0.0008	0.130	-0.0031	-0.490	-0.0111*	-1.814	-0.0125*	-1.897
Adj R^2 (%)	10.65		5.25		-0.12		9.29		8.54	
Panel B: Blogs										
Intercept	0.0045	0.250	0.0056	0.398	0.0011	0.096	0.0012	0.985	-0.0146	-0.961
Negative	0.0137**	2.018	0.0058	0.843	-0.0034	-0.731	0.0071	1.505	0.0051	1.063
Positive	-0.0216***	-3.044	-0.0026	-0.513	0.0001	0.023	-6.7567	-1.328	-0.0025	-0.948
Adj R^2 (%)	3.86		7.33		-0.85		8.03		2.26	
Panel C: Discussions										
Intercept	0.0228	0.934	0.0065	0.447	0.0031	0.286	0.0089	1.089	-0.0109	-0.731
Negative	0.0224***	2.849	0.0062*	1.829	-0.0003	-0.094	-0.0004	-0.116	0.0148**	2.609
Positive	-0.0231**	-2.004	-0.0006	-0.335	-0.0019	-0.505	0.0001	0.022	-0.0025	-0.572
Adj R^2 (%)	6.31		4.99		-1.33		5.21		8.57	

Notes: This table presents the impact of negative and positive sentiment on VIX futures returns, by types of posting and days of the week. The dependent variable is the returns of the VIX futures, whilst the independent variable is the sentiment index. Unreported control variables include lagged returns (up to two lags), lagged volatility of VIX futures (up to five lags), the lagged turnover of the VIX futures and the lagged news-based measure of 'economic policy uncertainty' (EPU). The table is presented in three panels based upon the sentiment of different media types, with each panel comprising of the five groups of time-series regressions from Monday to Friday. $***$ indicates significance at the 1% level; $**$ indicates significance at the 5% level; and $*$ indicates significance at the 10% level.

Table 6 Predictive ability of the sentiment index on returns, by market characteristics, Dec 2014 to Sep 2017

Variables	(1)		(2)		(3)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel A: Daily published number of postings						
1. News	amt_{low}		amt_{median}		amt_{high}	
Intercept	0.0140	1.622	0.0154	1.512	0.0166	1.651
Negative	0.0005	0.235	0.0115***	3.138	0.0252***	3.448
Positive	0.0003	0.123	-0.0113**	-2.557	-0.0235***	-4.434
Adj R^2 (%)	5.66		8.33		10.45	
2. Blogs						
Intercept	-0.0014	-0.181	0.0147*	1.968	0.0021	0.226
Negative	0.0032	0.811	0.0032	0.873	0.0204**	2.289
Positive	-0.0040	-1.064	-0.0046	-1.435	-0.0135**	-2.203
Adj R^2 (%)	4.41		1.07		8.92	
3. Discussions						
Intercept	0.0201**	2.341	-0.0036	-0.390	0.0030	0.207
Negative	0.0028	1.307	0.0049	1.160	0.0070	1.107
Positive	-0.0018	-1.085	0.0017	0.355	-0.0016	-0.247
Adj R^2 (%)	10.33		0.2		2.99	
Panel B: Trading Volume						
1. News	vol_{low}		vol_{median}		vol_{high}	
Intercept	0.0021	0.270	0.0108	0.781	0.0359***	3.016
Negative	0.0005	0.280	0.0031	0.672	0.0308***	4.583
Positive	-0.0009	-0.342	-0.0020	-0.504	-0.0195***	-3.373
Adj R^2 (%)	7.71		-1.08		16.73	
2. Blogs						
Intercept	-0.0073	-1.128	0.0084	0.913	0.0379***	3.292
Negative	-0.0009	-0.343	0.0000	0.006	0.0323***	4.420
Positive	-0.0011	-0.442	0.0008	0.429	-0.0165***	-3.033
Adj R^2 (%)	6.63		0.41		15.00	
3. Discussions						
Intercept	0.0012	0.163	0.0195	1.516	0.0296***	2.745
Negative	-0.0008	-0.450	0.0016	0.506	0.0200***	3.562
Positive	0.0019	1.084	0.0022	0.632	-0.0148***	-3.050
Adj R^2 (%)	7.44		3.20		8.95	

Table 6 (Contd.)

Variables	(1)		(2)		(3)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel C: Volatility						
1. News	$vola_{low}$		$vola_{median}$		$vola_{high}$	
Intercept	0.0018	0.458	0.0003	0.059	0.0362***	2.800
Negative	0.0028	2.248	0.0020	0.855	0.0259***	3.441
Positive	-0.0017	-0.885	-0.0004	-0.156	-0.0244***	-4.176
Adj R^2 (%)	-0.82		-0.15		11.56	
2. Blogs						
Intercept	-0.0003	-0.078	-0.0034	-0.631	0.0444***	3.995
Negative	0.0011	0.527	-0.0012	-0.634	0.0209***	3.431
Positive	-0.0001	-0.065	0.0019	1.231	-0.0234***	-3.749
Adj R^2 (%)	-0.36		-1.04		10.45	
3. Discussions						
Intercept	-0.0001	-0.024	-0.0015	-0.251	0.0306**	2.342
Negative	0.0006	0.602	-0.0007	-0.315	0.0170***	2.822
Positive	-0.0002	-0.303	0.0030	1.108	-0.0089	-1.372
Adj R^2 (%)	-1.22		-0.25		8.35	

Notes: This table reports the influence of sentiment on VIX futures, by types of postings and market characteristics. The table is presented in four panels based upon these characteristics, including the daily number of posts published, as well as trading volume, volatility and illiquidity of VIX futures on a daily basis. Based upon the size of each feature, the VIX futures returns and sentiment scores are divided into three groups from low to high across different types of postings. Each panel is composed of three groups of time-series regressions across each posting type. Unreported controls variables are included in each regression, comprising of lagged returns (up to two lags), lagged volatility of VIX futures (up to five lags), lagged turnover of VIX futures and the lagged news-based measure of 'economic policy uncertainty' (EPU). $***$ indicates significance at the 1% level; $**$ indicates significance at the 5% level; and $*$ indicates significance at the 10% level.

Table 7 Long-run predictive ability of the sentiment index, Dec 2014 to Sep 2017

Variables	News		Blogs		Discussions	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Panel A: Contemporaneous relationships ($Return_{w+0}$)						
Intercept	0.1099***	5.705	0.1038***	4.917	0.0875***	4.899
$Negative_w$	0.1060***	6.253	0.0747***	3.728	0.0306	1.474
$Positive_w$	-0.0783***	-3.897	-0.0657***	-2.781	-0.0211	-0.898
Controls	Yes		Yes		Yes	
Adj R^2 (%)	20.68		13.95		6.56	
No. of Obs.	148		142		147	
Panel B: One-week lagged sentiment index ($Return_{w+1}$)						
Intercept	0.0936***	4.688	0.0999***	5.240	0.0877***	3.930
$Negative_{w-1}$	0.0370**	2.228	0.0212	1.627	0.0056	0.299
$Positive_{w-1}$	-0.0375**	-2.266	-0.0225	-1.584	0.0002	0.016
Controls	Yes		Yes		Yes	
Adj R^2 (%)	6.61		6.82		5.01	
No. of Obs.	148		142		147	

Notes: This table presents a long-run analysis of the predictive ability of the sentiment index for VIX futures returns based upon weekly data, with the aggregate sentiment index being constructed by averaging the daily negative and positive sentiment scores of published information on a weekly basis. The VIX futures returns are calculated as the logarithm of the ratio of the close price of the last day to the open price of the first day of the week, reporting the contemporaneous and lagged one-week relationships between sentiment and the VIX futures across each media type. The variables, comprising of lagged returns, lagged volatility, the lagged turnover of the VIX futures and the lagged news-based measure of 'economic policy uncertainty' (EPU), are also reported at the weekly level, and included as controls in each of the regression, although the results are not reported here. *** indicates significance at the 1% level; ** indicates significance at the 5% level; and * indicates significance at the 10% level.

Table 8 Performance of unhedged positions based upon the different strategies

Variables	News		Blogs		Discussions		Always Short	
	Non-cost	After cost	Non-cost	After cost	Non-cost	After cost	Non-cost	After cost
Panel A: Strategy 1								
Return (%)	140.790	88.580	75.520	23.310	126.340	74.120	93.510	41.300
Short Return (%)	117.150	88.300	79.420	50.020	110.890	82.820	-	-
Long Return (%)	23.640	0.280	-3.900	-26.720	15.450	-8.700	-	-
S.D.	0.754	0.754	0.745	0.745	0.758	0.758	0.757	0.757
Sharpe Ratio	1.866	1.174	1.014	0.313	1.666	0.978	1.235	0.545
Sortino Ratio	3.105	1.886	1.597	0.476	2.854	1.612	1.725	0.742
Max.Drawdown	0.474	0.474	0.474	0.474	0.455	0.455	0.506	0.506
Win Rate	0.548	0.527	0.535	0.513	0.513	0.490	0.592	0.568
Long Frequency	308		289		312		-	-
Short Frequency	373		363		357		704	
Panel B: Strategy 2								
Return (%)	111.390	75.580	50.150	12.410	86.530	45.780	93.510	41.300
Short Return (%)	97.650	77.210	64.210	43.280	81.170	59.620	-	-
Long Return (%)	13.740	-1.620	-14.060	-30.870	5.360	-13.840	-	-
S.D.	0.622	0.621	0.611	0.611	0.676	0.675	0.757	0.757
Sharpe Ratio	1.792	1.218	0.820	0.203	1.281	0.678	1.235	0.545
Sortino Ratio	3.091	2.022	1.296	0.309	2.191	1.116	1.725	0.742
Max.Drawdown	0.474	0.474	0.474	0.474	0.455	0.455	0.506	0.506
Win Rate	0.563	0.538	0.530	0.507	0.503	0.479	0.592	0.568
Long Frequency	200		212		245		-	-
Short Frequency	262		258		274		704	

Table 8 (Contd.)

Variables	News		Blogs		Discussions		Always Short	
	Non-cost	After cost	Non-cost	After cost	Non-cost	After cost	Non-cost	After cost
Panel C: Strategy 3								
Return (%)	73.610	51.820	39.170	16.780	62.900	40.350	93.510	41.300
Short Return (%)	57.640	38.740	27.210	7.850	38.460	18.860	-	-
Long Return (%)	15.970	13.070	11.960	8.940	24.430	21.480	-	-
S.D.	0.466	0.464	0.455	0.4542	0.507	0.5062	0.757	0.757
Sharpe Ratio	1.580	1.116	0.861	0.3695	1.240	0.7971	1.235	0.545
Sortino Ratio	2.641	1.799	1.303	0.5402	2.092	1.2986	1.725	0.742
Max.Drawdown	0.474	0.474	0.474	0.4738	0.455	0.4551	0.506	0.506
Win Rate	0.627	0.590	0.596	0.5640	0.572	0.5503	0.592	0.568
Long Frequency	37		38		39		-	-
Short Frequency	242		239		251		704	

Notes: This table reports the profits and losses of unhedged VIX futures positions for the different trading strategies. Based upon trading conditions, the trading rule is shorting or buying one VIX future contract at the open price of the day, and then offseting the position at the close price of the day. The benchmark strategy is always to short VIX futures without considering any other conditions. The metrics measuring the trading performance such as returns, standard deviation and the Sharpe ratio are annualized. The maximum drawdown in a return series measures the magnitude of the dip from the point of maximum cumulative return to the minimum cumulative return.

Table 9 Performance of hedged positions based upon the different strategies

Variables	News		Blogs		Discussions		Always Short	
	Non-cost	After cost	Non-cost	After cost	Non-cost	After cost	Non-cost	After cost
Panel A: Strategy 1								
Return (%)	122.840	70.630	60.850	8.640	98.620	46.400	81.580	33.570
Short Return (%)	104.310	75.460	70.110	40.710	94.050	65.990	-	-
Long Return (%)	18.530	-4.830	-9.260	-32.080	4.560	-19.580	-	-
S.D.	0.647	0.647	0.639	0.639	0.651	0.651	0.657	0.649
Sharpe Ratio	1.898	1.091	0.952	0.135	1.515	0.713	1.241	0.517
Sortino Ratio	3.147	1.736	1.473	0.201	2.555	1.151	1.740	0.707
Max.Drawdown	0.390	0.390	0.390	0.390	0.375	0.375	0.439	0.414
Win Rate	0.537	0.520	0.527	0.505	0.501	0.481	0.580	0.561
Long Frequency	315		295		320		-	-
Short Frequency	389		380		372		704	
Panel B: Strategy 2								
Return (%)	96.000	60.190	40.500	2.760	66.340	25.590	81.580	33.570
Short Return (%)	86.920	66.480	56.230	35.300	70.180	48.630	-	-
Long Return (%)	9.080	-6.290	-15.740	-32.550	-3.840	-23.040	-	-
S.D.	0.532	0.531	0.524	0.524	0.581	0.581	0.657	0.649
Sharpe Ratio	1.805	1.134	0.773	0.053	1.142	0.441	1.241	0.517
Sortino Ratio	3.094	1.859	1.201	0.078	1.921	0.709	1.740	0.707
Max.Drawdown	0.390	0.390	0.390	0.390	0.375	0.375	0.439	0.414
Win Rate	0.542	0.527	0.520	0.497	0.490	0.466	0.580	0.561
Long Frequency	206		216		253		-	-
Short Frequency	274		269		284		704	

Table 9 (Contd.)

Variables	News		Blogs		Discussions		Always Short	
	Non-cost	After cost	Non-cost	After cost	Non-cost	After cost	Non-cost	After cost
Panel C: Strategy 3								
Return (%)	65.060	43.270	34.220	11.840	52.050	15.800	81.580	33.570
Short Return (%)	53.090	34.200	25.990	6.630	34.510	15.800	-	-
Long Return (%)	11.970	9.070	8.230	5.210	17.540	0.000	-	-
S.D.	0.396	0.394	0.390	0.389	0.432	0.341	0.657	0.649
Sharpe Ratio	1.644	1.098	0.878	0.304	1.206	0.463	1.241	0.517
Sortino Ratio	2.706	1.732	1.303	0.434	1.981	0.579	1.740	0.707
Max.Drawdown	0.390	0.390	0.390	0.390	0.375	0.230	0.439	0.414
Win Rate	0.601	0.580	0.581	0.550	0.557	0.537	0.580	0.561
Long Frequency	39		39		39		-	-
Short Frequency	254		250		259		704	

Notes: This table reports the trading performance of hedged positions for the different trading strategies. The hedged positions are S&P 500 futures and the hedge ratio, where the size of the S&P 500 futures hedge is based upon a 250-day rolling window with updated out-of-sample parameter estimates. Based upon the trading conditions, the trading rule is shorting or buying one VIX future contract and one S&P500 future contract at the open price of the day, and then offseting the positions at the close price of the day. The metrics measuring the trading performance such as returns, standard deviation and the Sharpe ratio are annualized. The maximum drawdown in a return series measures the magnitude of the dip from the point of maximum cumulative return to the trough.

Figure 1 Text content of the media coverage

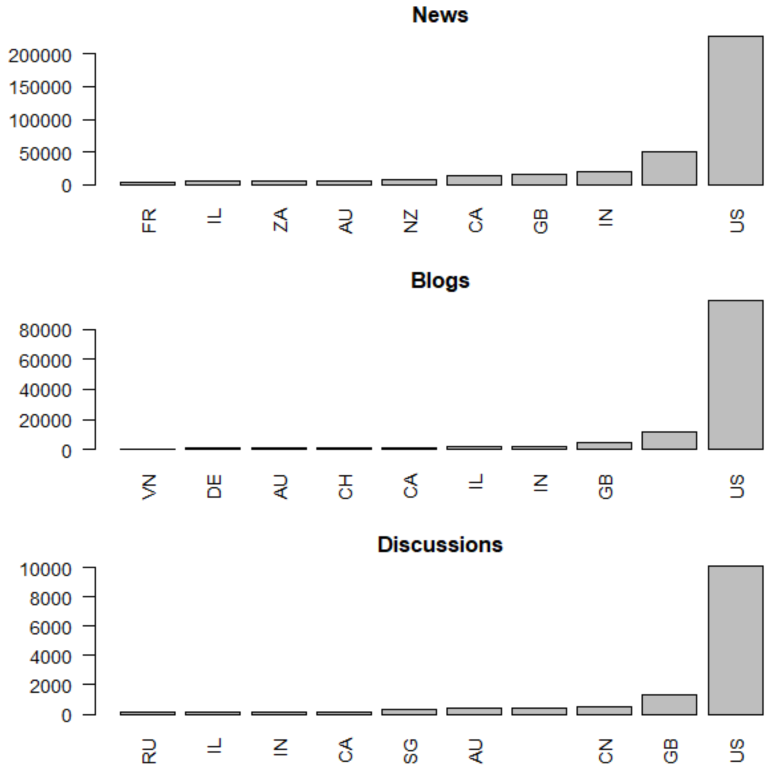

Figure 2 Top ten country sources of the news, blogs and discussions data

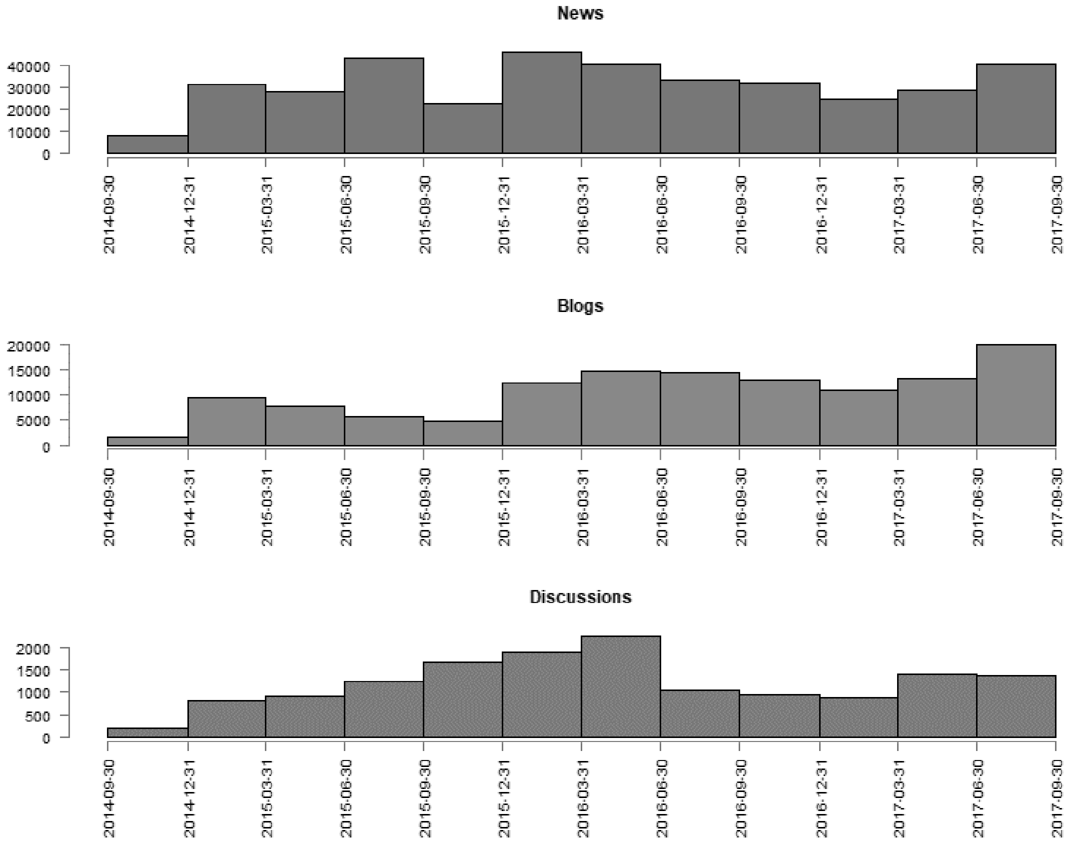

Figure 3 Number of posts published over the entire sample period

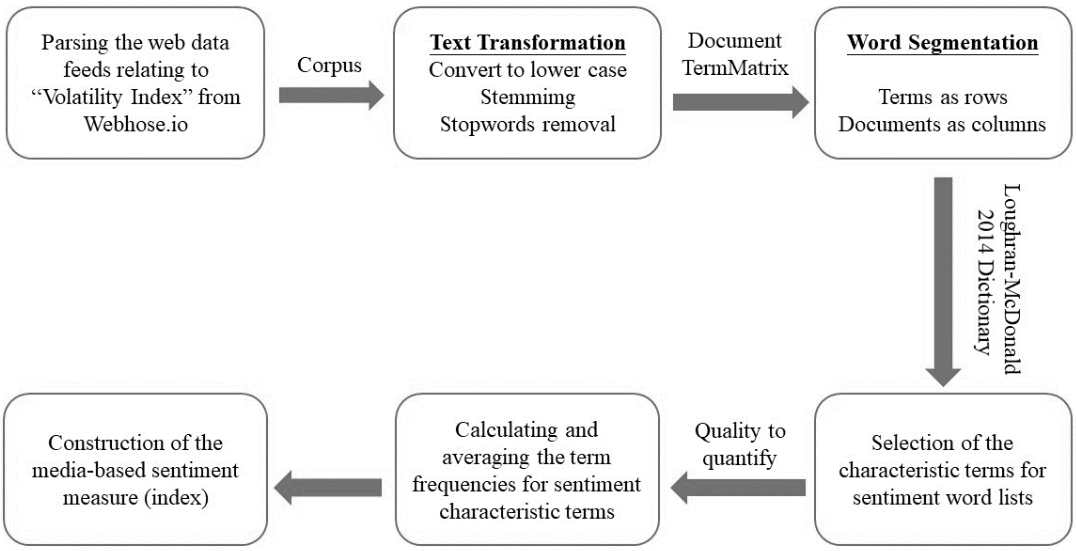

Figure 4 Information quantification process

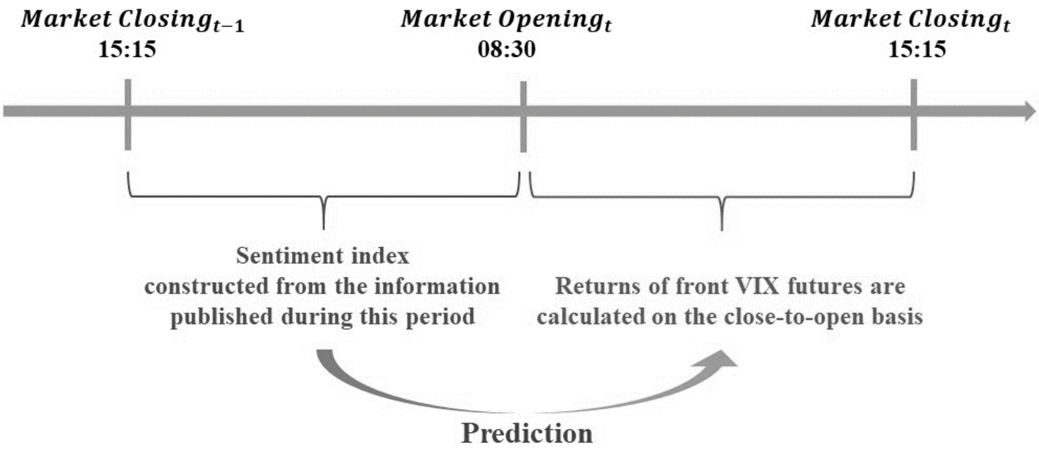

Figure 5 Measurement intervals of the sentiment index and VIX futures returns

Appendix A Variable Definitions

Variables	Definitions
Media-based Sentiment Index	
Sentiment Negative Positive	The sentiment index is constructed by taking the average word count for each post appearing in the sentiment word lists of the Loughran-McDonald Dictionary 2014. The sentiment index data are extracted on a daily basis, from Tuesdays to Fridays, from the information published during the overnight hours after the close of the previous day and before the open of the current day. For Mondays, the sentiment index is measured from the information released after the close on the previous Friday and before the Monday open.
Macroeconomic Announcements	
$Macro_t$	A dummy variable of macroeconomic announcements, which takes the value of 1 two days before and two days after the macroeconomic announcement date, otherwise 0.
Futures Characteristics	
VIX Futures	The front VIX futures contract with at least 7 days to settlement
VIX Return	The logarithm of the daily close prices divided by the daily open prices of the front VIX futures.
VIX Basis	The daily difference between each front VIX futures contract price and the VIX price.
VIX Volatility	Daily high prices minus low prices divided by the close prices of the front VIX futures contracts.
VIX Turnover	The daily ratio of trading volume to open interest of the front VIX futures contracts.
S&P 500 futures	The front S&P 500 futures contract with at least 7 days to settlement
EPU	The index of 'economic policy uncertainty' based upon newspaper coverage frequency.
Pricing Factors	
Rm-Rf	Market factor: the excess market return defined as the return on the value-weighted portfolio minus the risk-free rate.
SMB	The size factor: the differences between the returns on diversified portfolios of small and big stocks.
HML	The value factor: the differences between the returns on diversified portfolios of high and low BE/ME stocks

Appendix B   Top 10 Website Sources

Rating	Site	No.
1. News		
1	news.morningstar.com	22,539
2	seekingalpha.com	18,668
3	finance.yahoo.com	15,064
4	uniontradejournal.com	9,326
5	www.reuters.com	9,238
6	www.nasdaq.com	7,451
7	www.4-traders.com	6,308
8	www.wallstreetmorning.com	5,930
9	www.bloomberg.com	5,805
10	www.business-standard.com	5,078
2. Blogs		
1	darcnews.com	7,622
2	markets.financialcontent.com	3,777
3	finance.yahoo.com	2,266
4	finnewsreview.com	2,244
5	www.nasdaq.com	1,879
6	www.johnsonaliveinter.com	1,541
7	www.valuewalk.com	1,411
8	www.investopedia.com	1,362
9	thewallstreetreview.com	1,335
10	www.businessinsider.com	1,259
3. Discussions		
1	www.forexfactory.com	1,068
2	lkml.org	936
3	www.bogleheads.org	929
4	investorshub.advfn.com	852
5	seekingalpha.com	555
6	www.sfgate.com	395
7	www.siliconinvestor.com	363
8	www.investorvillage.com	296
9	einvesting.com	290
10	onlinetradersforum.com	254

Appendix C Top 20 Most Frequently Appearing Words

Rating	Negative	Positive	Uncertainty	Litigious	Constraining	Interesting	Superfluous
1	volatility	strong	may	referendum	required	drop	furthermore
2	against	gains	volatility	contracts	limit	march	nonetheless
3	volatile	good	could	claims	requirements	august	whilst
4	losses	positive	risk	contract	require	increases	efficacy
5	decline	best	volatile	regulatory	obligation	increasing	superannuation
6	loss	better	risks	law	requires	decrease	presumptive
7	negative	gains	might	legal	limits	death	ubiquitous
8	closed	despite	believe	court	dependent	aggressive	assimilate
9	cut	leading	uncertainty	herein	depends	cancer	assimilation
10	weak	highest	possible	regulations	impairment	soared	theses
11	concerns	strength	exposure	regulators	restrictions	ban	-
12	crisis	great	almost	settlement	compelling	sustainability	-
13	late	greater	nearly	moreover	bound	concerning	-
14	question	able	probably	whatever	mandate	freeze	-
15	closing	opportunities	seems	justice	commitments	reductions	-
16	weakness	boost	suggest	shall	restricted	lies	-
17	unemployment	benefit	appears	legislation	imposed	bridge	-
18	recession	stronger	anticipated	litigation	pledge	extraordinary	-
19	worst	popular	perhaps	ruling	constraints	aggressively	-
20	dropped	rebound	maybe	appeal	permission	secret	-