The Impact of Abnormal News Sentiment on Financial Markets

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Abstract: News sentiment has been empirically observed to have impact on financial market. However, finding a clear predictor of market returns using news sentiment remains a challenging task. This study investigates the relationship between news sentiment and cumulative market returns and volatility. We propose two methods for measuring the abnormal level of news sentiment, i.e. sentiment shocks and sentiment trend, and we analyze its relationship with market movements. The results show that abnormal levels of news sentiment are significant in predicting future market cumulative return and implied volatility of the S&P 500 index. Comparing the two methods, we find that the sentiment trend method demonstrates better performance than the sentiment shock method. In addition, our findings suggest that the strategy generated based on the abnormal news sentiment methods outperforms the buy-and-hold strategy through back-testing over the same time period.

Key words: News Sentiment, Financial Market Returns, Market Volatility, Abnormal Sentiment, Trading Strategy.

JEL codes: G14, G17, G11, D83, D84.

1. Introduction

Many studies have documented the evidence that news media has significant impact on financial market, and in some cases it drives major market activities (Mitchell et al. 1994; Barberis, Shleifer, and Vishny 1998; Scott, Stumpp, and Xu 2003; Antweiler and Frank 2004; Barber and Odean 2007; Mitra and Mitra 2011). Analyzing news content and consequently generating robust trading signals are becoming increasingly attractive to sophisticated investors. Algorithms or 'bots' have been developed by algorithmic trading firms to exploit speed advantages over traditional ways of consuming news information. In addition, recent studies confirm that media is vital to influencing investor sentiment and therefore affect asset prices, volatility and risk (Barber & Odean, 2007; DiBartolomeo & Warrick, 2005; Tetlock, Saar-Tsechansky, & MacSkassy, 2008). The latest advancement in natural language processing and machine learning algorithms makes it possible to process news data and calculate its sentiment in an automatic fashion (Alanyali, Moat, & Preis, 2013; Li Im, Wai San, Kim On, Alfred, & Anthony, 2013; Mao et al., 2014; Maragoudakis & Serpanos, 2015; Mizumoto, Yanagimoto, & Yoshioka, 2012; Nassirtoussi, Wah, Aghabozorgi, & Ling, 2014; Njolstad, Hoysaeter, Wei, & Gulla, 2014; Ruiz-Martínez, Valencia-García, & García-Sánchez, 2012; Schumaker, Zhang, Huang, & Chen, 2012). A number of studies further demonstrate the value of using media sentiment to make trading decisions (Crone & Koeppel, 2014; Kaya, 2010; Zhang & Skiena, 2010). However, the fundamental challenge remains: that is how to quantify the unstructured news content and how to decipher the linkage between the quantification process to market performance. It has been documented that the empirical lead-lag relations between news sentiment and price movement are dynamic over time, and therefore it is quite difficult to quantify the clear impact of news to market returns (Chan, 2003; Nardo, Petracco-Giudici, & Naltsidis, 2015).

The aim of this study is to examine the effect of abnormal sentiment shocks to cumulative market returns and volatility. We employ a heuristic search method to define 'abnormal' sentiment shocks generated from news articles, where two approaches are proposed: the first is to detect "sentiment shocks" based on moving average and standard deviation of the sentiment scores; the second is to identify "sentiment trends" which is an

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aggregated change of sentiment levels. We posit that not all the news have the same impact to investor's sentiment toward financial markets, and the abnormal shocks of news sentiment can provide us better signals in predicting cumulative market return and implied volatility of the S&P 500 index. The intuition behind this hypothesis is that if a large number of news articles from different sources report dramatic positive or negative tones about the market, these abnormal shocks will have lasting or persistent effect on market movement. Therefore, their impact to the cumulative returns and volatility during the period should be pronounced.

Our analysis show that these abnormal sentiment shocks do have persistent and robust effect to market performance. We show that methods using both sentiment shocks and sentiment trend can effectively predict future cumulative return and volatility of the S&P 500 index. Furthermore, we design a trading strategy based on these empirical findings, and its backtest results suggest that using news sentiment shocks and trend as trading signals can significantly outperform the basic buy-and-hold strategy. This demonstrates the potential benefits of including abnormal news sentiment analysis when making investment decisions.

The paper is structured as follows. Section 2 reviews existing literature on news sentiment and its effect on market movements. Section 3 discusses the data sample and the method used to extract sentiment from these news articles. Section 4 describes the abnormal sentiment approach to predict the cumulative returns and volatility. We discuss the key findings of the study in Section 5 followed by the conclusion with future research directions in Section 6.

2. Literature Review

2.1 Financial News Impact and Market Activity

The impact of financial news on trading volume and market volatility has been previously investigated and consistent findings have been reported across multiple studies. However, the relation between news and market returns remains elusive (Nardo et al., 2015). Three main areas of findings have been presented related to financial news impact on market activity. First, news flow is positively related to trading volume and volatility. Alanyali et al. studied a large number of news articles published by the Financial Times and concluded that the trading volume is positively correlated to the daily statistics of how often a company is mentioned on the day of and before the release of the news (Alanyali et al., 2013). In a similar study, Ahmad et al. showed that the textual sentiment extracted from firm-specific news is related to stock trading volume and returns (Ahmad, Kearney, & Liu, 2013). Second, asset price movement behaves differently with and without news. News about company fundamentals has been shown to cause momentum in stock price and trading volume (Scott et al., 2003), and stock price gain momentum with negative news release. In addition, price tends to exhibit reversal when there exists extreme price movements without public news announcement (Chan, 2003). Third, financial markets tend to overreact or underreact to news (Barberis et al., 1998). Specifically, it was shown that stock price underreacts to scheduled news such as earnings announcement, but overreacts to consecutive sequence of news with polarized sentiment.

2.2 Text Mining for Market Prediction

Textual information collected from various sources can be used as input for generating market prediction and developing trading strategies. These sources include major financial news websites, social media platforms, blog forums, and company disclosures and macroeconomic news. The typical modeling process includes pre-processing textual data, assigning labels with human experts or using transformed market data, and training models with machine learning algorithms(Xu, He, & Man, 2012). The primary objective is to develop better methods to process textual data for improved forecast accuracy. Typically there are three steps in the pre-processing stage: feature selection, dimensionality reduction and feature representation (Nassirtoussi et al., 2014). A number of machine learning algorithms have developed for text mining, such as Support Vector Machine (Hagenau, Liebmann, & Neumann, 2013; Zhai, Hsu, & Halgamuge, 2007), Neural Networks (Crone & Koeppel, 2014; Nikfarjam, Emadzadeh, & Muthaiyah, 2010), Naive Bayes (Yu, Duan, & Cao, 2013), Decision rules and Ensemble methods (Vu, Chang, Ha, & Collier, 2012). To extract features from textual data, several methods have been used. Bag-of-words (Pui Cheong Fung & Xu Yu, 2003; Zhai et al., 2007) is among the most frequently adopted methods, which separates the text into smaller components and disregard the order and co-occurrence of words. Another method is Latent Dirichlet Allocation (LDA), which categories words into concepts and features (Jin et al., 2013; Mahajan, Dey, & Haque, 2008).

2.3 Media Sentiment Analytics

Among the literature of sentiment extraction, two main schemes are commonly used to measure sentiment based on raw media text data. The first scheme is labeling previous news articles manually or along with the corresponding asset price changes. These labels are then being used to train a model for news sentiment classification (Crone & Koeppel, 2014; Kaya, 2010; Njolstad et al., 2014). The second scheme is a lexicon-based approach, which uses a polarity dictionary to identify positive and negative words in the news content (Li Im et al., 2013; Ruiz-Martínez et al., 2012). Das and Chen introduced five different algorithms as classifiers to extract sentiment form text, which include Naive Classifier, Vector Distance Classifier, Discriminant-Based Classifier, Adjective-adverb Phrase Classifier and Bayesian Classifier. By combining those classifiers with a voting scheme, they showed that their approach is better than the human and statistical benchmark based approach (Das & Chen, 2007).The applications of extracting media sentiment include the alpha-generating strategies and risk management methods. Due to the predictability of market returns based on the extracted sentiment, media sentiment analytics has been widely used for generating trading signals and portfolio strategies (Leinweber & Sisk, 2012; Tetlock, 2007). Furthermore, diBartolomeo has shown through his study that media sentiment is closely related to asset price volatility, quick adjustments of risk expectation over short time horizons (diBartolomeo, 2011). The advantage of extracting media sentiment automatically is that a larger quantity of text can be automatically processed in real time, Healy and Lo demonstrated a real-time news analytics framework to manage investment risks and returns with Thomson Reuters NewsScope data (Healy & Lo, 2011).

Overall, the existing literature shows a strong yet complex relationship between market sentiment and news. Various news analytics have been developed to advance our understanding of this complex relationship for better investment decisions. This study contributes the existing literature in news sentiment analysis and market forecasting through proposing the concept of abnormal news sentiment, which leads to two robust approaches to predicting market movement.

3. Data and News Sentiment

3.1 News Sentiment

In this study, we use the lexical-based approach in generating news sentiment. We collect a total of 678,378 news articles between July 13, 2012 and October 16, 2014 from the Northern Light Single Point business news portal, a data vendor that delivers historical archives of business news content around the globe. It enables a comprehensive search of online business news, newswires, and industry authority blogs with content that is updated every 15 minutes. We build a news crawler that extracts relevant market-related news entries from the portal database and pre-processes them into news sentiment. The news crawler features a Java-based platform that utilizes pre-specified keywords such as S&P 500, NASDAQ, Google, IBM, etc., and records attributes such as the title, summary, description and the sentiment. The data contains 569 business days across the evaluation period. We first convert the raw news content into daily news sentiment score for the empirical study. With the complex textual structure, we then decompose the raw text into individual words with the removal of stop words. We apply lemmatization techniques to convert different inflicted forms of a word into a uniform entity. For instance, we would regard “rising”, “risen” and “rises” as the word entity “rise”. For each word in the news text, we extract the associated score from the sentiment dictionary and finally, we generate the sentiment score for each news article by averaging all individual word scores. To compute the daily news sentiment, we aggregate all news articles published in each day and compute the daily average value of news sentiment scores (see equation below). In addition, the relative publication frequency of individual vendors is accounted for in the calculation.

$$Score_{news\_sentiment} = \frac{\sum_{i=1}^{n} I(i) * Score\,(i) * Vendor\,(i)}{n * \sum_{i=1}^{n} Vendor\,(i)},$$

$$\text{where } I(i) = \begin{cases} 1, & word\ i\ is\ in\ the\ SentiWordNet\ dictionary \\ 0, & word\ i\ is\ not\ in\ SentiWordNet\ dictionary \end{cases},$$

Score$_{\text{news\_sentiment}}$ is the daily news sentiment score, *Score(i)* is the sentiment score for each news article, *Vendor(i)* is the relative frequency of publication by each vendor, *n* is the total number of news article in a day.

3.2 Financial Market Data

For financial risk and return, we seek to select major indices that are representative of market movement. In this study, we collect data on both SPDR S&P 500 ETF Trust (SPY) and Volatility S&P 500 (VIX) from Bloomberg between July 13, 2012 and October 16, 2014. With the SPY price data and VIX index value, we calculate the daily return and volatility of SPY, and change of the VIX index. The daily return of SPY is calculated by applying the natural logarithm of the daily close price over its previous value, while the daily volatility of SPY is calculated as the standard deviation of the daily returns from the previous one month (21 trading days).

4. Methodology: Abnormal Sentiment Analysis

The objective of the study is to investigate whether abnormal levels of news sentiment lead to significant impact towards financial market movement. The hypothesis is that extreme bullish or bearish news sentiments can explain future market risk and return. This paper proposes two approaches to identify abnormal sentiment levels where news sentiment has significant deviation from its normal level. The first approach is to identify sentiment shocks, which are defined as noticeable spikes from the current period of news sentiment relative to the historical time series. The second approach is to identify sentiment trend, which measures the aggregated deviation from the trend of the most recent news sentiment. Both approaches focus on transforming news sentiment data to its abnormal level of deviation. These abnormal sentiment series are then used for regression analysis.

4.1 Sentiment Shocks

Sentiment shocks are spikes observed from the time series plot, primarily in the forms of spiking up or spiking down. These sentiment shocks are often caused by the release of unexpected macroeconomic data, central bank decisions and political events. In order to detect the sentiment spikes *ex ante*, the following formula is used to define an event with sentiment shock threshold:

$$S_{t0} > |\mu \pm M * \sigma| \qquad (1)$$

Where S_{t0} is sentiment value on day *t0*, *t0* represent the current day, μ is the mean of sentiment values from *t0-N* to *t0-1*, and σ is the standard deviation of sentiment values from *t0-N* to *t0-1*. *N* is the total number of look-back days, *M* is the multiplier on standard deviation.

When the sentiment value S_{t0} is larger than the threshold value, the sentiment value S_{t0} is tagged as a sentiment shock. *N* and *M* are two main variables in this setup that contribute to the control of shock detection sensitivity. Figure 1 shows the number of sentiment shocks with different value combination of *N* and *M*. It shows that the selected sample size is relatively stable with *N* larger than 5, and it is more sensitive to *M*. With the objective to stabilize the sample size and get at least 100 data points, we select the total number of look-back days to be 5 and 1.5 as the multiplier on standard deviation (i.e. *N* =5, *M = 1.5*).

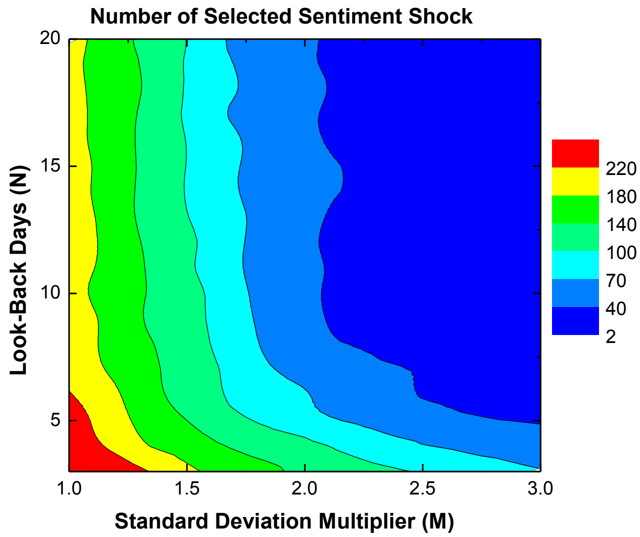

Figure 1. Contour plot of selected sample size out of 568 original data, M range from 1 to 3, N range from 3 to 20.

With the selected number of sentiment shocks, we perform regression analysis with current ($\tau = 0$) and future ($\tau = 1, 2, \ldots, t$) market cumulative return, volatility, VIX and Change of VIX. We treat the sentiment shock time series as an independent variable and seek to use it for explaining financial market returns and risk. Equation (2) and (3) show the regression models for cumulative return and VIX regression formula.

$$R_{it+\tau} = \alpha + \beta * S_{it} + \epsilon_{it+\tau} \qquad \tau = 1, 2, \ldots, \tag{2}$$

$$VIX_{it+\tau} = \alpha + \beta * S_{it} + \epsilon_{it+\tau} \qquad \tau = 1, 2, \ldots, \tag{3}$$

Where S_{it} is the *i*-th selected sentiment shock, $R_{it+\tau}$ is the τ day cumulative return, $VIX_{it+\tau}$ is the VIX value on τ day.

Table 1 shows the regression results for cumulative return and VIX. The beta coefficients for cumulative return are positive and negative for VIX. The p-values for cumulative return are significant till day 4, and for VIX are significant till day 10, with the exception of day 5. This finding illustrates that positive sentiment shocks lead to positive cumulative returns and less volatilities. In both cases, the p-values are increasing as the number of days increases. For cumulative return, the p-values for day 0 to day 2 are more significant than VIX, but its significance decays faster after day 2. Figure 2 shows the beta and error bar for the cumulative return regression with sentiment shocks. The beta coefficients are approaching zero and the error bars are becoming larger as the days further into the future. Figure 3 shows the regression results for VIX, as further into the future, beta coefficients are converging toward zero and the error bars are relatively stable.

Table 1. Sentiment Shock Regression

	Cumulative Return		VIX	
Day	***beta***	***p_value***	***beta***	***p_value***
1	0.036	3.05E-05***	-6.041	2.11E-03***
2	0.038	3.32E-04***	-5.396	6.82E-03***
3	0.030	1.69E-02**	-5.489	6.14E-03***
4	0.026	7.08E-02*	-5.428	6.32E-03***
5	0.014	3.71E-01	-3.113	1.35E-01
6	0.025	1.15E-01	-4.414	3.36E-02**
7	0.030	7.07E-02*	-4.295	4.47E-02**
8	0.029	9.53E-02*	-4.289	2.94E-02**
9	0.032	7.35E-02*	-3.792	3.76E-02**
10	0.032	8.41E-02*	-3.486	7.16E-02*
11	0.017	3.86E-01	-1.133	5.58E-01
12	0.017	3.80E-01	-1.527	3.81E-01

***: p value less than 0.01. **: p value less than 0.05. *: p value less than 0.1.

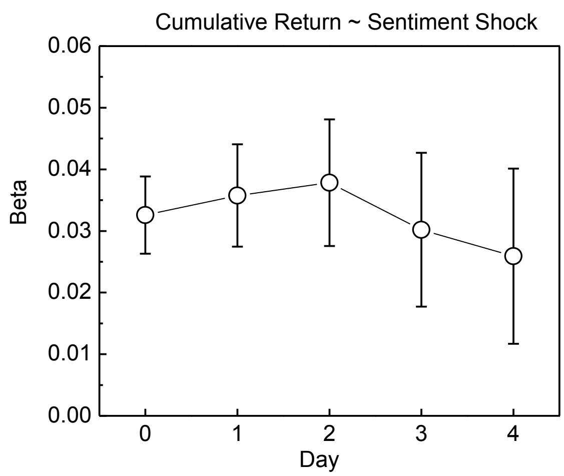

Figure 2. Cumulative return regress with sentiment shock, plot beta coefficients and error bars for days with significant p values.

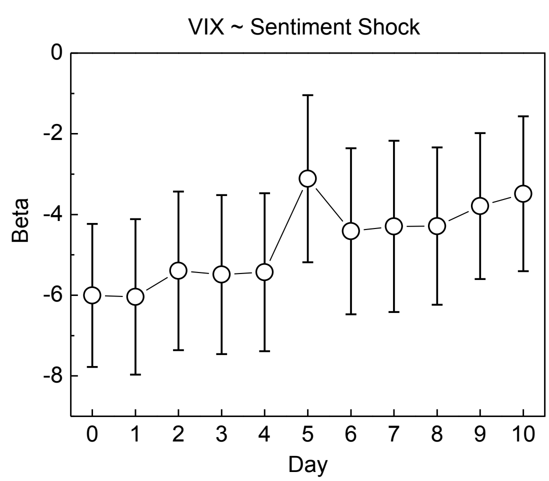

Figure 3. Current and future VIX regress with sentiment shock, plot the beta coefficients and error bars for days with significant p values.

4.2 Sentiment Trend

The second method to filter out abnormal sentiment days is to monitor the aggregated change of sentiment, or the sum of deltas of sentiment levels. The change of sentiment may be more informative than sentiment levels, especially aggregated over a period of time. For example, if for some consecutive days, the news sentiment is moving in one direction, the change of sentiment will have the same sign and a sentiment trend is formed. This kind of sentiment trend may be caused by a series of good news or bad news, and this may have a strong impact on investor sentiment and asset price. To identify this sentiment trend, the following formula is used:

$$CumulativeSentiment = \left|\sum_{i=t0-N}^{t0} \Delta S_i \right| > T \tag{4}$$

Where ΔS_i is the change of sentiment on day i, $t0$ represent the current day. N is the moving window size to sum the change of sentiment within it, T is the threshold value. If the aggregated value is larger than T, the last day in the moving window is selected as an abnormal sentiment day. N and T are variables in this formula, they can control the trend detection sensitivity. In Figure 4, the contour plot shows the selected sample size with different N and T values, and the pattern shows T is the dominant variable of the sample size. Values are selected so that the filtered sample size is stable and larger than 100. In this analysis, N = 15, T = 0.12.

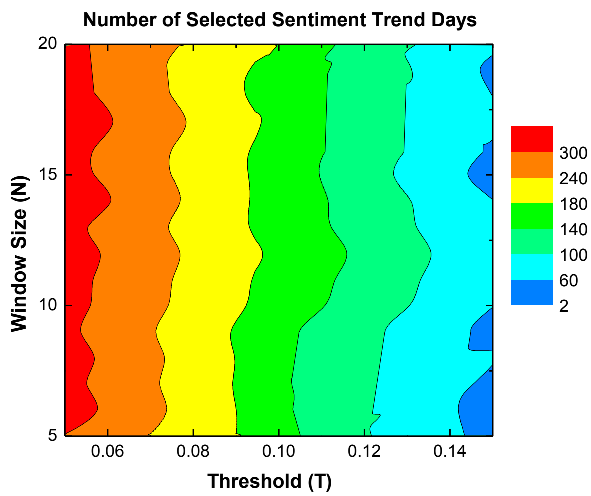

Figure 4. Contour plot of selected samples size out of 568 original data point, N range from 5 to 20, T range from 0.05 to 0.15.

With the Equation (4) and selected variable values, the abnormal sentiment trend days are found. Then we perform regression analysis using the summed change of sentiment with current $(\tau = 0)$ and future $(\tau = 1,2, \dots,)$ market cumulative return, volatility, VIX and Change of VIX. The cumulative return and VIX regression formulas are as follows:

$$R_{it+\tau} = \alpha + \beta * CumSentiment_{it} + \epsilon_{it+\tau} \quad \tau = 1,2, \dots, \tag{5}$$
$$VIX_{it+\tau} = \alpha + \beta * CumSentiment_{it} + \epsilon_{it+\tau} \quad \tau = 1,2, \dots, \tag{6}$$

Where $CumSentiment_{it}$ is the cumulative sentiment value of the i-th selected sentiment trend, $R_{it+\tau}$ is the τ day cumulative return, $VIX_{it+\tau}$ is the VIX value on τ day.

Table 2 shows the regression results for cumulative return and volatility with sentiment trend. Similar as the sentiment shock results, the results for volatility and change of VIX are insignificant and not shown. The beta coefficients for cumulative return are positive, and for VIX are negative. For sentiment trend regression, the p values for both cumulative return and VIX are significant up to Day 10. Figure 5 and Figure 6 show the beta and error bar for the cumulative return and VIX.

Table 2. Sentiment Trend Regression

	Cumulative Return		VIX	
Day	***Beta***	***p_value***	***beta***	***p_value***
1	0.026	1.8E-05***	-4.940	3.72E-04***
2	0.026	1.2E-04***	-4.496	8.11E-04***
3	0.026	1.1E-03***	-4.360	2.43E-03***
4	0.025	4.2E-03***	-4.132	2.36E-03***
5	0.022	1.8E-02**	-3.413	5.51E-03***
6	0.027	9.5E-03***	-4.006	1.69E-03***
7	0.023	4.1E-02**	-3.597	3.91E-03***
8	0.023	5.9E-02*	-3.533	4.57E-03***
9	0.029	2.4E-02**	-3.849	3.90E-03***
10	0.025	6.4E-02*	-3.169	1.19E-02**
11	0.019	1.7E-01	-2.482	5.50E-02*
12	0.015	2.6E-01	-1.605	1.83E-01

***: p value less than 0.01. **: p value less than 0.05. *: p value less than 0.1.

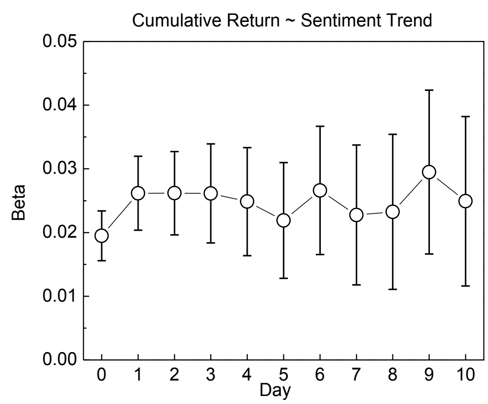

Figure 5. Cumulative return regress with summed change of sentiment, plot the beta coefficients and error bars, the p values are significant till day 10.

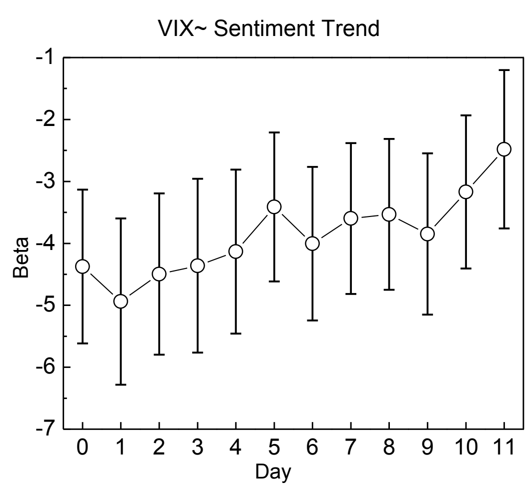

Figure 6. Current and future VIX regress with summed change of sentiment, plot the beta coefficients and error bars, the p values are significant till day 11.

4.3 Trading Strategy Backtest

Based on the analysis of sentiment shock and sentiment trend methods, we design and backtest a trading strategy based on the generation of the buy, sell and hold signals from each method. The trading rules are as follows:

$$\begin{cases} \textit{Buy or Cover Short:} & \textit{Abnormal Positive Sentiment signal} \\ \textit{Sell or Sell Short:} & \textit{Abnormal Negative Sentiment signal} \\ \textit{Hold Position:} & \textit{No Signal and Holding days} < D \end{cases}$$

where an abnormal positive sentiment signal is generated, when $S_{t0} > \mu + M * \sigma$ for the sentiment shock method and $\sum_{i=t0-N}^{t0} \Delta S_i > T$ for the sentiment trend method; or an abnormal negative sentiment signal is generated, when $S_{t0} < \mu - M * \sigma$ for the sentiment shock method and $\sum_{i=t0-N}^{t0} \Delta S_i < -T$ for the sentiment trend method; D is defined as the maximum holding days.

For the back-testing of the trading strategy, SPY is selected as the financial instrument. The strategy allows both long and short positions, and a small transaction cost is added to each trade transaction based on the historical bid-ask spread and a brokerage fee. The testing time period is from July 13, 2012 to October 16, 2014. In addition, we establish a benchmark resembling to a simple buy and hold strategy for performance comparison. As shown in Table 3, both the sentiment shock and sentiment trend strategy outperform the buy-and-hold benchmark in terms of mean return, volatility and risk-adjusted return (Sharpe ratio). Comparing between the two proposed approaches, the sentiment trend based strategy yields a more superior performance than the sentiment shock method with a better Sharpe ratio.

Table 3. Backtest results of different strategies

	Annualized Performance			
	Average No. of Trades	**Mean Return**	**Volatility**	**Sharpe Ratio**
Sentiment Shock	43.92	22.68%	7.93%	2.86
Sentiment Trend	45.69	23.18%	7.94%	2.92
Buy and Hold	NA	14.04%	11.27%	1.25

5. Discussion

This study utilizes two methods to identify time periods with abnormal level of news sentiment and performs regression analysis on these abnormal sentiment measures to explain market returns and risk. The results in Table 1 and Table 2 demonstrate that both methods can explain the variations of future market cumulative returns and the implied volatility of the S&P 500 market index. This shows that investors' reaction to modest level of news sentiment does not have persistent effect over certain time period, but in the case of extreme bullish or bearish news sentiment, market tend to have persistent and significant reaction, which can be exploited for profitable trading opportunities. We find that our approaches, ether in the form of identifying sentiment shocks or sentiment trend, are novel and effective for explaining future market cumulative returns. Another key finding of this study suggests that both methods have better predictive power for VIX than cumulative return, which implies a strong correlation between volatility and news sentiment. This confirms the existing findings that news sentiment is linked to volatile market conditions (Ho, Shi, & Zhang, 2013; L. A. Smales, 2014; L. a. Smales, 2015). Our results also find that the beta coefficients for VIX are significant for a larger number of days into the future, and yet the errors are relatively stable over time. This phenomenon can be attributed to the fact that the VIX index is calculated as a one-month implied volatility and it is less volatile than the daily market returns. The last key finding is that the sentiment trend approach exhibits better predictive power and consistency over the sentiment shock approach. The p-values for cumulative return and VIX are both significant until Day 10 and Day 11. Intuitively, the outperformance from the sentiment trend approach is reasonable because a series of good or bad news has larger impact on the market than a single shock.

6. Conclusions and Future Plan

In the paper, we show that the two approaches based on the detection of abnormal news sentiment are effective in explaining future cumulative returns and market volatility. The analysis shows that both methods can produce persistent and robust predictions of future market cumulative return and volatility. We show that the sentiment trend method has better predictive power and consistency than the sentiment shocks method. And the beta coefficients of the sentiment trend method are significant up to day 10 into the future. The findings align with the intuition that a large number of news articles with extreme positive or negative tones can generate abnormal shocks, which in turn will trigger lasting or persistent effect to market movement. Therefore, their impact to the cumulative returns and volatility during the period should be pronounced. This effect is even more significant, when there is a trend of sentiment changes in the same direction, which is reflected through the sentiment trend approach. Moreover, the backtest results indicate that using news sentiment shocks and news sentiment trend as trading signals can significantly outperform the basic buy-and-hold strategy. These findings showcase the potential benefits of detecting abnormal news sentiment in making investment decisions.

For future work, the current study can be extended to investigate the impact of abnormal sentiment on individual company stock returns and volatilities. We foresee that the individual stock effect should be similar as the index result presented in this study, and therefore a more diversified trading strategy can be formulated with stocks from different sectors and industries. The other future direction is to investigate at a finer time scale at the intraday level of how abnormal news sentiment affects market movement.

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