SOCIAL NETWORK FINANCIAL SENTIMENT: CONSTRUCTING PROXIES AND TESTING RETURNS PREDICTABILITY ON S&P500 FUTURES RETURNS

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Abstract

This article examines the ability of StockTwits social network sentiment proxies to predict S&P500 Futures. Positive and negative levels and first-difference sentiment proxies were constructed from 59,907,378 tweets. Using the lexicon approach and Loughran-McDonald positive and negative word lists, this study considers the tweets' informal language and 140-character constraint. It was found that one standard deviation of change in negative word sentiment compared to the previous day predicts lower S&P500 Futures by 3.4 basis points after controlling for past returns and macroeconomic variables. The results are robust to macro announcements, futures turnover, major Asian and European market returns, the day-of-the-week effect, the January effect, and the holiday effect. Investors can easily replicate the methodology to construct the social network sentiment proxies introduced in this study and employ these proxies in their investment strategies. This study hopes to spur more research to construct and improve social network sentiment proxies for various financial markets.

JEL Classification Codes: G14, G04

Keywords: Social media; social network sentiment; futures market

1. INTRODUCTION

Over recent years, social-media usage has increased rapidly (Alattar & Shaalan, 2021). According to an April 2021 survey, 7 out of 10 Americans use social media (Pew Research Centre, 2021). Of the respondents, 42% reported using Twitter, with 30% of the respondents saying they tweet a few times a day, 16% of them saying they tweet at least once a day, and 53% saying they tweet less frequently (Pew Research Centre, 2021). These users view current news and issues on social media (Mehta et al., 2021). Considering the popularity of social media, social network sentiment proxies have emerged as the latest sentiment indicator (Alsayat, 2022; Cookson & Niessner, 2020; Guégan & Renault, 2021; Lehrer et al., 2021; Mehta et al., 2021; Öztürk & Bilgiç, 2021; Shen et al., 2022). For example, the U.S Social Sentiment Index by Wall Street Journal and the IHS Markit that measures U.S. economic and social mood using Twitter tweets (WSJ Graphics, 2019).

From social network sentiment, investors can gain insights about a company (Ontario Securities Commission, 2022) or predict stock market movements (Yeo, 2022). Hence, it is no surprise that about five million investors with investible assets above $100 000 (Yeo, 2022) and 75% of investors in general (Hill, 2022) use social media for their investment decision making. Wall Street brokers included a sentiment analysis in their stock market algorithm (Yeo, 2022). However, a social network sentiment proxy is not readily available.

Some investors and researchers utilize

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users' voluntary sentiment disclosure (Guégan & Renault, 2021; Liew & Budavari, 2016) but only 10% to 20% of tweets have this disclosure (Liew & Budavari, 2016). Some buy sentiment proxies from a third party, even if they are unable to determine the prevalence of irrelevant posts or tweets incorporated in the proxies (Agrawal et al., 2018; Bandara, 2016; Siganos et al., 2014). Investors and researchers could construct social network sentiment proxies but they must filter words that are unrelated to financial markets, include informal language that refers to the financial market, and prevent misclassification of words used in the tweets to prevent miscalculated sentiment scores. Social network sentiment proxies for financial market analysis should be constructed from investment-based social media like StockTwits because these tweets focus on financial markets or investments compared to non-financial social media such as Twitter and Facebook (Hu & Tripathi, 2012). Otherwise, researchers and investors using social-media tweets must remove irrelevant tweets in their analysis to improve the accuracy of their sentiment scoring analysis (Hu & Tripathi, 2012), a process which is time consuming, and which requires thorough pre-processing.

This study built positive and negative social network financial sentiment proxies based on 59,907,378 tweets on StockTwits from 1st August 2009 to 31st January 2017. This sample period was chosen based on data availability (Cookson & Niessner, 2020). It was decided to use a simple lexicon approach that could be easily replicated by researchers and practitioners. Before counting the positive and negative words in the tweets based on Loughran-McDonald positive and negative word lists, tweets were checked for the presence of bots to ensure that all tweets in the sample were sent by humans. Since users tweet in informal language, an additional list of words commonly used on StockTwits was also used; this included words such as bull and bearish, to represent positive and negative sentiments, and sentiment scores were adjusted for negation and sarcasm. The study aimed to address whether these social network financial sentiment proxies, could predict S&P500 Future daily returns. Most social-media sentiment studies have examined the equity market, or recently, the cryptocurrency market (Guegan & Renault, 2021; López-Cabarcos et al. 2021; Öztürka & Bilgiç, 2021). This study focuses on the futures market since investors in the futures market have been looking for indicators, including sentiment proxies, which can predict the direction of futures returns. Based on the findings, a higher negative sentiment compared to the previous day predicts subsequent S&P500 Future returns reversals, even after controlling for past returns, the economic policy uncertainty (EPU) index, and the Aruoba-Diebold-Scotti (ADS) business conditions index. This finding is robust when considering macro announcements, turnover, day-of-the-week effects, the January effect, the holiday effect, and major Asian and European market returns.

This research paper proceeds as follows. A review of the previous literature on sentiments is first presented. This is followed by an explanation of the steps taken to construct StockTwits Positive and StockTwits Negative sentiment proxies and other collected data. The returns predictability of all sentiment proxies is examined, followed by the study's conclusions.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Sentiment and Returns

The noise trader framework explains the relationship between sentiment and returns (De Long et al., 1990). There are two types of investors in financial markets. The first group are noise traders. The second group are sophisticated investors. Unlike sophisticated investors, noise traders do not have access to insider information, they lack information, and are influenced by sentiment when making trade decisions (De Long et al., 1990). When noise traders believe that the intrinsic value of a stock is greater (or less) than its current market price, they become optimistic (or pessimistic). However, their beliefs are not based on the cash flow and risk prospects of the company (Baker & Wurgler, 2007). If they are more pessimistic (or optimistic) than the average investor, they demand less (or more) of that stock and sell off the stock if they hold it (Baker & Wurgler, 2007). A lower (or higher) demand for the stock will bid the stock price down (or up; De Long et al., 1990). Thus, stock returns decrease (or increase) when noise traders are more optimistic (or pessimistic; Baker & Wurgler, 2007). Sentiment will predict returns if sentiment influences returns. However, the resulting price changes will only be temporary since the change is not based on any fundamental value of the stock (Tetlock, 2007; Da et al., 2015). Sophisticated investors cannot arbitrate this change in stock price because they have a short trading horizon and are concerned that the price change will continue before the price reverses to reflect its fundamental value (De Long et al., 1990).

2.2 Positive Sentiment and Negative Sentiment

Positive sentiment and negative sentiment have asymmetric effects on returns (Shen et al., 2022). Negative sentiment predicts returns (Garcia, 2013; Lee et al., 2017; Omura & Todorova, 2019; Tetlock, 2007) but positive sentiment does not (Chen et al., 2014; Liu & McConnell, 2013). Investors only process a limited amount of information because they have limited cognitive processing abilities (Baumeister et al., 2001). Thus, they focus more on negative sentiment than on positive sentiment (Baumeister et al., 2001; Rozin & Royzman, 2001). Furthermore, investors are more concerned about avoiding losses than acquiring profits (Lee et al., 2017).

2.3 Social Network Sentiment Proxies

On social media, users participate, share, and discuss opinions, on a certain topic by tweeting (Puri et al., 2020; Zhang, 2014). These voluntarily tweets are user-generated content (UGC). Since these tweets reflect what social-media users feel (Bollen et al., 2011; Oh & Sheng, 2011; Puri et al., 2020; Siganos et al., 2014; Sul et al., 2014; Zhang, 2014), social network sentiment proxies capture the user's actual sentiment through their tweets. Hence, tweets can be used to detect changes in the public mood following events (Kramer, 2010).

When social-media users interact through concise, 140-character tweets, they share their sentiment with other social-media users (Bollen et al., 2011; Oh & Sheng, 2011; Sul et al., 2014). Kramer (2010) posits that online participation is usually followed by offline activities, meaning this shared sentiment could predict returns if it makes users trade more (Bollen et al., 2011; Oh & Sheng, 2011; Sul et al., 2014). Social media could influence financial markets (Hill, 2022) because it has empowered a new generation of investors by giving them access to information and peer-to-peer sharing (Royal Bank of Canada, 2022). Social media has helped democratize access to investment insights (Royal Bank of Canada, 2022).

Although sentiment is not based on any fundamentals (Brown & Cliff, 2004), investors may act on social media sentiment if they believe that their actions can increase their profits (Black, 1986). However, like previous studies using market-based and survey sentiment proxies, previous studies on social network sentiment proxies have found mixed results regarding whether sentiment predicts returns (Choudhury et al., 2018; Cookson & Niessner, 2016; Giannini et al., 2017; Siganos et al., 2014).

This UGC characteristic is unique to social network sentiment proxies compared to market-based and survey sentiment proxies. Examples of market-based sentiment proxies are the Baker Wurgler index, closed-end fund discounts, the number of initial public offerings, the first-day returns of initial public offerings, turnover, the put-call ratio, and the Chicago Board Options Exchange Market

Volatility Index (VIX). Examples of survey sentiment proxies are the American Association of Individual Investors Bull Bear Spread, the Conference Board Consumer Confidence Index, the Michigan Consumer Confidence Index, the Shiller Institutional U.S. One-Year Confidence Index and the Investor Intelligence Bullish Sentiment Index.

2.4 Sentiment Proxies in the Futures Market

There have been few studies on the relationship between sentiment and futures returns. Sentiment proxies that have been found to predict futures returns are the monthly Baker Wurgler sentiment index (Lutzenberger, 2014; Zheng, 2015), weekly sentiment proxies constructed using the Disaggregated Commitments of Traders (DCOT) report (Wang, 2001), the daily VIX, the put-call ratio, the Arms Index (Chen & Chang, 2005; Simon & Wiggins, 2001), trading volume, open interest, the buy-sell imbalance, and the psychological line index (Yang & Gao, 2014). In one example, Simon and Wiggins (2001) found that the VIX, the S&P100 put-call ratio, and the trading index (TRIN) could forecast S&P500 Futures returns over a 10-day horizon, a 20-day horizon, and a 30-day horizon.

In another example, Wang (2001) constructed a large hedger sentiment proxy, a large speculator sentiment proxy, and a small trader proxy from large hedger, large speculator, and small trader, data in the DCOT. Wang (2001) found that large speculator sentiment and large hedger sentiment predict futures returns, but small trader sentiment does not predict futures returns (Wang, 2001). These findings show that sentiments of different types of traders have different returns predictability (Fisher & Statman, 2000; Sanders et al., 2003). Wang et al. (2018) employed the Baidu Search Volume Index, China's version of the Google Search Volume Index to examine the futures market with sentiment extracted from desktop search devices and sentiment extracted from mobile search devices. Again, each category of sentiment yields different results regarding the predictability of futures returns.

Trading strategies that incorporate the VIX, the S&P100 put-call ratio, and the TRIN have been shown to yield higher returns compared to trading strategies that do not include a sentiment proxy (Chen & Chang, 2005). Similarly, Wang (2001) found that combining both weekly large speculator sentiment and large hedger sentiment in a trading strategy produced higher returns compared to using only past returns in the trading strategy.

Based on these studies, this study tests the null hypothesis that social network sentiment does not predict daily futures returns.

3. THE CONSTRUCTION OF SOCIAL NETWORK SENTIMENT PROXY

3.1 Tweet Pre-Processing

The sample was first examined for tweets sent by bots even though StockTwits has reputable anti-bot protection. Bots could provide false information on StockTwits that affects users' sentiments and opinions (Baraniuk, 2018). On Twitter, about 23 million users engage third-party applications such as bots, and 1.4 million users have retweeted, liked, or followed tweets sent by bots (Baraniuk, 2018). Although it was found that bots are an unlikely concern on StockTwits, caution was necessary regarding any conclusion about bots as bots constantly evolve to mimic human behavior and avoid detection (Schafer et al., 2017; Syeed, 2017). An HTML cleanup was then performed (Das & Chen, 2007) to replace HTML tags in the tweets with the characters they represented. Some retweets were found in the sample. Following Liew and Budavari (2016), retweets were kept because sentiment from these retweets could have a stronger impact on returns compared to other tweets. Finally, characters and tweets that were irrelevant for sentiment analysis, were removed; these tweets included duplicates, tweets that were not related to investments, punctuation, control characters, digits, and the character '@' as well as its accompanying words since they consist of usernames to which the tweets are directed. Unnecessary spaces between words were also removed. The final sample of tweets consisted of 59,907,378 tweets posted between 1st August 2009 and 31st January 2017.

3.2 Calculating Sentiment Scores

This study employed the lexicon approach to construct StockTwits Positive and StockTwits Negative sentiment proxies (Chen et al., 2014; Liu & McConnell, 2013; Tetlock, 2007). For each tweet, the number of positive and negative words was counted based on three word lists. A higher proportion of positive words (or negative words) relative to the total number of words indicates higher positive (or negative) sentiment in that tweet (Loughran & McDonald, 2016). The first word lists used were the Loughran-McDonald positive and negative word lists (Ahern & Sosyura, 2014; Chen et al., 2014; Liu & McConnell, 2013). The second pair of word lists consisted of the informal words in tweets, such as bearish and bullish, that refer to positive and negative sentiments. These lists capture words that are not captured by the formal-language Loughran-McDonald word lists. The third pair of lists consisted of positive similes and negative similes. Positive similes reflect positive sentiments such as happiness and excitement about good news. Conversely, negative similes reflect negative sentiments such as sadness, frustration, helplessness, anger, and regret, over losses or bad market movements. The 140-character limitation for each tweet encourages users to utilise symbolic and figurative text such as similes (Bharti et al., 2015) to convey their meaning and emotion.

3.3 Question Tweets

Question tweets are neutral. Thus, it was important to ensure that they are not considered as positive or negative (Lunando & Purwarianti, 2013).

3.4 Negation

Negation reverses a tweet's polarity (Lunando & Purwarianti, 2013). A total of 31,713,360 tweets were randomly selected and manually checked for negation. It was found that 17.4% had one or more negation. The frequency of negation in a sample has been found to range from 13.5% (Reitan et al., 2015) to 32% (Councill et al., 2010). According to Dadvar et al. (2011), words affected by negation vary from the first word after the negation word to five words after the negation word. From the 31,713,360 sample, it was found that five words after the negation word best captured the reverse in a tweet's polarity, and negation was adjusted for accordingly.

3.5 Sarcasm

Sarcastic tweets read as the opposite of their actual sentiment (Lunando & Purwarianti, 2013). Certain features in tweets have been shown to identify sarcasm with 45% to 85% accuracy (Carvalho et al., 2009; Lunando & Purwarianti, 2013). It was therefore important to look for sarcasm by investigating interjection words, hashtags, punctuation marks, capitalised phrases, and laughter expressions in the tweets. It was found that most of the tweets were not sarcastic. For example, some tweets with laughter expressions were sarcastic. However, the majority of these tweets did not affect the sentiment scores as they did not use words from the word lists. In another example, hashtags were used to index certain keywords or topics to separate or rank certain words in the tweet.

3.6 Daily Sentiment Scores

The positive, negative, and total word counts were summated based on the date tweets were tweeted. Positive, negative, and total word counts from non-trading days were incorporated into the next trading day (Garcia, 2013). The positive and negative word counts were then divided by the total word count to allow for easy comparison across tweets with different total word counts (Ahern & Sosyura, 2014; Garcia, 2013). Finally, the scores were transformed into percentages.

In addition to levels of sentiment proxies, the first difference of the StockTwits Positive and StockTwits Negative (hereafter, referred to as Δ) sentiments were calculate as previous studies could not ascertain which of the two sentiment forms affect returns (Brown & Cliff, 2004; Wang et al., 2006). A total of 1,869 daily observations of StockTwits Positive, StockTwits Negative, Δ StockTwits Positive, and Δ StockTwits Negative sentiment scores were obtained.

4. RESEARCH METHOD AND DATA

4.1 The Model

The relationship between StockTwits sentiment and returns was tested using Equation 1:

$$r_{t+k} = \mu_i + \alpha_i SENT_{i,t} + \sum \gamma_m \, Control_t^m + \varepsilon_{t+K,} \qquad (1)$$

where $SENT_{i,t}$ denotes sentiment i for day t, and i is either StockTwits Positive or StockTwits Negative. The term r_{t+K} is the S&P500 Futures return on day $t + K$, where K ranges from 0 to 5. Control variables included lagged returns on futures, the EPU Index, and ADS Index. The Akaike information criterion and the Bayesian information criterion were employed to determine the optimal lag for futures returns. Tests indicated lag 4 as the optimal lag. The EPU Index and the ADS Index are proxies for macroeconomic variables. All the data in Equation 1 were standardized to have a mean of 0 and standard deviation of 1. The Newey and West (1987) *t*-statistics were used, as they are known to be robust to autocorrelations and heteroscedasticity. Nevertheless, autocorrelations were tested for in each model using the Durbin-Watson test statistic. The variance inflation factor (VIF) was employed to check for multicollinearity amongst the variables and a VIF close to 1 was found. If the social network financial sentiment proxies influence returns, α_i would be significantly different from 0.

Although previous studies on news found that news predicts returns (Mehta et al., 2021; Shen et al., 2022), social network financial sentiment on StockTwits is not based on any fundamentals of the underlying S&P500 Futures stocks or any news on StockTwits about a change in these fundamentals. Hence, sentiment-induced demand shock is only temporary as over time stock prices revert to their intrinsic values (Da et al., 2015). Sentiment theory predicts returns reversals for this sentiment-induced mispricing (Da et al., 2015; Tetlock, 2007; Wang et al., 2018).

4.2 The Data

The sample period covers 1st August 2009 to 31st January 2017 due to data availability (Cookson & Niessner, 2020). Daily S&P500 Futures returns were calculated as the natural logarithm of current settlement price to the previous day's settlement price ratio. The settlement price of the futures contract was used in conjunction with the nearest delivery date until the delivery month when it was switched to the settlement price of the second nearest futures contract (Bessembinder, 1992; Wang, 2001). Daily settlement prices were collected from DataStream.

Past returns (Goldenberg, 1988) and macroeconomic variables (Bessembinder, 1992) influence futures returns. Thus, these were controlled for in the examination (Da et al., 2015). The EPU index (Da et al., 2015; Johnson & Lee, 2014) and the ADS business conditions index (Da et al., 2015; Tharann, 2019) were used as the macroeconomic variables. Baker et al. (2016) developed the EPU Index to capture economic policy uncertainty using newspaper articles while Aruoba et al. (2009) developed the ADS Index to capture business conditions using six economic indicators. Daily EPU Index data was collected from a public website[2] and daily ADS business conditions index data was collected from the Federal Reserve Bank of Philadelphia's website.[3]

4.3 Preliminary Data Analysis

Table 1 presents the summary statistics. The mean sentiment for StockTwits Negative was higher than the mean sentiment for StockTwits Positive. However, the average 140-character tweet of StockTwits users had three negative financial words and three positive financial words. These findings suggest that sentiment on StockTwits is not dominantly positive or negative. This study notes that the Loughran-McDonald positive word lists contains only one sixth of the number of words found in the Loughran-McDonald negative word lists. Thus, there is a possibility that some positive words in tweets are not captured. The average of the first-difference sentiment proxies indicates that subsequent sentiments are about as optimistic or pessimistic as the day before.

The StockTwits Negative sentiment proxies had a higher standard deviation compared to the StockTwits Positive sentiment proxies. These findings show that the negative sentiment on StockTwits is more variable than the positive sentiment.

The last two columns in Table 1 report the results of the Augmented Dicker-Fuller (ADF) tests. In accordance with the results presented in Table 1, the unit root null hypothesis is rejected for all levels and all first-difference sentiment proxies at the 10% significance level. The data can be said to be stationary.

Table 2 reports pairwise correlations between StockTwits sentiment proxies and macroeconomic variables.

Table 1 Summary Statistics

Variable	Mean	Median	Stand. Dev.	ADF (drift)	ADF (trend)
S&P 500 Index Futures	0.03	0.10	1.14	-65.77	-65.77
StockTwits Positive	1.99	1.98	0.17	-16.86	-16.88
StockTwits Negative	2.06	1.99	0.29	-13.53	-16.14
Δ StockTwits Positive	0.02	0.01	0.19	-52.12	-52.10
Δ StockTwits Negative	0.05	0.02	0.25	-59.38	-59.37
EPU Index	-0.08	-0.08	0.62	-83.27	-83.51
ADS Index	0.00	0.001	1.48	-60.78	-60.82

Table 2 Correlation Matrix

Levels Sentiment

	Variable	StockTwits Positive	2	3
2	StockTwits Negative	0.24***		
3	EPU Index	-0.01	0.03	
4	ADS Index	-0.01	0.00	0.01

Δ Sentiment

	Variable	Δ StockTwits Positive	2	3
2	Δ StockTwits Negative	0.08***		
3	EPU Index	0.04	-0.03	
4	ADS Index	-0.01	0.01	0.01

Note: *** = Significance at the 1% confidence level.

[2] http://www.policyuncertainty.com/
[3] https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index

As shown in Table 2, the StockTwits Positive sentiment proxies are positively correlated with the StockTwits Negative setiment proxies, for both levels and the first-difference sentiment proxies. These correlations are statistically significant at 1% and are not close to -1. Positive sentiment is not necessarily the opposite of negative sentiment. These findings suggest that positive sentiment and negative sentiment are separate sentiments. Most sentiment studies, especially studies utilising market-based sentiment proxies, could not separate their sentiment proxies into a positive sentiment proxy and negative sentiment proxy because of the limitations in the sentiment proxies. For these studies, a higher value on the sentiment index indicated positive sentiment, while a lower value on the sentiment index indicated a negative sentiment. Based on the assumptions of these studies, the correlation between StockTwits positive sentiment and negative sentiment should be -1. Studies such as those of Tetlock (2007), Garcia (2013), Omura and Todorova (2019), Yin et al. (2021) and Öztürk & Bilgiç (2021), which have separate positive and negative sentiment proxies, find different returns predictability results for the positive sentiment proxy and negative sentiment proxy. The correlation findings in Table 2 support the findings of these studies and the call for separate positive and negative sentiment measures, as they capture different sentiments.

In addition, these correlation findings demonstrate a discussion on StockTwits wherein users share their opinions about the financial market and investments (Guégan & Renault, 2021). Some users may tweet positive words about the financial market and investments, while others tweet negative ones. As a result, there is no dominant positive sentiment or negative sentiment on StockTwits. This type of discussion on StockTwits fulfils the objective of the platform.

The results in Table 2 also show that all sentiment proxies have a very low and insignificant correlation with the macroeconomic variables. These results seem to suggest that the sentiments on StockTwits are very unlikely to be based on economic conditions and business conditions. These findings support Baker and Wurler's (2007) and Da et al.'s (2015) argument that sentiment is not driven by fundamentals.

5. RESULTS AND DISCUSSION

5.1 Empirical Results

Table 3 presents the results derived from Equation 1. Results from $k = 2$ to $k = 5$ are not discussed since their point estimates are not statistically and economically significant. Based on the results shown in Table 3, the null hypothesis for StockTwits Positive and Δ StockTwits Negative are rejected at the 10% significance level. StockTwits Positive and Δ StockTwits Negative predict subsequent futures returns even after controlling for lagged returns, the EPU Index, and the ADS Index. On the contrary, the null hypothesis for StockTwits Negative and Δ StockTwits Positive cannot be rejected. These sentiment proxies do not predict S&P500 Futures returns.

StockTwits Positive has a negative relationship with S&P500 Futures returns of the following day. A 1 standard deviation increase in the number of positive words tweeted on StockTwits predicts a decrease in the S&P500 Futures returns of 3.3 basis points for the following day. On the other hand, Δ StockTwits Negative has a positive relationship with the S&P500 Futures returns of the following day. A 1 standard deviation increase in the negative word count in StockTwits tweets compared to the negative word count on the previous day predicts a subsequent increase in the S&P500 Futures returns of 3.4 basis points.

Consistent with the noise trader framework, sentiment-induced demand shock affects the S&P500 Futures price. However, this change in the S&P500 Futures price is temporary as it is not driven by any change in fundamentals (Baker & Wurgler, 2007; Nayak, 2010). As shown in Table 3, the change in sign from negative on day t to positive on day $t+1$ illustrates that an increase in Δ StockTwits Negative corresponds with a decrease in contemporaneous S&P500 Futures returns on day t and predicts reversal of the S&P500 Futures returns on the next day. Table 3 illustrates a change in sign for the StockTwits Positive coefficient although the relationship between StockTwits Positive and contemporaneous returns is not statistically significant. The returns reversals in Table 3 support the correlation findings in Table 2, namely that these sentiments are unrelated to

Table 3 StockTwits Sentiment and S&P500 Futures Returns

	Levels Sentiment		**Δ Sentiment**	
	(1)	(2)	(3)	(4)
	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)
StockTwits Positive	0.046	-0.033*	0.075	0.003
	(0.96)	(-1.77)	(1.15)	(0.19)
EPU	-0.029	-0.007	-0.032	-0.009
	(-1.21)	(-0.28)	(-1.33)	(-0.36)
ADS	0.001	0.026***	0.001	0.027***
	(0.11)	(10.04)	(0.1)	(10.2)
Ret (t)		-0.033		-0.035
		(-0.86)		(-0.85)
Ret (t-1)	-0.039	0.018	-0.037	0.015
	(-0.98)	(0.34)	(-0.94)	(0.28)
Ret (t-2)	0.02	-0.063*	0.026	-0.061*
	(0.36)	(-1.88)	(0.45)	(-1.88)
Ret (t-3)	-0.058*	-0.022	-0.059*	-0.02
	(-1.68)	(-0.64)	(-1.71)	(-0.56)
Ret (t-4)	-0.017	-0.071**	-0.016	-0.072***
	(-0.49)	(-2.22)	(-0.48)	(-2.33)
Adjusted R^2	0.005	0.011	0.01	0.01
StockTwits Negative	-0.091***	-0.007	-0.108***	0.034*
	(-3.78)	(-0.28)	(-3.86)	(1.78)
EPU	-0.026	-0.007	-0.032	-0.008
	(-1.02)	(-0.28)	(-1.28)	(-0.3)
ADS	0.001	0.027***	0.001	0.027***
	(0.08)	(10.08)	(0.12)	(10.23)
Ret (t)		-0.036		-0.029
		(-0.91)		(-0.74)
Ret (t-1)	-0.049	0.015	-0.039	0.016
	(-1.11)	(0.27)	(-0.91)	(0.3)
Ret (t-2)	0.015	-0.063*	0.03	-0.065**
	(0.32)	(-1.87)	(0.6)	(-1.96)
Ret (t-3)	-0.061*	-0.022	-0.055	-0.021
	(-1.87)	(-0.65)	(-1.62)	(-0.6)
Ret (t-4)	-0.021	-0.072**	-0.019	-0.071**
	(-0.63)	(-2.27)	(-0.56)	(-2.24)
Adjusted R^2	0.013	0.01	0.018	0.011

Notes: The table shows α_i estimates, Newey-West (1987) t-statistics in parentheses, and the adjusted R-squared values. All coefficients are standardized coefficients.***, **, and * = significance at the 1%, 5%, and 10% confidence levels respectively.

economic conditions and business conditions. In addition, these findings are consistent with sentiment theory and corroborate previous findings by Tetlock (2007) and Da et al. (2015).

The findings for StockTwits Positive and Δ StockTwits Negative are economically significant considering the mean of daily returns shown in Table 1 is 3 basis points. This returns predictability is only for the following day as social media transmits information quickly (Da et al., 2015; Zhang, 2014). As a result, sentiment on social media like StockTwits changes rapidly (Lehrer et al., 2021).

Despite the economic and statistical significance, the adjusted *R*-square for both StockTwits Positive and Δ StockTwits Negative is only 1.1%. This low adjusted *R*-square indicates that Equation 1 only explains a small amount of variation in the S&P500 Futures daily returns. Although academics and practitioners have argued that social network financial sentiment proxies outperform previous sentiment proxies because of the UGC characteristic, the 1.1% adjusted *R*-square is lower than the 2.7% adjusted *R*-square for the FEARS sentiment proxy constructed from Google Search Volume Index in Da et al. (2015) as well as the 2% adjusted *R*-square for well-known large speculator sentiment and large hedger sentiment computed from actual trader positions reported in the COT report in Wang (2001). The adjusted *R*-square for social network financial sentiment proxies from StockTwits by Guégan and Renault (2021) was only 0.6% for a frequency of 15 minutes. The findings here suggest that social network financial sentiment proxies from all tweets in social media are not necessarily better than other sentiment proxies, although the tweets are from investment-based social media.

As seen in Table 3, the levels and first-difference sentiment proxies show different findings with respect to returns. Previous studies, such as from Brown and Cliff (2004) and Wang et al. (2006), utilised levels and first-difference sentiment proxies as no studies have clarified the level of sentiment or first-difference that best predicts returns. These prior studies considered market-based sentiment proxies, survey sentiment proxies and, as also shown in this study, social media sentiment proxies. In addition, the positive and negative sentiment findings illustrate the asymmetry of returns predictability findings in Tetlock (2007), Garcia (2013), Omura and Todorova (2019), Yin et al. (2021) and Shen et al. (2022). Like Fisher and Statman (2000), Sanders et al. (2003) and Wang (2003) have identified, different sentiment proxies have different relationships with returns. All the findings about social network financial sentiment proxies in Table 3 reiterate the findings of these prior studies.

In addition to the sentiment proxies, coefficients for lagged returns and the ADS Index in Table 3 corroborate the findings by Goldenberg (1988) and Bessembinder (1992) that past returns in the futures market and macroeconomic variables affect returns in the futures market. The significant coefficients for lagged returns until lag 4 support the findings from the AIC and BIC tests that lag 4 is the optimal lag for Equation 1. The finding that ADS coefficients are significant at the 1% significance level for all sentiment proxies except the EPU Index coefficients which is not significant, suggests that once business conditions are considered, economic policy uncertainty does not influence returns in the futures market.

5.2 Robustness Check

Other potential explanations for the results could be a liquidity shock, the day-of-the-week effect, the January effect, the holiday effect, or major Asian and European markets with different closing and opening hours relative to the United States. The results of this study are presented in Table 4. The Durbin-Watson test for all these control variables was close to 2, while the VIF test results were close to 1.

5.2.1 Liquidity Shock

Liquidity shocks were first tested for via macro announcements (Da et al., 2015).

Macro announcements were defined as producer price index (PPI) announcements, employment announcements, and Federal Open Market Committee (FOMC) interest rate announcements (Da et al., 2015; Savor & Wilson, 2013). These announcements contain economic information (Jones et al., 1998) and, like sentiment, move the futures price away from its fundamental value (Da et al., 2015; Fabozzi et al., 1994) by influencing sentiment or portfolio rebalancing (Da et al., 2015). PPI announcements were collected with employment announcement dates from the Bureau of Labor Statistics's website[4] and FOMC interest rate announcements dates from the Federal Reserve website.[5] Macro announcement days were removed from the observations (Da et al., 2015) while it was found that all results except those for StockTwits Positive remained statistically and economically significant. However, StockTwits Positive no longer predicted S&P500 Futures returns once the macro announcement days were removed from the sample. This finding shows that StockTwits Positive does not predict daily futures returns but merely captures the effect of macro announcements on daily futures returns.

Futures turnover (Da et al., 2015) was considered in the second test. In this, futures

Table 4 Results for Robustness Checks

	No Macro Announcements				Turnover			
	Levels Sentiment		**Δ Sentiment**		**Levels Sentiment**		**Δ Sentiment**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ret (t)	Ret (t + 1)	Ret (t)	Ret (t + 1)	Ret (t)	Ret (t + 1)	Ret (t)	Ret (t + 1)
StockTwits Positive	0.045	-0.028	0.07	-0.007	0.047	-0.034*	0.074	0.004
	(0.96)	(-1.49)	(1.14)	(-0.36)	(1.02)	(-1.83)	(1.18)	(0.2)
Adjusted R^2	0.004	0.01	0.008	0.009	0.006	0.012	0.01	0.01
StockTwits Negative	-0.087***	0.007	-0.119***	0.036**	-0.09***	-0.008	-0.108***	0.033*
	(-3.46)	(0.29)	(-4.48)	(2.08)	(-3.74)	(-0.34)	(-4.25)	(1.82)
Adjusted R^2	0.011	0.009	0.02	0.01	0.013	0.01	0.018	0.012
	Day-of-the-Week, January and Holiday Effect				**Asian and European Returns**			
	Levels Sentiment		**Δ Sentiment**		**Levels Sentiment**		**Δ Sentiment**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ret (t)	Ret (t + 1)	Ret (t)	Ret (t + 1)	Ret (t)	Ret (t + 1)	Ret (t)	Ret (t + 1)
StockTwits Positive	0.046	-0.033*	0.076	0.003	0.013	-0.045**	0.036	0.005
	(1.22)	(-1.69)	(1.29)	(0.16)	(0.5)	(-2.11)	(1.16)	(0.23)
Adjusted R^2	0.005	0.011	0.01	0.009	0.46	0.017	0.498	0.014
StockTwits Negative	-0.093***	-0.007	-0.112***	0.032*	-0.079***	-0.003	-0.08***	0.037*
	(-3.47)	(-0.33)	(-3)	(1.69)	(-4.84)	(-0.11)	(-4.05)	(1.93)
Adjusted R^2	0.013	0.009	0.018	0.01	0.468	0.014	0.505	0.016

Notes: The table shows α_i estimates, Newey-West (1987) t-statistics in parentheses, and adjusted *R*-squared values. All coefficients are standardized coefficients. ***, **, and * = significance at the 1%, 5%, and 10% confidence levels respectively.

[4] https://www.bls.gov/
[5] https://www.federalreserve.gov

turnover was calculated as the total number of futures contracts traded each day (volume) divided by open interest (Yung & Liu, 2009). Volume and open interest data were obtained from DataStream. This turnover is included as an additional control variable in Equation 1. As shown in Table 4, turnover has very little effect on the results.

5.2.2 The Day-of-the Week Effect, the January Effect, and the Holiday Effect

The next robustness test assessed the regularities in the financial market. The day-of-the week effect, the January effect, and the holiday effect were included as additional controls in Equation 1 (Da et al., 2015). Due to the day-of-the-week effect, returns on certain days are higher than other days (Cross, 1973; French, 1980), while due to the January effect, returns are higher in January than in other months (Rozeff & Kinney, 1976). The holiday effect refers to how returns on days prior to a holiday are higher than on other days (Ariel, 1990; Fabozzi et al., 1994). Exchange-close holidays that were considered included New Year's Day, Presidents Day, Good Friday, Memorial Day, the Fourth of July, Labor Day, Election Day, Thanksgiving Day, and Christmas Day. In addition, exchange-open holidays like Groundhog's Day, Martin Luther King Jr. Day, Valentine's Day, St. Patrick's Day, Mother's Day, Flag Day, Father's Day, Columbus Day, Halloween, Election Day, and Veterans Day were also included. Little impact was found that of any of these effected the results.

5.2.3 Major Asian and European Markets

The Nikkei (Japan), the Hang Seng (Hong Kong), the Strait Times Index (Singapore), the TAISE 50 (Taiwan), the Shenzhen Composite Index (China), the FBM KLCI (Malaysia), the BSE 30 (India), and the FTSE 100 (UK) were considered (Singh et al., 2010). The CAC 40 and the DAX 30, were also considered but the VIF test indicated multicollinearity between the FTSE 100, the CAC 40, and the DAX 40. This VIF test result is not surprising since the FTSE 100 influences the CAC 40 and the DAX 30 (Yang & Bessler, 2004). These returns were included as additional control variables in Equation 1. The findings suggest that the returns predictability as shown in Table 3 did not capture the effects of these markets on S&P500 Futures returns.

6. CONCLUSION

Overall, this study found that a greater number of negative social media words compared to the previous day can indicate a negative sentiment to the returns on that day but this negative sentiment tends to be reversed on the following day. This number of negative social media words does not have the same relationship with returns in the futures market as that of positive words. These positive words and negative words on social media are neither highly correlated nor the opposite of each other. When users on social media do not tweet negatively, it was shown that they do not necessarily feel positive about the futures market.

This study shows that sentiment proxies from social media predict returns in the futures market. These findings have implications on researchers, companies that construct sentiment proxies from social media, investors who use these proxies for trading decisions, and companies that want to maintain good investor relations.

For companies that construct sentiment proxies from social media and investors that utilize these proxies, the findings could be employed, or the methods shown in this paper could be improved to construct social network sentiment proxies. Furthermore, the next day returns predictability suggests the formation of sentiment proxies in real-time, daily, half-hour time periods, one-hour time periods, and so forth. Finally, companies should measure the positive and negative sentiment on social media separately. This study suggests separate positive and negative sentiment proxies rather than a sentiment proxy whereby low sentiment values indicate negative sentiment, and high sentiment values indicate positive sentiment. For researchers, these findings on social media support the call for a new, flexible, positive and negative emotion framework in the psychology literature.

Consumers and investors could easily share their opinion and experiences about a company on social media (Ontario Securities Commission, 2022) and as the findings in this study illustrate, this sentiment could potentially affect their sales or stock price. For companies that wish to maintain good investor relations, the findings in this study suggest that they should monitor the sentiment about their products and company. By doing so, companies gauge potential issues or queries that their consumers and investors have (Hill, 2022), whilst also connecting and engaging effectively with their consumers and investors. After all, the influence of social media is here to stay, and is likely to be increasing over time.

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