Can Social Media Sentiment Predicts Futures Returns?

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Abstract

We utilise tweets during trading hours and non-trading hours from StockTwits, an investment-based social media, to produce positive and negative sentiment measures. Then, we determine whether StockTwits sentiment could predict US index futures returns. We find positive sentiment from trading hours tweets could predict next day's returns of S&P500 Futures, Emini S&P500 Futures, Emini Dow Futures and Emini NASDAQ100 Futures. A one percent increase in positive sentiment indicates a decrease of 0.054% in Emini NASDAQ100 Futures next day return and 0.044% in EMini Dow Futures next day return.

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I. Introduction

StockTwits positive sentiment predicts next day index futures returns. We use 31,713,360 tweets posted on StockTwits from 1st August 2009 to 31 August 2015 to determine if the sentiment from these tweets could predict daily returns of four well-known futures contract, S&P500 Futures, EMini S&P500 Futures, EMini Dow Futures and NASDAQ100 Futures contracts. StockTwits is a social media that was created with the objective of providing a platform where investors can share their ideas and exchange their information about financial markets or specific stocks (StockTwits Inc., 2016). We divide these tweets into New York Stock Exchange trading hours tweets and non-trading hours tweets based on the time users post them. We divide the tweets into non-trading hours tweets and trading hours tweets to determine if the sentiment from these categories have different predictive ability. Antweiller and Frank (2004) expects that investors posts more after trading hours and take a position based on their posting when the market opens. On the other hand, they expect that investors who post during trading hours are day traders or investors who just post while they are working. Based on Antweiller and Frank (2004) s' expectations that more investors tweet when the market closes and take actions when the market opens, then we would expect that the StockTwits sentiment measures from tweets posted after trading hours are more strongly related to futures returns. However, based on Antweiller and Frank (2004) s' actual findings that people post more during trading hours and if these users take positions in the stock market, we would expect that the StockTwits sentiment measures from tweets posted during trading hours are more strongly related to futures returns. Then, we calculate the number of positive and the number of negative words in the tweets on each day before dividing these numbers with total words in the tweets. These are our positive and negative sentiment scores. We find that most of the sentiment scores from tweets during non-trading hours could not predict following days returns but positive sentiments from tweets during trading hours could predict the following day returns. A one standard deviation change in the positive sentiment measure predictably lowers NASDAQ index futures returns by 0.054%.

Unlike previous social media sentiment studies, we choose to focus on whether StockTwits sentiment could predict daily index futures returns. Futures market is attractive to investors because they could take higher leverage and exposure as speculators in the futures market compared to the equity market. However, this attribute too has caused futures trading to be risky[1]. Not only that, investors in US equity market and international equity market observes the US futures market to foresee future

[1] The futures market can suffer very sharp decrease due to the release of gloomy statistics (https://www.cnbc.com/2014/10/16/after-market-rout-us-stocks-to-focus-on-earnings.html)

movements in equity market[2]. For example, existing studies shows the S&P500 index futures lead S&P500 index (Kawaller, Koch & Koch, 1987; Stoll & Whaley, 1990; Chan, 1992). As such, indicators that could predict the direction of the futures market, including sentiment indicators, is of particular interest to both academicians and investors in the futures market. Currently, sentiment indicators that are known to predict index futures returns are market variables[3] and trader-position reports[4]. Based on our findings, trading hours social media sentiment provides an alternative sentiment indicator to index futures returns. However, StockTwits positive sentiment has different predictability across futures contract with different underlying equity indices. From the four futures contract, StockTwits positive sentiment has the strongest relationship with EMini Nasdaq100 Futures returns and weakest relationship with EMini Dow futures returns.

II. Theoretical Framework

This study adopts the working definition of investor sentiment from Brown and Cliff (2004). Sentiment represents the expectations of market participants relative to a norm. An investor who is bullish (bearish) will expect returns to be above (below) their average value. Thus, bullish represents expected stock price increase while bearish represents expected stock price decrease. This sentiment shifts over time, sometimes excessively optimistic and sometimes excessively pessimistic (Thaler, 1992).

Investor sentiment influences market behaviour because noise traders trade on this sentiment as though it is information (Wang, Keswani & Taylor, 2006). This notion of noise trader was first introduced by Black (1986) and further explained in De Long et al. (1990)s' noise trader framework. According to the framework, these noise traders trade upon advices they receive from newspaper and social media since they have no access to insider information to conduct their own research. Thus, they are influence by the sentiment in these media. When there are more noise traders than rational investors, asset prices will respond to the changes in the sentiment of these noise traders hence become more volatile (Shleifer, 2000). In this case, the price of stocks reflects not only information that traders trade on but also noise that noise traders trade on. However, traditional approach in finance contends that

[2] The futures market could provide us information on how the stock market behaves when it is open for trading (http://www.marketwatch.com/story/stock-futures-pointing-to-sharp-losses-when-us-re-opens-tuesday)
[3] Baker Wurgler sentiment index (Zheng, 2015; Lutzenberger, 2014), sentiment index that is similar to the Baker Wurgler sentiment index (Gao & Suss, 2015), VIX, put-call ratio and The Arms Index or TRIN (Simon & Wiggins, 2001; Chen & Chang, 2005) trading volume, open interest, buy-sell imbalance and psychological line index for the China futures market (Gao & Yang, 2017; Gao & Yang, 2017b; Yang & Gao, 2014)
[4] Disaggregated Commitments of Traders (DCOT) report (Bahloul & Bouri, 2016a; Bahloul & Bouri, 2016b; Tornell & Yuan, 2014; Chen & Maher, 2013; Wang, 2004; Wang 2003; Wang, 2001)

investor sentiment does not influence market behaviour because rational investors or arbitrageurs will move stock prices towards their fundamental values when sentiment-prone investors drive prices away. Proponents of behavioural finance assert that rational investors are unlikely to offset these trades by noise traders because of the noise trading risk, the risk that this noise traders' belief will continue to move further away from its means before reverting (Wang et al, 2006). This limited arbitrage occurs because these rational traders have short trading horizon and risk averse (De Long et al., 1990; Thaler, 1992).

The noise trader framework posits that investor sentiment has a positive relationship with returns and negative relationship with volatility. When these noise traders overestimate (underestimate) the expected returns, they are more bullish (bearish) than average thus would demand more (less) and bid up (down) the price of the asset (Shleifer, 2000). Bullish (bearish) changes in sentiment result in downward (upward) adjustments in volatility (Brown, 1999; Lee et al., 2002). On the other hand, the bargain shopper perspective explained by Brown and Cliff (2004) argues that investor sentiment has a negative relationship with returns. According to Brown and Cliff (2004), when investors are bearish and the price of stocks decreases, some investors would purchase the stocks because the stocks have become a bargain (Brown & Cliff, 2004). Investors will see a buying opportunity and becomes bullish (Brown & Cliff, 2004).

Limited cognitive processing abilities could help explain how noise traders make their decision based on sentiment. For investors to make optimal investment decisions, they would need a list of choices, apply complex mathematical tools to determine the probability of outcomes for each choices, assign weights to alternatives and finally, choose the choice with the highest weighted value (Karl-Erik, 2001) that maximises their expected utility (Edwards, 1954). However, Simon (1972) argued that investors have bounded rationality because they could not possibly know all outcomes due to their limited search and computational capacities (Simon, 1972). Furthermore, investors might suffer from information overload from all available information. As a result, they would be confused (Malhotra, 1984). Investors will most likely apply simplifying strategies (Wright & Kriewall, 1980, p. 279), focus on fewer cues (Malhotra, 1984) and overweight any negative evidence (Wright & Weitz, 1977). When investors use their affective impression as their simplifying strategy (Nofsinger, 2002), they are applying affect heuristic (optimism and pessimism). This is how their sentiment influences their financial decision making.

III. Data and Methodology

I. Data

This study utilises 31 713 360 tweets from 154 174 users in the sample period of August 1st 2009 to August 31st 2015. The number of tweets increases exponentially from August 2009 to the middle of 2013 before slightly decreasing. On average, most of the users in StockTwits perceives themselves to have intermediate and professional experience in investment although in 2015, the number of users who did not specify their investment experience is higher than the total of intermediate and professional experience. In 2015, 10% of the 2015 users who tweeted claim to be novice investors. Based on this information, it seems that the users who tweets are likely to have a good knowledge about investments since they admitted to have some level of experience in investment. The low level of novice might indicate that StockTwits users who tweets might be investors hence their collective sentiment could have a predictive relationship with the futures market. Of the 31 713 360 tweets, the number of tweets from users who claim to trade futures contracts range from 29 439 to 1 150 522. Given the high number of tweets from users who claim to trade futures contract, StockTwits sentiment could have predictability on futures returns.

We collect the futures return data from Datastream. Similar to Wang (2003), we create a daily time series for the futures returns as the percentage change in settlement prices of the contract with the nearest delivery date using a roll-over strategy. We collect the daily economic policy uncertainty (EPU) Index from a public website[5], Aruoba-Diebold-Scotti (ADS) business conditions index from the Federal Reserve Bank of Philadelphia website[6] and CBOE VIX from CBOE website[7].

II. Quantifying Tweets into Sentiment Scores

The first step to quantify the tweets into daily sentiment scores is to process the tweets. The total number of tweets from 1 August 2009 to 31 August 2015 is 31, 786, 774 tweets. After processing the tweets, we have 31 713 360 tweets in our sample.

[5] http://www.policyuncertainty.com/
[6] https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index
[7] https://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data

The second step to quantify the tweets into daily sentiment scores to divide the tweets into NYSE non-trading hours tweets and NYSE trading hours tweets based on the time the tweets were posted. The non-trading hours tweets are tweets posted from 4.00pm at day t-1 to 9.30am Eastern time at day t while trading hours tweets are tweets posted from 9.30am to 4.00pm Eastern time at day t.

The third step to quantify the tweets into daily sentiment scores is to calculate the number of positive words and negative words in each tweets. For each tweet *i* tweeted on date *t*, we count the number of positive words, g_{it}, negative words, b_{it} and total number of words, w_{it}. We use the Loughran McDonald positive and negative word lists to identify positive and negative words in the tweets. The positive word list and negative word list consist of 354 words and 2355 words respectively. We choose Loughran McDonald word lists that is developed from the finance domain (Rogers et al., 2011; Ferris et al., 2013) and has been extensively used in the accounting and finance research domain (Garcia, 2013; Chen et al., 2014; Engelberg, 2008; Solomon, 2014; Dougal et al., 2012; Liu & McConnell, 2013; Gurun & Butler, 2012; Solomon, Soltes & Sosyura, 2014; Ahern & Sosyura, 2014).

The final step to quantify the tweets into daily sentiment scores is to normalize the positive word count, g_{it} and negative word count, b_{it} by dividing those word counts with total number of words, $w_{it.}$ (Garcia, 2013; Rogers at al., 2011). Once we have the normalised sentiment scores, we transform these scores into percentage. Previous studies have also employ these calculations to determine the final positive and negative scores (Kothari et al., 2009; Hanley & Hoberg, 2010; Heston & Sinha, 2015; Rogers et al., 2011; Solomon et al., 2014; Ahern & Sosyura, 2014; Garcia, 2013). We follow Garcia (2013)'s approach who quantifies the words in the New York Times' "Financial Markets" column and "Topics in Wall Street" columns into positive, negative and neutral tone to incorporate the tweets posted on non-trading days. To do so, we include the word count of tweets that were posted on non-trading day in the next trading day. In total, there are 1531 daily observations for the social media sentiment from the period of August 2009 to August 2015. We summarise these calculations in the equations below.

When the market is open on consecutive days, t & t+1, the daily measure of positive tweet content, G_{it}:

$$G_{it} = \frac{\sum_i g_{it}}{\sum_i w_{it}} \qquad \text{Equation (1)}$$

where the summation is over all tweets written on date *t*.

When the market is open on consecutive days, t & t+1, the daily measure of negative tweet content, B_{it}:

$$B_{it} = \frac{\sum_i b_{it}}{\sum_i w_{it}} \qquad \text{Equation (2)}$$

For non-consecutive market days, all the tweets posted from when the market is close to when the market is open are included on the next trading day when the market is open. For where the market was closed for h days, such that h>0, the positive tweet content and negative tweet content is

$$G_{it} = \frac{\sum_{i,s=t}^{s=t+h} g_{it}}{\sum_{i,s=t}^{s=t+h} w_{it}} \qquad \text{Equation (3)}$$

$$B_{it} = \frac{\sum_{i,s=t}^{s=t+h} b_{it}}{\sum_{i,s=t}^{s=t+h} w_{it}} \qquad \text{Equation (4)}$$

Figure 1.0 provides insights on some essential characteristics about the sentiment scores. First, Figure 1 (a) and Figure 1 (b) indicate the presence of outliers. To mitigate this concern, we winsorize the positive sentiment and negative sentiment at 1% level (0.5% on each tail) (Baker & Wurgler, 2006; Da et al., 2015). In addition, we plot daily positive sentiment scores and negative sentiment scores by year to examine for trend and seasonality issues[8]. These plots reveal that the positive sentiment scores increase in January compared to other months and decreases on Monday respectively. Thus, we regress our sentiment scores with weekday dummies and month dummies, an approach taken by Da et al. (2015). Garcia (2013) performs a similar treatment in the regression.

[8] We do not plot the data for the period of 2009 because the 2009 period are too short to provide insight into trends and seasonality. The plot is available upon request.

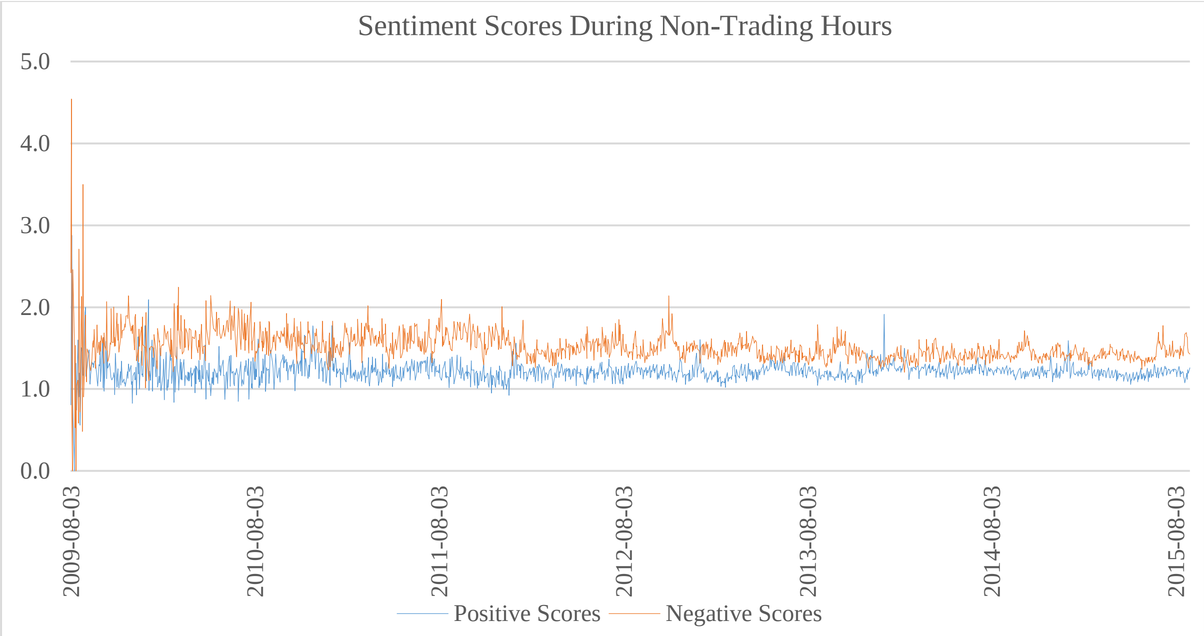

Figure 1.0 (a)

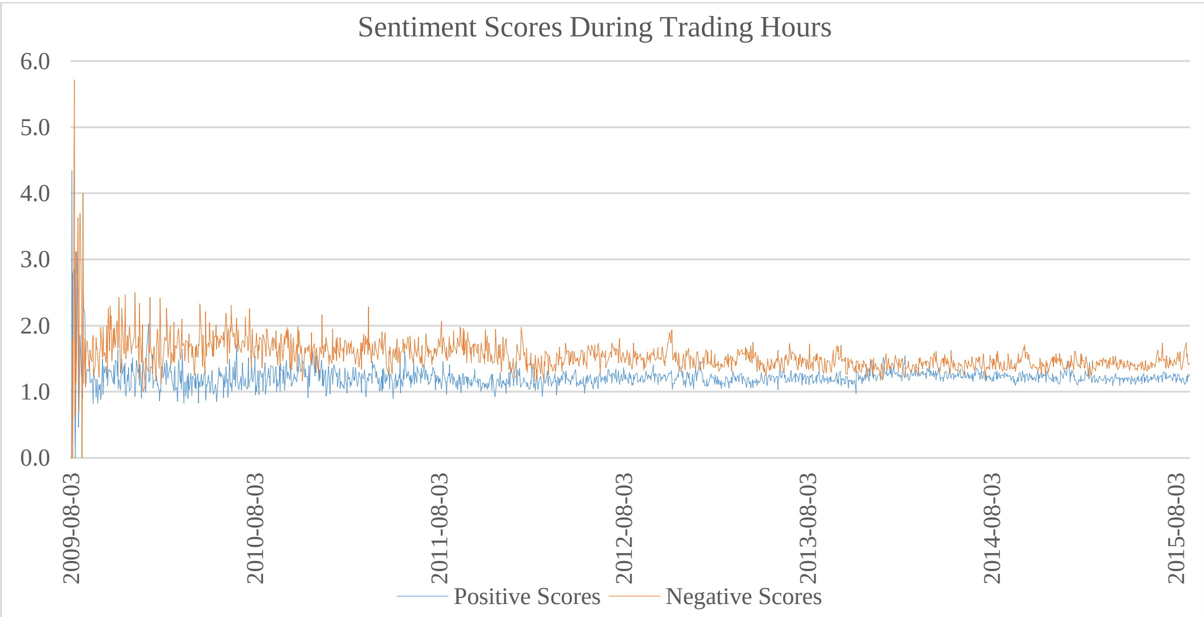

Figure 1.0 (b)

Figure 1.0: Plots of positive and negative sentiment scores during non-trading hours and trading hours. Each plot presents the daily positive and negative sentiment scores from August 2009 to August 2015. The y-axis is the sentiment scores in percentage while the x-axis is the date of the sample period and is in yearly unit. The positive sentiment scores are calculated based on Equation (1) and Equation (3) while the negative sentiment scores are calculated based on Equation (2) and Equation (4).

III. Measuring StockTwits Sentiment Predictability over Futures Returns

We test whether StockTwits sentiments could predict the four futures contract returns using the model in Equation 5.0. Da et al. (2015) applies this model to test the predictability of their Financial and Economic Attitudes Revealed by Search (FEARS) Index on S&P500 Index returns.

$$R_{i,t+k} = \beta_0 + \beta_1 S_t + \sum \gamma_m \, Control_{i,t}^{m} + u_{i,t+k} \quad (5)$$

whereby $R_{i,t+k}$ is the return for S&P500 futures contract, EMini S&P500 futures contract, EMini Dow Futures contract or NASDAQ100 futures contract. S_t is the StockTwits positive sentiment or StockTwits negative sentiment. The control variables $Control_{i,t}^{m}$ are lagged asset-class returns (up to five lags), a news-based measure of economic policy uncertainty (EPU), Aruoba-Diebold-Scotti (ADS) business conditions index and CBOE VIX. The latter three control variables are macroeconomic variables.

The economic policy uncertainty (EPU) Index is developed by Baker, Bloom and Davis (2016). It is based on Newsbank news aggregator that covers about 1500 U.S newspapers and is calculated based on the frequency of articles that contain the words "economic" or "economy", "uncertain or uncertainty", "Congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House". This EPU index has captured policy uncertainty surrounding major events like tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the collapse of Lehman Brothers, the 2011 debt ceiling dispute. The next control variable is the daily Aruoba-Diebold-Scotti (ADS) business conditions index. This index constitutes six economic indicators which are the quarterly real GDP, manufacturing and trade sales, industrial production, personal income less transfer payments, monthly payroll employment, weekly initial jobless claims (Federal Reserve Bank of Philadelphia, 2017).

IV. Empirical Results

I. Descriptive Statistics

Table 1.0 presents descriptive statistics for StockTwits sentiment and other sentiment proxies. We use other sentiment proxies as a benchmark to discuss StockTwits sentiment.

Table 1.0: Summary Statistics

The table reports sample statistics for the tweets from StockTwits and other sentiment proxies. These data are collected from the period of August 2009 to August 2015 with 1531 daily observations. The positive and negative tone, all measured in percentages, are constructed using lexicon-based method. The word lists employed are the positive and negative Loughran and McDonald (2011) words lists. Panel A, Panel B and Panel C illustrates the summary statistics based on the frequency of the data. The values here reflect the data prior to winsorization, detrend and standardisation.

	Min	Mean	Median	25%-quant	75%-quant	Max	Stand. dev.
Panel A: Daily data							
StockTwits Sentiment							
Non-trading hours sentiment							
Positive	0.00	1.21	1.20	1.15	1.26	2.88	0.13
Negative	0.00	1.52	1.49	1.40	1.60	4.55	0.20
Trading hours sentiment							
Positive	0.00	1.21	1.20	1.14	1.26	4.35	0.18
Negative	0.00	1.54	1.50	1.40	1.64	5.71	0.26
Other Sentiment Proxies							
CBOE VIX	10.32	18.63	17.00	14.05	21.43	48.00	6.12
VXD	9.71	17.02	15.44	13.45	19.11	41.45	5.27
VXN	11.36	19.82	18.43	15.52	22.45	46.63	5.77
Number of observations	1531						
Panel B: Weekly data							
StockTwits Sentiment							
Positive	1.24	8.65	8.60	8.35	8.85	12.45	0.72
Negative	1.44	10.56	10.42	9.93	11.12	16.01	1.01
Other Sentiment Proxies							
AAII Bullish	19.31	38.16	38.31	32.36	43.09	63.28	7.88
AAII Neutral	13.95	30.61	30.18	26.67	33.88	49.79	6.47
AAII Bearish	15.05	31.22	30.12	25.41	35.74	57.07	7.75
Number of observations	318						
Panel C: Monthly data							
StockTwits Sentiment							
Positive	20.51	37.45	37.66	36.51	38.50	42.24	2.70
Negative	16.61	45.64	45.84	43.42	47.92	53.62	4.79
Other Sentiment Proxies							
Michigan Index	55.80	77.43	76.00	72.30	82.50	98.10	9.06
Baker Wurgler	-0.90	-0.27	-0.24	-0.34	-0.14	0.17	0.22
Yale Institutional	56.34	69.43	68.47	64.65	74.23	82.73	6.95
Yale Individual	44.74	60.50	63.35	50.75	67.82	74.33	8.95
Number of observations	74						

For StockTwits daily sentiment, mean positive sentiment score is 1.21% of total words in the tweets. This indicates that on average of 140 maximum total words in a tweet, there are approximately 2 positive words. Compared to positive words, on average, there are approximately 3 negative words for 140 maximum total words in a tweet. There is slightly more negative words for each tweet. As a result, the average negative sentiment score is 1.52% of total words in the non-trading hours tweets and 1.54% of total words in the trading hours tweets. This finding corroborates Garcia (2013)'s findings that on average, an article has more negative words than positive words. However, this finding is inconsistent with Hochreiter (2015)'s that investigates StockTwits. One potential explanation for this difference is the sample period. Hochreiter (2015) looks at the period from 2010 to 2014 while this study explores period from August 2009 to August 2015. Another potential explanation is that we employ Loughran McDonald positive word lists which contains only 354 words, one sixth of the words in the Loughran McDonald negative word lists. Thus, there could be other positive words that are not captured through our approach. On the other hand, Hochreiter (2015) obtains the data from PsychSignal that employs linguistic inquiry and word count (LIWC) application. This finding is also the opposite of Nofer (2015), Antweiller and Frank (2004) as well as Das and Chen (2007). Nofer (2015) looks at Twitter while both Antweiller and Frank (2004) and Das and Chen (2007) looks at Yahoo's message boards. Looking at the weekly AAII sentiment, the average for bullish sentiment is higher than the average for bearish sentiment with 38.16% and 31.22% respectively. In other words, on average, the AAII investors surveyed are more optimistic than they are pessimistic. This finding is opposite to the weekly StockTwits sentiment. The average StockTwits negative sentiment is higher than the average StockTwits positive sentiment.

Panel C presents the standard deviation for StockTwits sentiment measures is higher than the standard deviation for Baker Wurgler Sentiment Index but lower than the standard deviation of the University of Michigan Sentiment Index, Yale Institutional Sentiment Index and Yale Individual Sentiment Index. The same can be said about investors surveyed in the Yale Institutional Sentiment Index and Yale Individual Sentiment Index. It is also lower than the standard deviation of the daily CBOE VIX and weekly AAII. The results that StockTwits sentiment has lower variability compared to institutional investors sentiment seems to echo Wang (2001)'s findings that their small traders' sentiment has lower variability compared to large traders' sentiment. Wang (2001) suggest their findings could be due to small traders trade less actively than large traders.

II. StockTwits Sentiment Predictability in Futures Contract

From Table 2.0 and Table 3.0, there are three major findings on whether StockTwits sentiment could predict futures returns. First, non-trading hours StockTwits sentiment could not predict futures next day returns while sentiment from trading hours tweets could predict futures next day returns. Second, positive sentiment could predict next day's returns but negative sentiment measure could not predict following day's returns. It only has significant relationship with contemporaneous returns. Third, both sentiments have different predictive ability across different futures contract. Even when we replace the winsorised sentiment measures with unwinsorised sentiment measures in Equation 5.0, the relationship between StockTwits sentiments and returns remains significant.[9]

Table 2.0: Regressions of Daily Non-Trading Hours Sentiment on Futures Returns

The table reports results for Equation 5 regression when k = 0 for Model 1 to k = 5 for Model 6 for positive and negative sentiment. This sentiment is determined from tweets posted from 4.00 pm to 9.30 a.m. The dependent variable is log-return of S&P500 futures in Panel A, EMini S&P500 futures in Panel B, EMini Dow futures in Panel C and EMini NASDAQ100 futures in Panel D. The independent variable is the StockTwits sentiment measure while the control variables are lagged returns up to five lags, Aruoba-Diebold-Scotti (ADS) business conditions index, new-based measure of economic policy uncertainty (EPU) and CBOE VIX. The sample period is from August 2009 to August 2015, with a total of 1531 daily observations. The reported standard error is Newey-West standard error and the sentiment measure have been winsorised at 0.5% on each tail.

	(1) Return (t)	(2) Return (t + 1)	(3) Return (t + 2)	(4) Return (t + 3)	(5) Return (t + 4)	(6) Return (t + 5)
Panel A: S&P500 Futures						
Positive	-0.00002	-0.00044	-0.00020	-0.00006	-0.00004	0.00032
	(0.00030)	(0.00029)	(0.00022)	(0.00023)	(0.00025)	(0.00026)
Adjusted R^2	0.04497	0.01146	0.00461	0.00873	0.00177	0.00227
Negative	0.00046	-0.00025	-0.00041	0.00011	-0.00038	-0.00057
	(0.00031)	(0.00027)	(0.00031)	(0.00031)	(0.00034)	(0.00035)
Adjusted R^2	0.04662	0.01001	0.00563	0.00879	0.00298	0.00393
Panel B: EMini S&P500 Futures						
Positive	-0.00002	-0.00044	-0.00020	-0.00006	-0.00004	0.00032
	(0.00030)	(0.00029)	(0.00022)	(0.00023)	(0.00025)	(0.00026)
Adjusted R^2	0.04496	0.01144	0.00462	0.00872	0.00183	0.00235
Negative	0.00046	-0.00025	-0.00041	0.00011	-0.00039	-0.00057
	(0.00031)	(0.00027)	(0.00031)	(0.00031)	(0.00034)	(0.00035)
Adjusted R^2	0.04661	0.00998	0.00563	0.00878	0.00306	0.00399
Panel C: EMini Dow Futures						
Positive	-0.00010	-0.00036	-0.00028	-0.00018	-0.00008	0.00021
	(0.00027)	(0.00025)	(0.00020)	(0.00019)	(0.00021)	(0.00023)
Adjusted R^2	0.03352	0.00870	0.00308	0.00654	0.00173	0.00016
Negative	0.00050**	-0.00032	-0.00029	0.00012	-0.00039	-0.00049
	(0.00025)	(0.00023)	(0.00026)	(0.00026)	(0.00029)	(0.00031)
Adjusted R^2	0.03592	0.00811	0.00294	0.00629	0.00322	0.00207
Panel D: EMini NASDAQ100 Futures						
Positive	0.00029	-0.00050*	-0.00015	-0.00001	0.00007	0.00038
	(0.00030)	(0.00029)	(0.00023)	(0.00024)	(0.00025)	(0.00028)
Adjusted R^2	0.04272	0.01098	0.00351	0.00735	-0.00248	-0.00131
Negative	0.00048	-0.00012	-0.00033	0.00018	-0.00036	-0.00072**
	(0.00032)	(0.00030)	(0.00030)	(0.00032)	(0.00033)	(0.00037)
Adjusted R^2	0.04356	0.00895	0.00411	0.00757	-0.00161	0.00112

Notes: ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

[9] These results can be provided upon request

Table 3.0: Regressions of Daily Trading Hours Sentiment on Futures Returns

The table reports results for Equation 5 regression when k = 0 for Model 1 to k = 5 for Model 6 for positive and negative sentiment. This sentiment is determined from tweets posted from 9.30 a.m. to 4.00 pm. The dependent variable is log-return of S&P500 futures in Panel A, EMini S&P500 futures in Panel B, EMini Dow futures in Panel C and EMini NASDAQ100 futures in Panel D. The independent variable is the StockTwits sentiment measure while the control variables are lagged returns up to five lags, Aruoba-Diebold-Scotti (ADS) business conditions index, new-based measure of economic policy uncertainty (EPU) and CBOE VIX. The sample period is from August 2009 to August 2015, with a total of 1531 daily observations. The reported standard error is Newey-West standard error and the sentiment measure have been winsorised at 0.5% on each tail.

	(1) Return (t)	(2) Return (t + 1)	(3) Return (t + 2)	(4) Return (t + 3)	(5) Return (t + 4)	(6) Return (t + 5)
Panel A: S&P500 Futures						
Positive	0.00070**	-0.00053**	0.00014	0.00025	0.00008	0.00001
	(0.00032)	(0.00027)	(0.00025)	(0.00030)	(0.00024)	(0.00026)
Adjusted R^2	0.04990	0.01239	0.00441	0.00930	0.00182	0.00128
Negative	-0.00090***	-0.00021	-0.00013	-0.00010	0.00016	-0.00016
	(0.00027)	(0.00027)	(0.00025)	(0.00027)	(0.00029)	(0.00028)
Adjusted R^2	0.05194	0.00989	0.00436	0.00877	0.00200	0.00149
Panel B: EMini S&P500 Futures						
Positive	0.00071**	-0.00053**	0.00014	0.00025	0.00008	0.00001
	(0.00032)	(0.00027)	(0.00025)	(0.00030)	(0.00024)	(0.00026)
Adjusted R^2	0.04990	0.01238	0.00442	0.00929	0.00188	0.00135
Negative	-0.00090***	-0.00021	-0.00013	-0.00010	0.00016	-0.00015
	(0.00027)	(0.00027)	(0.00025)	(0.00027)	(0.00029)	(0.00028)
Adjusted R^2	0.05192	0.00988	0.00436	0.00877	0.00206	0.00156
Panel C: EMini Dow Futures						
Positive	0.00056*	-0.00044*	0.00011	0.00006	0.00006	0.00002
	(0.00029)	(0.00023)	(0.00023)	(0.00027)	(0.00021)	(0.00022)
Adjusted R^2	0.03742	0.00957	0.00225	0.00617	0.00168	-0.00038
Negative	-0.00067***	-0.00014	-0.00004	-0.00004	0.00009	-0.00002
	(0.00025)	(0.00023)	(0.00024)	(0.00024)	(0.00026)	(0.00024)
Adjusted R^2	0.03831	0.00728	0.00209	0.00615	0.00173	-0.00038
Panel D: EMini NASDAQ100 Futures						
Positive	0.00078*	-0.00054**	0.00039	0.00037	0.00012	0.00004
	(0.00042)	(0.00026)	(0.00028)	(0.00030)	(0.00022)	(0.00030)
Adjusted R^2	0.04723	0.01142	0.00466	0.00853	-0.00239	-0.00251
Negative	-0.00100***	-0.00000	-0.00017	-0.00002	0.00021	-0.00022
	(0.00030)	(0.00030)	(0.00027)	(0.00027)	(0.00030)	(0.00027)
Adjusted R^2	0.04955	0.00885	0.00356	0.00735	-0.00217	-0.00217

Notes: ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

One possible explanation why the non-trading hours sentiment and trading hours sentiment have different predictive ability on futures returns is the different category of users who tweets during these hours. Antweiller and Frank (2004) suggest that day traders post during working hours i.e. during trading hours hence in their study, they find more message posting during working hours. A closer inspection on StockTwits indicates the proportion of day trader's tweets that contributes to StockTwits sentiment. Figure 2.0 illustrates that 19% and 43% of the tweets come from day traders and swing traders. Thus, most of the tweets are likely from investors who trade during the stock trading hours.

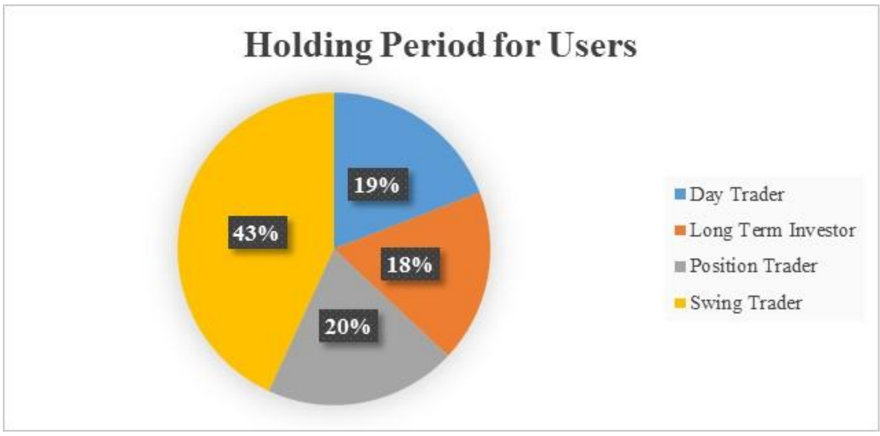

Figure 2.0: Pie chart of the holding period for StockTwits users. The pie chart indicates investment-holding period for users who tweeted from August 2009 to August 2015.

Figure 3.0 presents that 43% of these tweets come from users who adopt technical analysis approach.

Figure 3.0: Pie chart of the trading approach for StockTwits users. The pie chart indicates the investment trading approach of users who tweeted from August 2009 to August 2015.

Since they are technical traders, these users could have tweeted with each other to exchange their ideas or reasons for certain price movements or trends (Zhang, 2014). These users who tweets during trading hours could be short horizon traders who utilises technical analysis to trade and make profit from market movement. This aligns with StockTwits objective, to provide a platform for investors to share ideas and exchange information about financial markets and specific stocks (StockTwits Inc., 2016). Antweiller and Frank (2004) posit that individual investors think about their investments at home after working hours and tweet on StockTwits before they placing an order the next morning when the market opens for trading. Thus, the non-trading hours StockTwits sentiments could possibly reflect their sentiment. Most likely, these investors are position trader and long term investor as shown in Figure 2.0. These investors are unlikely to trade actively in the futures market since futures market has higher risk than the equity market hence their sentiment could not predict futures next day returns.

Looking at the relationship between trading hours sentiment and futures returns in Table 3.0, the positive coefficient for the positive sentiment measure at k = 0 indicates that days when there is an increase in the futures return, there is an increase in the number of positive tweets as well. However, the negative and significant coefficient for the positive sentiment measure at k = 1 suggest that when there is an increase in the number of positive tweets in StockTwits, there is a decline in futures returns the following day. The StockTwits positive sentiment could predict reversal after controlling for lagged returns, ADS Index, EPU Index and VIX. A one percent increase in positive sentiment indicates a decrease of 0.053% in S&P500 futures returns the following day. Although this figure seems small, investors in futures market risk huge losses due to the leverage characteristics. Table 3.0 also shows that the movement in futures returns reverses itself within a week, similar to the findings in Tetlock (2007). This reversal indicates that this initial movement in futures returns is not due to any change in the fundamental of companies listed in the underlying equity indices. This reversal aligns with the theories of investor sentiment that posit investor sentiment is the expectations of investors about future cash flows and risks that are not based on fundamentals (Baker & Wurgler, 2007; Da et al., 2015). The finding that StockTwits positive sentiment predicts reversals indicate that StockTwits positive sentiment is a contrarian sentiment indicator for the futures market (Sanders, Irwin and Leuthold (2003). According to Sanders et al. (2003), futures traders utilised sentiment indicators to gauge the market sentiment. Based on the theory of contrary opinion, they then make trading decisions. This finding adds StockTwits positive sentiment to the list of other contrarian indicators of the futures market like CBOE VIX, put-call ratio and trading index on NYSE (TRIN) (Simon & Wiggins, 2001). In addition, given that this is a social media sentiment, results that predictability is only for next day returns and not for a longer period. According to Zhang (2014), one of the difference between other media and social media is that social media provides faster information transmission (Zhang, 2014). In this case, sentiment as well.

Contrary to the positive coefficient for the positive sentiment, the negative coefficient for the negative sentiment measure at k = 0 indicates that days when there is a decline in the equity indices return, there is an increase in the number of negative tweets. The adjusted R square in Table 2.0 and Table 3.0 are lower than the adjusted R square in Da et al. (2015). However, these adjusted R square

are comparable to the adjusted R square of well-known large speculator sentiment and large hedger sentiment computed from actual trader position reported in the COT report (Wang, 2001b).

Table 3.0 also highlight one interesting question. Why does StockTwits positive sentiment could predict futures next day return but StockTwits negative sentiment could not? Previous studies too supports this asymmetric effect on stock returns. Psychology literatures provide an insight to this question. According to Nofsinger (2002), investors' action is driven by what they think, which in turn is driven by what they feel i.e. sentiment. Because emotion processing is linked to risk-taking and risk-avoiding behaviour (Nofsinger, 2002), sentiment can affect investors' perception of risk and in addition, the focus of their attention (Dolan, 2002). As a result, the way investors search for information, analyse the information and their motivation to make decision will differ depending on whether investors have positive or negative sentiment (Peterson, 2007). When investors have positive sentiment, they are optimistic and focus on the potential gain from a decision (Peterson, 2007). As a result, they overvalue the asset or select optimistic choices (Brown & Cliff, 2005). In this situation, investors take the reward approach to make their decision and will take more risks (Peterson, 2007). On the other hand, when investors have negative sentiment, they are pessimistic and focus on the potential loss from a decision (Peterson, 2007). Hence, they will undervalue assets or opt for pessimistic choices (Brown & Cliff, 2005). Investors take the loss avoidance approach to make their decisions thus will exhibit risk averse behaviour (Peterson, 2007). According to Nofsinger (2005), investors tend to invest in risky assets when they are in positive sentiment compared to when they are in negative sentiment. Previous study by Chung, Hung and Yeh (2012) supports our findings. They find that positive sentiment has a predictive ability on stock returns compared to negative sentiment. One explanation is overconfident. Brown and Cliff (2005) suggest that as more and more users become optimistic, other users who are already optimistic will be more optimistic. A study by Tang, Liu, McQueen, Counts, Jain, Zheng and Zhao (2017) on two investment discussion boards i.e. Investors Hub and Yahoo Message Board find that users in are predominantly optimistic. This optimistic group will be overconfident (Moussaid, Kammer, Analytis & Neth, 2013) and based on Barber and Odean (2001), they will trade more and as a result lower the returns. This question is more pronounced because Tetlock (2007) and Garcia (2013) find that negative sentiment has predictability over DJIA[10]. However, we put forth several potential

[10] Their findings could be explained by negativity bias. Investors give more importance on negative events than positive events (Rozin & Royzman, 2001) due to their limited cognitive processing ability to process all the information that is available to them (Baumeister, Bratslavsky, Finkenauer & Vohs, 2001). Hence, investors become selective on the information that they thoroughly consider in their decision-making. As a result, they pay more attention and attribute more towards negative news, or in this context, the sentiment (Baumeister et al., 2001). Thus, negative sentiment have larger influence on them than the positive sentiment. In addition, investors to recall their memories about negative events quicker than positive events (Baumeister et al., 2001). In this case, negative sentiment trigger investor's memory of their emotional experience due to a similar negative event in the past thus investors try to avoid experiencing the similar event again by making a decision and influencing returns (Shiller, 2015). Based on the negativity bias, Tetlock (2007) focuses only on negative words. Many existing

explanations for this different results. Both Tetlock (2007) and Garcia (2013) measure media sentiment. For example, Garcia (2013)'s media sentiment measure is based on the Financial Markets and Topics in Wall Street columns published in New York Times. These articles are written by journalists and read by investors. For this study, we are looking at tweets by investors themselves. Thus, the media sentiment and StockTwits sentiment differ in this aspect.

In addition, Table 3.0 shows StockTwits sentiments has different impact on different futures contracts. The positive sentiment has the strongest relationship with EMini Nasdaq100 Futures returns, whether it is with contemporaneous returns or next day returns. Similarly, the negative sentiment has the strongest contemporaneous relationship with EMini Nasdaq100 Futures contemporaneous returns. Moreover, Table 2.0 shows that the only predictive relationship for StockTwits is between positive sentiment and EMini NASDAQ100 futures returns. From Table 3.0, StockTwits positive and negative sentiment have the least impact on EMini Dow Futures returns. These findings conform to behavioural theory on the effect of sentiment on different stocks. Sentiment on StockTwits has the highest impact on EMini NASDAQ100 Futures because the underlying security for NASDAQ100 futures is NASDQ100 index that comprises of technology stocks. These stocks are hard for investors to value. These stocks are more volatile but have large potential for distress or growth potential (Baker & Wurgler, 2007). Baker and Wurgler (2007) termed these stocks as speculative stocks and these stocks are more driven by sentiment compared to bond-like stocks. Due to the difficulty to value the worth of technology stocks, there is also limit to which *rational* investors could arbitrage, a mechanism in which proponents of the efficient market hypothesis argue would prevent sentiment to have an influence over market behaviour since it will move the price of these stocks closer to its fundamental value (Baker & Wurgler, 2007). On the other hand, the underlying stocks for EMini Dow Futures are thirty widely followed stocks. Thus, investors could more easily ascertain the value of these stocks. Table 2.0 and Table 3.0 results on the significant relationship between StockTwits sentiments and EMini Dow Futures returns corroborates Lee et al. (2002)'s argument that a sentiment measure should have a significant relationship with DJIA returns if the sentiment measure has an impact on market behaviour. However, Table 3.0 illustrates the relationship between StockTwits sentiment and EMini S&P500 Futures returns are almost similar compared to the relationship between StockTwits sentiment and S&P500 Futures standard contract returns. This suggest StockTwits sentiment does not has different influence on futures returns due to the characteristics that differentiate between these S&P500 futures contracts and EMini S&P500 Futures returns and the popularity of EMini S&P 500 Futures. This finding corroborates the Dungey, Fakhrutdinova and Goodhart (2008)'s preliminary investigations findings.

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studies apply the Tetlock (2007)'s assumption and focus on negative words (Solomon, 2014; Chen et al., 2014; Liu & McConnell, 2013; Gurun & Butler, 2012).

V. *Changes in Sentiment and Extreme Sentiment Measures*

Wang, Keswani and Taylor (2006) argues that there is no agreement over the form of sentiment that affects investors. Thus, we employ various sentiment measures to ascertain which sentiment measures best capture StockTwits sentiment predictive ability on futures returns. These additional measures include changes in sentiment measures and extreme StockTwits sentiments measures. The changes in sentiment measures are change in StockTwits positive sentiment and change in StockTwits negative sentiment. The extreme StockTwits sentiment measures are top 25% quantile and bottom 25% quantile measures.

According to Baker and Wurgler (2007), investor sentiment could have an influence on returns through the change in investor sentiment. If investors were sensitive to sentiment changes in StockTwits, then changes in sentiment would predict returns (Wang et al., 2006). Bandara (2016) finds a positive relationship between changes in StockTwits sentiment and trading volume of 100 most mentioned stocks and S&P500 Index. We find that levels sentiment measures capture StockTwits sentiment predictive ability better than the changes in sentiment measures. Table 5.0 highlights that change in positive and change in negative sentiment measures only have stronger relationship with contemporaneous returns for all four futures contract compared to levels sentiment. Our findings corroborate with Edelen et al. (2010) s' findings. In addition, Table 4.0 and Table 5.0 further suggests that StockTwits negative sentiment does not have predictive ability over futures returns.

Table 4.0: Regressions of Daily Non-Trading Hours Sentiment on Futures Returns

The table reports results for Equation 5 regression when k = 0 for Model 1 to k = 5 for Model 6 for change in positive and change in negative sentiment. This sentiment is determined from tweets posted from 4.00 pm to 9.30 a.m. The dependent variable is log-return of S&P500 futures in Panel A, EMini S&P500 futures in Panel B, EMini Dow futures in Panel C and EMini NASDAQ100 futures in Panel D. The independent variable is the StockTwits change in sentiment measure while the control variables are lagged returns up to five lags, Aruoba-Diebold-Scotti (ADS) business conditions index, new-based measure of economic policy uncertainty (EPU) and CBOE VIX. The sample period is from August 2009 to August 2015, with a total of 1531 daily observations. The reported standard error is Newey-West standard error and the sentiment measure have been winsorised at 0.5% on each tail.

	(1) Return (t)	(2) Return (t + 1)	(3) Return (t + 2)	(4) Return (t + 3)	(5) Return (t + 4)	(6) Return (t + 5)
Panel A: S&P500 Futures						
Δ Positive	0.00050	-0.00022	-0.00004	-0.00003	-0.00023	0.00021
	(0.00031)	(0.00027)	(0.00022)	(0.00025)	(0.00026)	(0.00026)
Adjusted R^2	0.04137	0.01002	0.00458	0.00816	0.00202	0.00151
Δ Negative	-0.00024	0.00006	-0.00032	0.00050	0.00001	-0.00021
	(0.00024)	(0.00027)	(0.00033)	(0.00033)	(0.00029)	(0.00023)
Adjusted R^2	0.03948	0.00958	0.00560	0.01062	0.00147	0.00150
Panel B: EMini S&P500 Futures						
Δ Positive	0.00050	-0.00021	-0.00004	-0.00003	-0.00023	0.00021
	(0.00031)	(0.00027)	(0.00022)	(0.00025)	(0.00026)	(0.00026)
Adjusted R^2	0.04138	0.01000	0.00458	0.00816	0.00209	0.00158
Δ Negative	-0.00024	0.00006	-0.00032	0.00050	0.00001	-0.00021

	(0.00024)	(0.00027)	(0.00033)	(0.00033)	(0.00029)	(0.00023)
Adjusted R^2	0.03950	0.00957	0.00559	0.01061	0.00154	0.00156
Panel C: EMini Dow Futures						
Δ Positive	0.00034	-0.00009	-0.00003	-0.00013	-0.00016	0.00014
	(0.00027)	(0.00023)	(0.00019)	(0.00022)	(0.00024)	(0.00022)
Adjusted R^2	0.02951	0.00710	0.00199	0.00591	0.00184	-0.00032
Δ Negative	-0.00008	-0.00008	-0.00025	0.00048*	-0.00006	-0.00016
	(0.00021)	(0.00024)	(0.00028)	(0.00028)	(0.00025)	(0.00020)
Adjusted R^2	0.02811	0.00708	0.00279	0.00864	0.00154	-0.00024
Panel D: EMini NASDAQ100 Futures						
Δ Positive	0.00076**	-0.00033	-0.00005	-0.00001	-0.00015	0.00011
	(0.00031)	(0.00027)	(0.00023)	(0.00026)	(0.00026)	(0.00029)
Adjusted R^2	0.04032	0.00968	0.00559	0.00686	-0.00234	-0.00223
Δ Negative	-0.00033	0.00013	-0.00028	0.00048	0.00016	-0.00036
	(0.00028)	(0.00026)	(0.00028)	(0.00031)	(0.00027)	(0.00023)
Adjusted R^2	0.03632	0.00886	0.00627	0.00883	-0.00232	-0.00120

Notes: ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table 5.0: Regressions of Daily Trading Hours Sentiment on Futures Returns

The table reports results for Equation 5 regression when k = 0 for Model 1 to k = 5 for Model 6 for change in positive and change in negative sentiment. This sentiment is determined from tweets posted from 9.30a.m. to 4.00 pm. The dependent variable is log-return of S&P500 futures in Panel A, EMini S&P500 futures in Panel B, EMini Dow futures in Panel C and EMini NASDAQ100 futures in Panel D. The independent variable is the StockTwits change in sentiment measure while the control variables are lagged returns up to five lags, Aruoba-Diebold-Scotti (ADS) business conditions index, new-based measure of economic policy uncertainty (EPU) and CBOE VIX. The sample period is from August 2009 to August 2015, with a total of 1531 daily observations. The reported standard error is Newey-West standard error and the sentiment measure have been winsorised at 0.5% on each tail.

	(1) Return (t)	(2) Return (t + 1)	(3) Return (t + 2)	(4) Return (t + 3)	(5) Return (t + 4)	(6) Return (t + 5)
Panel A: S&P500 Futures						
Δ Positive	0.00152***	-0.00034	0.00001	0.00025	-0.00011	0.00019
	(0.00028)	(0.00027)	(0.00023)	(0.00030)	(0.00026)	(0.00024)
Adjusted R^2	0.06230	0.01072	0.00457	0.00877	0.00159	0.00140
Δ Negative	-0.00133***	-0.00018	-0.00012	0.00001	0.00031	0.00028
	(0.00028)	(0.00025)	(0.00028)	(0.00028)	(0.00031)	(0.00026)
Adjusted R^2	0.05675	0.00987	0.00472	0.00815	0.00249	0.00182
Panel B: EMini S&P500 Futures						
Δ Positive	0.00152***	-0.00034	0.00001	0.00025	-0.00010	0.00019
	(0.00028)	(0.00027)	(0.00023)	(0.00030)	(0.00026)	(0.00024)
Adjusted R^2	0.06235	0.01072	0.00456	0.00875	0.00165	0.00147
Δ Negative	-0.00133***	-0.00018	-0.00012	0.00000	0.00031	0.00028
	(0.00028)	(0.00025)	(0.00028)	(0.00028)	(0.00031)	(0.00026)
Adjusted R^2	0.05674	0.00987	0.00471	0.00815	0.00254	0.00192
Panel C: EMini Dow Futures						
Δ Positive	0.00125***	-0.00025	0.00010	0.00008	-0.00008	0.00015
	(0.00025)	(0.00023)	(0.00021)	(0.00027)	(0.00022)	(0.00020)
Adjusted R^2	0.04826	0.00781	0.00210	0.00578	0.00159	-0.00028
Δ Negative	-0.00109***	-0.00019	-0.00010	0.00009	0.00017	0.00034
	(0.00024)	(0.00022)	(0.00024)	(0.00025)	(0.00027)	(0.00023)
Adjusted R^2	0.04340	0.00747	0.00211	0.00580	0.00188	0.00090
Panel D: EMini NASDAQ100 Futures						
Δ Positive	0.00169***	-0.00054*	0.00008	0.00032	-0.00014	0.00020
	(0.00030)	(0.00030)	(0.00023)	(0.00029)	(0.00024)	(0.00024)
Adjusted R^2	0.06048	0.01126	0.00563	0.00774	-0.00238	-0.00200

Δ Negative	-0.00158***	0.00001	-0.00021	0.00002	0.00037	0.00018
	(0.00030)	(0.00024)	(0.00029)	(0.00029)	(0.00030)	(0.00028)
Adjusted R^2	0.05708	0.00872	0.00595	0.00687	-0.00136	-0.00205

Notes: ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

In addition to changes in sentiment level, there possibility that noise traders only trade when the sentiment is at extreme levels (Wang et al., 2006) hence these extreme levels could have an influence on futures returns. However, previous studies have find that extreme levels of sentiment do not have significant relationship with futures returns (Simon & Wiggins, 2001). We find that only StockTwits extremely high positive sentiment and StockTwits extreme bottom 25% negative sentiment could predict next day returns for all four contracts.

Table 6.0: Regressions of Top 25% Daily Trading Hours Sentiment on Futures Returns

The table reports results for Equation 1 regression when k = 0 for Model 1 to k = 5 for Model 6 for top 25% positive and negative sentiment measure. This sentiment is determined from tweets posted from 9.30 am to 4.00 p.m. The dependent variable is S&P500 futures returns in Panel A, EMini S&P500 futures returns in Panel B, EMini Dow futures returns in Panel C and EMini NASDAQ100 futures in Panel D. The independent variable is the top 25% positive and top 25% negative StockTwits sentiment measure while the control variables are lagged returns up to five lags, Aruoba-Diebold-Scotti (ADS) business conditions index, new-based measure of economic policy uncertainty and CBOE VIX. The sample period is from August 2009 to August 2015, with a total of 1531 daily observations. The reported standard error is Newey-West standard error and the sentiment measure have been winsorised at 0.5% on each tail.

	(1) Return (t)	(2) Return (t + 1)	(3) Return (t + 2)	(4) Return (t + 3)	(5) Return (t + 4)	(6) Return (t + 5)
Panel A: S&P500 Futures						
Positive	0.00016	-0.00085***	0.00042	0.00001	0.00038	0.00015
	(0.00033)	(0.00032)	(0.00041)	(0.00043)	(0.00031)	(0.00032)
Adjusted R^2	0.07489	0.04136	0.00963	0.00945	-0.00231	-0.00569
Negative	0.00018	0.00007	0.00010	-0.00025	0.00029	-0.00043
	(0.00040)	(0.00053)	(0.00030)	(0.00044)	(0.00028)	(0.00045)
Adjusted R^2	0.05983	0.00867	0.00950	0.07227	0.00159	0.00438
Panel B: EMini S&P500 Futures						
Positive	0.00016	-0.00085***	0.00042	0.00001	0.00037	0.00015
	(0.00033)	(0.00032)	(0.00041)	(0.00043)	(0.00030)	(0.00032)
Adjusted R^2	0.07480	0.04133	0.00954	0.00944	-0.00228	-0.00573
Negative	0.00018	0.00007	0.00010	-0.00025	0.00029	-0.00043
	(0.00040)	(0.00053)	(0.00030)	(0.00044)	(0.00028)	(0.00045)
Adjusted R^2	0.05973	0.00859	0.00957	0.07188	0.00167	0.00438
Panel C: EMini Dow Futures						
Positive	0.00016	-0.00069**	0.00045	-0.00000	0.00020	0.00017
	(0.00024)	(0.00029)	(0.00032)	(0.00043)	(0.00025)	(0.00026)
Adjusted R^2	0.05915	0.03048	0.01197	0.00432	-0.00656	-0.00486
Negative	0.00020	0.00013	0.00036	-0.00022	0.00024	-0.00027
	(0.00035)	(0.00048)	(0.00026)	(0.00039)	(0.00025)	(0.00040)
Adjusted R^2	0.04414	0.00456	0.01241	0.06777	-0.00330	-0.00471
Panel D: EMini NASDAQ100 Futures						
Positive	-0.00020	-0.00097***	0.00045	-0.00007	0.00044*	0.00009
	(0.00040)	(0.00031)	(0.00046)	(0.00044)	(0.00023)	(0.00044)
Adjusted R^2	0.06072	0.03254	-0.00374	0.00723	-0.00192	-0.00543
Negative	-0.00001	0.00017	0.00002	-0.00023	0.00012	-0.00038
	(0.00033)	(0.00047)	(0.00037)	(0.00041)	(0.00029)	(0.00053)
Adjusted R^2	0.06034	0.00753	0.00365	0.06708	-0.00368	-0.00237

Notes: ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table 7.0: Regressions of Bottom 25% Daily Trading Hours Sentiment on Futures Returns

The table reports results for Equation 1 regression when k = 0 for Model 1 to k = 5 for Model 6 for bottom 25% positive and negative sentiment measure. This sentiment is determined from tweets posted from 9.30 am to 4.00 p.m. The dependent variable is S&P500 futures returns in Panel A, EMini S&P500 futures returns in Panel B, EMini Dow futures returns in Panel C and EMini NASDAQ100 futures in Panel D. The independent variable is the bottom 25% positive and bottom 25% negative StockTwits sentiment measure while the control variables are lagged returns up to five lags, Aruoba-Diebold-Scotti (ADS) business conditions index, new-based measure of economic policy uncertainty and CBOE VIX. The sample period is from August 2009 to August 2015, with a total of 1531 daily observations. The reported standard error is Newey-West standard error and the sentiment measure have been winsorised at 0.5% on each tail.

	(1) Return (t)	(2) Return (t + 1)	(3) Return (t + 2)	(4) Return (t + 3)	(5) Return (t + 4)	(6) Return (t + 5)
Panel A: S&P500 Futures						
Positive	-0.00059	-0.00067	0.00051	0.00073	-0.00001	0.00062
	(0.00060)	(0.00057)	(0.00054)	(0.00050)	(0.00058)	(0.00057)
Adjusted R^2	0.07056	0.01832	0.00608	0.02272	0.00530	0.04994
Negative	-0.00073	0.00067*	0.00067	0.00001	0.00100*	0.00149*
	(0.00051)	(0.00038)	(0.00044)	(0.00050)	(0.00055)	(0.00081)
Adjusted R^2	0.03681	0.00064	0.01268	-0.01702	0.00470	0.00368
Panel B: EMini S&P500 Futures						
Positive	-0.00058	-0.00067	0.00051	0.00073	-0.00001	0.00061
	(0.00060)	(0.00057)	(0.00054)	(0.00050)	(0.00058)	(0.00057)
Adjusted R^2	0.07043	0.01858	0.00598	0.02251	0.00553	0.04997
Negative	-0.00073	0.00066*	0.00067	0.00001	0.00101*	0.00149*
	(0.00051)	(0.00038)	(0.00044)	(0.00050)	(0.00055)	(0.00081)
Adjusted R^2	0.03643	0.00066	0.01297	-0.01689	0.00466	0.00351
Panel C: EMini Dow Futures						
Positive	-0.00063	-0.00046	0.00057	0.00045	0.00005	0.00048
	(0.00056)	(0.00044)	(0.00050)	(0.00045)	(0.00046)	(0.00052)
Adjusted R^2	0.07279	0.01832	0.01184	0.02414	0.00441	0.05091
Negative	-0.00070	0.00059*	0.00046	-0.00019	0.00092*	0.00132*
	(0.00043)	(0.00034)	(0.00044)	(0.00041)	(0.00048)	(0.00078)
Adjusted R^2	0.02528	-0.00286	0.00247	-0.01115	0.00668	0.00068
Panel D: EMini NASDAQ100 Futures						
Positive	-0.00103	-0.00025	0.00088*	0.00120**	0.00042	0.00084
	(0.00065)	(0.00053)	(0.00053)	(0.00052)	(0.00059)	(0.00075)
Adjusted R^2	0.08141	0.02602	0.00488	0.02566	0.00062	0.02759
Negative	-0.00035	0.00114**	0.00091*	0.00027	0.00096*	0.00163**
	(0.00055)	(0.00053)	(0.00047)	(0.00045)	(0.00056)	(0.00068)
Adjusted R^2	0.01295	0.00708	0.01156	0.00370	0.01123	0.01114

Notes: ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

VI. Predictability with Different Time Horizon

In addition to different sentiment measures, we need to consider different horizon for each sentiment measure because sentiment indicators will have different predictability over futures return depending on which investment horizon that interests technical analysts (Simon & Wiggins, 2001; Clarke & Statman, 1998; Solt & Statman, 1988). Thus, we explore whether relationship between StockTwits sentiments and futures returns is different for weekly and monthly returns. We aggregate the daily sentiment scores into weekly and monthly sentiment measures to determine the predictability of StockTwits sentiment over different period. Table 8.0 and Table 9.0 report the results.

Table 8.0: Regressions of Weekly Sentiment on Futures Returns

The table reports results for Equation 1 regression when k = 0 for Model 1 to k = 5 for Model 6 for weekly positive and negative sentiment measures. The dependent variable is weekly S&P500 futures returns in Panel A, EMini S&P500 futures returns in Panel B, EMini Dow futures returns in Panel C and EMini NASDAQ100 futures in Panel D. The independent variable is the weekly StockTwits sentiment measure while the control variables are lagged weekly returns up to five lags, weekly Aruoba-Diebold-Scotti (ADS) business conditions index, weekly new-based measure of economic policy uncertainty and weekly CBOE VIX. The sample period is from August 2009 to August 2015. The reported standard error is Newey-West standard error and the sentiment measure have been winsorised at 0.5%.

	(1) Return (t)	(2) Return (t + 1)	(3) Return (t + 2)	(4) Return (t + 3)	(5) Return (t + 4)	(6) Return (t + 5)
Panel A: S&P500 Futures						
Positive	0.00294***	0.00103	-0.00022	-0.00230**	-0.00076	0.00161
	(0.00100)	(0.00103)	(0.00107)	(0.00107)	(0.00110)	(0.00104)
Adjusted R^2	0.10967	0.00306	-0.01770	0.03257	0.02352	0.04436
Negative	-0.00247	0.00057	-0.00039	0.00186	0.00080	-0.00131
	(0.00174)	(0.00133)	(0.00167)	(0.00146)	(0.00130)	(0.00123)
Adjusted R^2	0.09760	0.00103	-0.01760	0.02504	0.02307	0.04070
Panel B: EMini S&P500 Futures						
Positive	0.00294***	0.00104	-0.00022	-0.00231**	-0.00076	0.00161
	(0.00100)	(0.00103)	(0.00107)	(0.00107)	(0.00110)	(0.00104)
Adjusted R^2	0.10969	0.00313	-0.01775	0.03259	0.02355	0.04431
Negative	-0.00247	0.00057	-0.00039	0.00186	0.00079	-0.00131
	(0.00174)	(0.00133)	(0.00167)	(0.00146)	(0.00130)	(0.00122)
Adjusted R^2	0.09765	0.00109	-0.01765	0.02506	0.02308	0.04068
Panel C: EMini Dow Futures						
Positive	0.00206**	0.00027	-0.00014	-0.00209**	-0.00067	0.00145
	(0.00086)	(0.00099)	(0.00092)	(0.00101)	(0.00083)	(0.00095)
Adjusted R^2	0.07680	0.00081	-0.01296	0.02736	0.01755	0.02938
Negative	-0.00148	0.00102	-0.00006	0.00196	0.00013	-0.00085
	(0.00162)	(0.00130)	(0.00155)	(0.00135)	(0.00103)	(0.00123)
Adjusted R^2	0.06862	0.00229	-0.01301	0.02173	0.01636	0.02480
Panel D: EMini NASDAQ100 Futures						
Positive	0.00453***	0.00095	-0.00006	-0.00218*	-0.00123	0.00188*
	(0.00131)	(0.00108)	(0.00107)	(0.00117)	(0.00110)	(0.00109)
Adjusted R^2	0.10964	0.00148	-0.01237	0.02615	0.02490	0.03694
Negative	-0.00384*	0.00069	-0.00181	0.00186	0.00184	-0.00209
	(0.00200)	(0.00147)	(0.00183)	(0.00168)	(0.00144)	(0.00144)
Adjusted R^2	0.08812	0.00042	-0.00897	0.02155	0.02583	0.03539

Notes: ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table 9.0: Regressions of Monthly Sentiment on Futures Returns

The table reports results for Equation 1 regression when k = 0 for Model 1 to k = 5 for Model 6 for monthly positive and negative sentiment measures. The dependent variable is monthly S&P500 futures returns in Panel A, EMini S&P500 futures returns in Panel B, EMini Dow futures returns in Panel C and EMini NASDAQ100 futures in Panel D. The independent variable is the StockTwits monthly sentiment measure while the control variables are lagged monthly returns up to five lags, Aruoba-Diebold-Scotti (ADS) business conditions index, new-based measure of economic policy uncertainty and CBOE VIX. The sample period is from August 2009 to August 2015. The reported standard error is Newey-West standard error and the sentiment measure have been winsorised at 0.5%.

	(1) Return (t)	(2) Return (t + 1)	(3) Return (t + 2)	(4) Return (t + 3)	(5) Return (t + 4)	(6) Return (t + 5)
Panel A: S&P500 Futures						
Positive	-0.00568	-0.00222	-0.00391	0.00121	-0.00182	0.00093
	(0.00382)	(0.00425)	(0.00323)	(0.00501)	(0.00275)	(0.00262)
Adjusted R^2	0.11922	-0.02610	-0.07555	-0.11066	-0.10291	-0.11466
Negative	-0.00597	-0.00496	-0.01194***	-0.00087	-0.00157	-0.00499*
	(0.00526)	(0.00343)	(0.00370)	(0.00397)	(0.00492)	(0.00272)
Adjusted R^2	0.11497	-0.01702	-0.01656	-0.11127	-0.10392	-0.10331
Panel B: EMini S&P500 Futures						
Positive	-0.00567	-0.00221	-0.00390	0.00121	-0.00182	0.00092
	(0.00382)	(0.00425)	(0.00324)	(0.00501)	(0.00275)	(0.00262)
Adjusted R^2	0.11913	-0.02611	-0.07550	-0.11062	-0.10282	-0.11465
Negative	-0.00596	-0.00497	-0.01193***	-0.00087	-0.00157	-0.00500*
	(0.00526)	(0.00343)	(0.00370)	(0.00397)	(0.00491)	(0.00272)
Adjusted R^2	0.11489	-0.01699	-0.01659	-0.11125	-0.10383	-0.10323
Panel C: EMini Dow Futures						
Positive	-0.00708**	-0.00360	-0.00186	0.00008	-0.00124	0.00331
	(0.00311)	(0.00406)	(0.00294)	(0.00497)	(0.00253)	(0.00221)
Adjusted R^2	0.07520	0.00318	-0.06663	-0.11238	-0.10318	-0.09500
Negative	-0.00416	-0.00566*	-0.00884**	-0.00226	-0.00226	-0.00377
	(0.00496)	(0.00321)	(0.00375)	(0.00381)	(0.00477)	(0.00275)
Adjusted R^2	0.04848	0.01180	-0.02701	-0.10960	-0.10149	-0.09508
Panel D: EMini NASDAQ100 Futures						
Positive	-0.00539	0.00091	-0.00492	0.00241	-0.00423	-0.00285
	(0.00408)	(0.00392)	(0.00423)	(0.00442)	(0.00368)	(0.00346)
Adjusted R^2	0.08805	0.00187	-0.04886	-0.07359	-0.07763	-0.09776
Negative	-0.00940	-0.00235	-0.01464***	0.00302	0.00241	-0.00820**
	(0.00631)	(0.00387)	(0.00429)	(0.00278)	(0.00492)	(0.00337)
Adjusted R^2	0.10525	0.00349	0.01454	-0.07340	-0.08510	-0.07853

Notes: ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

First, both StockTwits sentiments become less significant over longer period of time. The weekly StockTwits positive sentiment has significant relationship with contemporaneous returns but no significant predictive relationship with next week returns. Weekly StockTwits negative sentiment only has significant contemporaneous relationship with EMini Nasdaq 100 futures returns. The monthly StockTwits sentiment has no significant relationship with contemporaneous returns or next month returns. The only exception to this is the relationship between StockTwits sentiment and EMini Dow Futures returns. This finding is contrary to Simons and Wiggins (2001)s' findings on the relationship of VIX, put-call ratio and trading index on NYSE (TRIN) to S&P500 futures returns.

Second, positive sentiment has significant relationship with EMini Dow Futures contemporaneous returns while the negative sentiment has predictive over the following two months returns. EMini Dow Futures returns in the following month is likely to decline by 0.6% when there is a one percent increase in the negative sentiment. This is opposite of the findings using daily StockTwits that the relationship between StockTwits sentiment and EMini Dow Futures is the least significant compared to the relationship with three futures contract returns.

VII. Conclusion

By using StockTwits tweets, we compose sentiment measures to capture positive and negative sentiment during non-trading hours and trading hours. Overall, trading hours StockTwits positive sentiment could predict next day returns for S&P500 Futures contract, EMini S&P500 Futures, Dow Jones Futures and NASDAQ100 Futures. The sentiment influence is the largest for NASDAQ100 and weakest for Dow Jones Futures. There is no much difference in the influence of investor sentiment on S&P500 Futures standard contract and EMini S&P500 Futures contract. However, much of the predictive effect is temporary as we see in ensuing days; there is no longer a significant relationship between these two variables. In addition, there is a change in signs across all results that indicate the reversal effect. This aligns with the sentiment theories.

In addition, we explore various sentiment measures and extend the investment. None of the changes in sentiments has significant predictive power on futures returns, except for trading hours change in positive sentiment on EMini Nasdaq100 Futures returns. All of the trading hours changes in sentiments have significant contemporaneous relationship with futures returns. As for extreme levels of sentiment, we find that only top 25% positive sentiment and bottom 25% negative sentiment have predictability ability on all four futures returns. However, most of this predictability disappear for weekly and monthly returns. Despite these findings, further research is required to tap into this real-time investor sentiment proxy that will extend our understanding on the realm of investor behaviour.

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