The Role of Option-based Information on StockTwits, Options Trading Volume and Stock Returns

Zin Yau Heng
Department of Economics
The University of Queensland
z.heng@uq.net.au

Dr. Henry Leung
The University of Sydney Business School
henry.leung@sydney.edu.au

Abstract:

We examine the relationship between activities of information channels and stock returns. The activities of information channels are signals from the options trading market and sentiments of StockTwits. Besides, we also examine whether those activities are shared across information channels. We use a net trade options volume ratio as a proxy for signals from the options market and use bullishness and agreement variables as proxies for sentiments of StockTwits. We partition the net trade options volume by different options maturity lengths and moneyness. We find that signals from all options maturity lengths and moneyness except for the medium and deeply out of the money groups have positive and significant associations with the bullish sentiments. Second, we show possible significant evidence of pooling equilibrium between activities in information channels and the stock market. The pooling equilibrium activities exhibit that informed investors not only invest in the options market and send bullish information through the options market and StockTwits. Third, the signals from options with deep leverage show possible positive and significant future returns. Fourth, signals from some options trading groups (such as long, ATM, ITM, DITM, and DOTM) have a significant and positive associations with agreements on the StockTwits. Fifth, the agreement on the StockTwits show possible significant and positive associations to the stock returns. Lastly, the agreement on sentiments has a possible positive and significant association with the current and future stock returns.

Keywords: Option Trading Volume, Sentiments, Agreement on Sentiments, Stock Returns.
JEL: G32, G40

1 Introduction

Stock-related information will eventually reflect into the stock prices after a passage of time.[1] Generally, this information is pieces of unorganised raw fundamental data with noise. The analysts attempt to decode the fundamental data to predict the true prices. After passage of time, the effort of data evaluation from analysts will gradually make data more organised and complete and thus, eliminate the noise (Manela, 2014). As such, the speed of data diffusion and decoding of the data are critical to stock price valuation (Fama, 1998). Institutional investors can decode the latest pieces of information to earn self-financial interest (Hendershott et al., 2015). In contrast, retail investors struggle to access information and decode the financial information. Therefore, these retail investors may observe information from multiple information channels for their investment decisions. Gan et al. (2020) argued that social media is the dominant source of information sentiments. Some information channels are signals from options trading, sentiments from social media, and others. According to Pan and Poteshman (2006), retail investors can observe the options trading volume as a signal in determining future stock price movements, since the options with deep leverage have significant predictive power on future stock returns. Apart from the signals from the options market, Leung and Ton (2015) and Renault (2017) showed that sentiments from social media have predictive powers on future stock returns.

A branch of studies investigates relationships between activities from social media and the stock market. Antweiler and Frank (2004) showed that investor can use internet stock message boards (i.e., Yahoo! Finance and Raging Bull dataset) to predict the stock markets, such as market volatility and stock returns. Recently, a few studies used the dataset of investment-focused social media platform, StockTwits, to examine the interrelationships between StockTwits activities and the stock market. Renault (2017) showed that the first half-hour changes in investor sentiments enable a forecast of the last half-hour S&P 500 index ETF return. They also document the presence of sentiments-driven noise trading at the intraday level. Using similar StockTwits datasets, Cookson and Niessner (2020) examined the source of disagreement combined with information

[1] Information was revealed after passage of time denotes that the stock price gradually absorbs the true information.

on the users' investment approaches (e.g., technical, fundamental). They showed that an exhaustive disagreement is split evenly between both sources of disagreement, but within-group disagreement is more tightly related to trading volume than cross-group disagreement.

Black (1975) explored informed traders who transact informed trading activities in the options market because the investment in the options market provides higher leverage for higher returns. Chakravarty et al. (2004) used the modification of Hasbrouck (1995) “Information share” to show that the options market price discovery is connected to trading volume and spreads in both markets, and stock volatility. The informed traders trade in both stock and options markets and explore the options-implied volatility on the stock returns. Besides, a group of researchers focuses on relationships between options volumes and the stock market (Aggarwal & Wu, 2006; Chan et al., 2002; Easley et al., 1998; Pan & Poteshman, 2006; Stephan & Whaley, 1990). Easley et al. (1998) demonstrated an asymmetric information model that informed investors may invest in equity or options markets. They showed an important informational role for the volume of certain types of options trades, especially options with deep leverage. Chan et al. (2002) showed that the net trade options volume of a stock has great predictive ability for options and stock quote revisions. The net trade options volume is measured based on buyer-initiated volume minus seller-initiated volume. However, the net trade options volume shows no evidence of incremental predictive ability. Pan and Poteshman (2006) argued for an application of pooling equilibrium between options trading and stock market. The pooling equilibrium activities indicate that informed investors simultaneously trade the options and trade the stocks. Options trading, especially with deep leverage, plays a critical role as information for stock price predictions. Therefore, informed trading options with deep leverage can exploit a financial incentive.

Unlike previous literature, I explore interrelationships between signals from options trading and sentiments of StockTwits. Furthermore, this study explains the pooling equilibrium activities between activities on information channels (i.e., signals from the options market and sentiments on social media) and the stock market (Black, 1975; Easley et al., 1998; Pan & Poteshman, 2006). Lastly, this study aims to explore stock returns predictability of information channels from both options trading market and StockTwits.

Motivated by Chan et al. (2002), we use the net trade options volume ratio to present signals from the options market. The ratio acts as a proxy of signals (i.e., information) from informed trader's action on the stock. The ratio is formulated by the net trade options volume divided by the total options volume (see Section 2 for detail). The net trade options volume is the total number of calls minus the total number of puts. The net trade volume can predict quoted movement of options and stock returns (Admati & Pfleiderer, 1988; Kyle, 1985). We partition the net trade options volume by the different option contract groups. These main groups are classified in maturity length and moneyness. The maturity length group consists of short-term, medium-term, and long-term contracts. The moneyness implies the leverage of the options. The options with OTM and DOTM groups indicate options with leverage. The option with DOTM and OTM indicates an option trading in the deep leverage and leverage contracts, respectively. Besides, we follow the Antweiler and Frank (2004) approaches to create Bullishness and Agreement indexes as proxies of information activities from StockTwits. The details of Bullishness and the Agreement variables are discussed in Section 3.3.

Given key variables of signals from both options market and sentiments from StockTwits, we use fixed effect regression to show that all options maturity lengths and moneyness, except for the medium and DOTM groups, have positive and significant associations with bullish sentiments. These significant relationships indicate the sharing information activities shared across two information channels. Moreover, the significant positive relationships between signals from options trading with OTM and bullish sentiments from social media indicate a potential manipulative information transmission strategy (Schmidt, 2020). We also report that signals from options trading (such as long-term maturity, ATM, ITM, DITM, and DOTM) lead to more agreed sentiments in StockTwits.

Moreover, we report significant evidence of pooling equilibrium activities between activities from multiple information channels and stock returns. The options trading with different groups (such as overall options groups, short group, medium group, and DITM groups) and bullish sentiments (bullishness) have positive and significant relationships to the stock returns. The positive and significant relationship indicates that investors not only simultaneously trade in both the options market and trade stocks, but also send bullish sentiments to the StockTwits (Leung & Ton, 2015; Pan & Poteshman, 2006). The shared information among multiple information sources (i.e., StockTwits and Option trading markets) improves the likelihood of perceived price movements. The signals from options with deep leverage (i.e., DOTM) show a significant and negative relationship to the returns at $t = 0$. The information from the options trading with DOTM indicates that the informed investors trade the options trading with DOTM while the stock is stale to respond, but it may respond in near future. As such, our result exhibits that signals from options trading with DOTM have significant predictive and positive power on future stock returns (Pan & Poteshman, 2006). However, the signals from options trading with the OTM group and bullish sentiments show limited evidence of predictive returns. Meanwhile, the agreement of sentiments helps in maintaining the positive significant interrelationship with current and future stock returns.

We contribute to the literature on the pooling equilibrium of stock price information (Black, 1975; Easley et al., 1998; Pan & Poteshman, 2006). In contrast to previous literature, this study extends to investigate the significant interrelationships between multiple information channels (i.e., the options market and social media platforms) and stock returns. We show evidence of a significant relationship in the pooling equilibrium between multiple information channels and the stock market. Furthermore, we show that the agreement on sentiments (in the StockTwits) has a significant and positive relationship with stock returns.

Second, we contribute to the sharing-information literature (Chan et al., 2015; Renault, 2017; Tetlock, 2007). In contrast to Chan et al. (2015), we use the net trade options volume to explore significant relationships between signals from options trading and sentiments from StockTwits. Moreover, we show that signals from options trading activities improve the agreement on sentiments.

Finally, we contribute to the literature on informational share price prediction (Pan & Poteshman, 2006; Renault, 2017). In contrast to Pan and Poteshman (2006), we not only demonstrate the possible significant predictive power of information from options trading with deep leverage (i.e., DOTM), but also shows that more agreement on sentiments sustains future positive stock returns.

However, this study shows that bullish sentiments and options trading with leverage (i.e., out of the money) have limited significant and positive predictive power on future returns.

2 Hypotheses Development

Stock-related information is crucial to a price valuation. However, most retail investors suffer from interpreting stock-related information and accessing privileged information. Fortunately, the information from some information channels (such as signals from the options market and sentiments on social media) shows significant stock price prediction (Pan & Poteshman, 2006; Renault, 2017). Therefore, these investors observe informational channels to find any valuable information for the stock price valuations.

The investment information can be transmitted through several channels, such as signals from the options market, and sentiments from social media. Informed investors tend to trade in the options market, especially those options with deep leverage (Black, 1975; Easley et al., 1998; Pan & Poteshman, 2006). Informed investor trading in the options market triggers a signal as stock price sentiments. Meanwhile, the shared information helps to improve the likelihood of the stock price moving in its perceived value (Antweiler & Frank, 2004; Leung & Ton, 2015; Renault, 2017). The first hypothesis tests whether signals from options trading have significant associations with sentiments on StockTwits.

Given information transmission across information channels, investors observe signals from the options market and believe positive and significant relationships between signals from the option market and agreement on the StockTwits. As such, the second hypothesis tests whether signals from the options market improve the agreement on sentiments.

The sharing-information literature extends to the study of pooling equilibrium, in which the informed traders not only share information between the options market and StockTwits, but also simultaneously trade in the stock market. The third hypothesis tests whether there are significant relationships between multiple information channels and stock returns.

Before information integrating into the stock prices, informed traders trade in the options market. Users from StockTwits can observe signals from the options market and send the sentiments through social media. Thereafter, the information from multiple channels has significant predictive power on the share prices. The fourth hypothesis tests whether signals of options trading and sentiments from social media have significant predictive power on future stock returns.

Finally, this information forms an investment bandwagon based on the agreement on sentiments. This bandwagon may sustain the future stock returns movement. Therefore, the fifth hypothesis tests whether the agreement on sentiments has a positive relationship with current and future stock returns.

3 Data and Methods

The data were derived from three sources: StockTwits[2], the Center for Research in Security Price (CRSP), and OptionMetrics. Both CRSP and OptionMetrics datasets are retrieved from the Wharton Research Data Services (WRDS) platform.

3.1 Stocktwits Dataset

We use a dataset from the social microblogging website, StockTwits.com (henceforth "StockTwits"). StockTwits is a social media platform tailored for sharing ideas and news about financial assets. This platform had approximately two million users by summer 2019 (Muhn, 2019). Alexa internet ranked StockTwits as the 1788th most popular website in the United States in April 2022 (Alexa, 2022).

2 The proprietary StockTwits dataset is obtained from Henry Leung.

StockTwits users need to create a user profile. User profiles include basic personal information, such as username, location, date of join, and personal website. The user can also indicate their investment approach (choices include Fundamentals, Growth, Technical, Value, Momentum or Global Macro), holding period (Day Trader, Swing Trader, Position Trader or Long-Term Investor) and investment experience (Novice, Intermediate or Professional). The user can also choose not to disclose any of the above. Figure 1 shows an example of an investment profile.

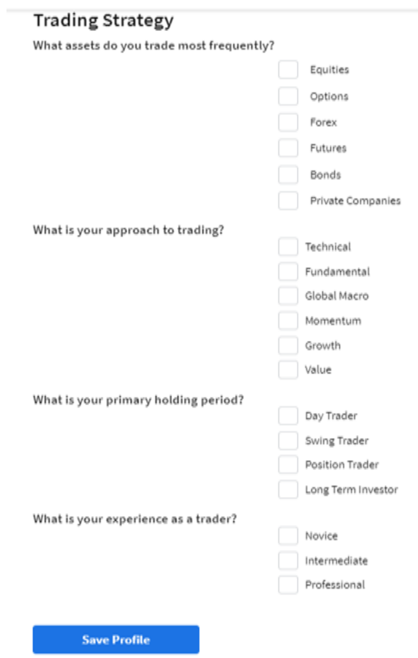

Figure 1 Profile Setting Panel

On the user's page, the user profile shows the user's tweeting-related information, such as Ideas (number of tweets originated by the user), Following (accounts the user is following), Followers (followers of the account), Liked (number of likes received) and Watchlist (list of stocks the user is following). The amount of information that users may provide in their profiles may vary across users. Figure 2 and Figure 3 show two users' profiles pages to illustrate. For instance, user *LiveSquawk*, in Figure 2, reveals his investment approach, location, investment experience and individual webpage; whereas user *inchartitrust* does not reveals any user information.

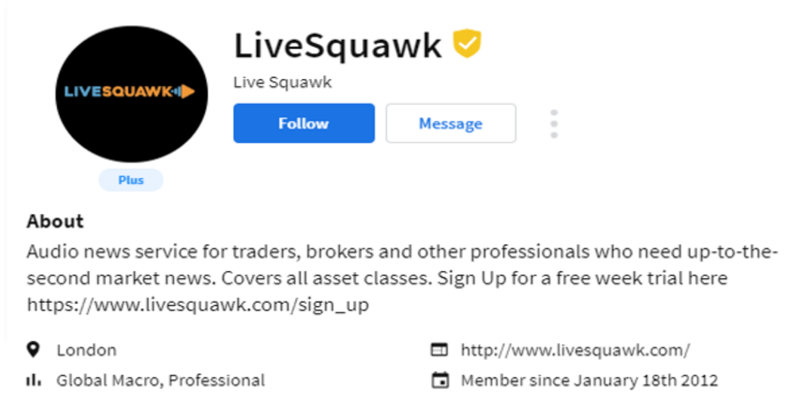

Figure 2 User Profile Page Sample 1

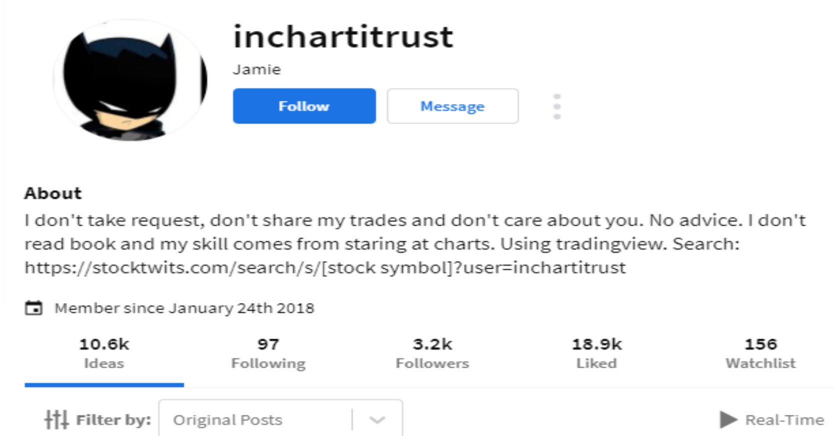

Figure 3 User Profile Page Sample 2

Each tweet is a short message with up to 140 characters (old format, before May 2019) or up to 1000 characters (new format, after May 2019). Users can refer to a specific stock by quoting a “Cashtag” (the character $) right before the stock tickers, for example, "$bac" for "Bank of America." Furthermore, there is an option to indicate the sentiments (bullish or bearish) of the tweets. See Figure 4 for the posting tweet panel and Figure 5 and Figure 6 for tweet samples.

The StockTwits datasets shows messages related to a certain type of asset classes such as equities, bonds, private companies, forex, future, and option.

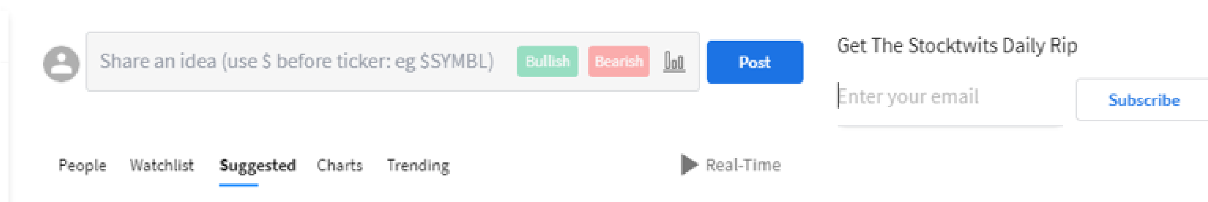

Figure 4 Tweet Message Panel

Figure 5 Tweeting Sample 1

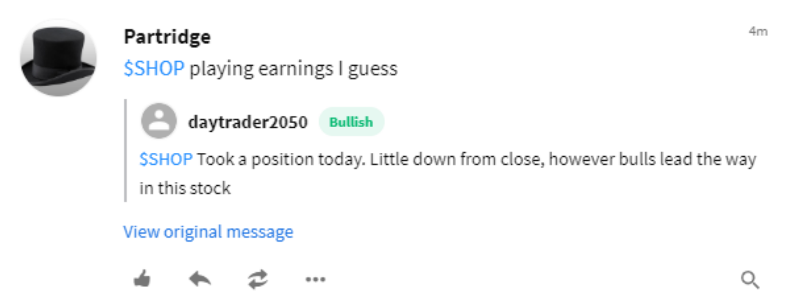

Figure 6 Tweeting Sample 2

This StockTwits dataset is adjusted to match a regular trading hour of the exchanges, moving all tweets posted after 4 pm one day forward, and moving non-trading days (weekend and public holidays) to the next available trading day. The dataset adjusts the time zone of StockTwits (i.e., GMT +0) to the time zone of the US stock market (i.e., daylight saving GMT −4 or non-daylight saving GMT −5).

The StockTwits dataset consists of tweets from 1 October 2012 to 29 March 2018 that contain cashtags of stocks listed in the United States market. The raw dataset contains 20,456,317 tweets. We discard observations without self-claimed sentiments (no claim on the sentiments).[3]

3.2 CRSP and OptionMetrics

The CRSP dataset provides daily stock-related information, such as returns, trading volume and shares outstanding. The OptionMetrics provides options-related information, such as the bid-ask spread of call and put options prices with different strike prices and different maturity lengths, options trading volume of call and put options, and others. We sum the options volume groups based on call and put, respectively. Then, we classify maturity of the options volume groups as long, medium, and short. The options volume groups that expire after 180 days are classified as long maturity groups, ones with expiry > 30 days and ⩽ 180 days are medium maturity groups, and ones with expiry ⩽ 30 days are short maturity groups.

Moreover, we also partition the options volume groups based on moneyness. Moneyness is used to measure the leverage of options trading. Options trading with leverage do it through options contracts with OTM and DOTM. The main driver for partitioning along this measure is that options volume groups with multiple moneyness provides traders with varying leverage levels. According to Black (1975) and Easley et al. (1998), options leverage is the main driver of a pooling equilibrium, where an informed trader chooses to invest in the options market. Easley et al. (1998) and Pan and Poteshman (2006) demonstrated that the traders select not between a single call/put and stock, but rather between calls and puts with varying degrees of leverage and stock. The call or put volume is partitioned into five categories of moneyness, adopting the options strike price

[3] Cookson (2020) include the imputed sentiment in this study.

ratio to the underlying spot price. For instance, Table 1 shows that a 3% OTM call options has a strike-to-spot ratio between 1.03 and 1.10; on the other hand, a 3% OTM put options has a strike-to-spot ratio between 0.97 and 0.9. The detailed classification of the options leverage is shown in Table 1.

	Strike-to-Spot Ratio: Call	**Strike-to-Spot Ratio: Put**
Spot value (X):		
Option with ATM group	97% ≤ X ≤ 103%	97% ≤ X ≤ 103%
Option with ITM group	103% < X ≤ 110%	90% ≤ X < 97%
Option with DITM group	X > 110%	X < 90%
Option with OTM group	90% ≤ X < 97%	103% < X ≤ 110%
Option with DOTM group	X < 90%	X > 110%

The table shows call and put options with different levels of moneyness. The call and put options with ATM group indicate spot value are priced between 103% - 97% of the strike price. The ITM groups indicates the spot value are priced between 103% - 110% and 90% - 97% of strike price of call option and put option, respectively. The DITM groups indicates the spot value are priced above 110% and 90% of strike price of call option and put option, respectively. The OTM groups indicates the spot value are priced above 90% - 97% and 103% - 110% of strike price of call option and put option, respectively.

Table 1 Classification of Option Leverage

We combine StockTwits, CRSP and OptionMetrics datasets and only select the message related to the options asset class. The data of stocks without closing price in the CRSP dataset are removed. This leaves the dataset with 66,731 observations (of which consists of 2,488 stocks).

3.2.1 Main Variables Construction

The main variables are proxies of information transmitted from StockTwits and options market. A proxy of the sentiments on the StockTwits is bullishness variable (i.e., bullish sentiments). Moreover, we also create an agreement variable on sentiments.

Bisides, I also construct a proxy of signals as Net Trade Options Volume ratios from the options trading market partitioned with different maturity and moneyness groups.

3.3 Bullishness and Agreement

We follow Antweiler and Frank (2004) to build Bullishness and Agreement variables from the StockTwits datasets. The Bullishness variable is used to set the criteria of an event with bullish sentiments. Bullishness is the daily number of net bullish sentiments. The total number of sentiments is $M_{i,t} \equiv \mathrm{M}_{\mathrm{i,t}}^{\mathrm{bullish}} + \mathrm{M}_{\mathrm{i,t}}^{\mathrm{bearish}}$, for $i = (1,2, \ldots)$ is the number of stock and *t* is the date, where $M_i \in N$. The bullishness variable is defined as

$$Bullishness_{i,t} = \frac{M_{i,t}^{bullish} - M_{i,t}^{bearish}}{M_{i,t}} \tag{1}$$

where *t* is the date of day 0 of the event. The standardised bullishness index, $Bullishness_t$, in time t is

$$Bullishness_{i,t}^{*} = \ln \left[\frac{2 + M_{i,t}\left(1 + Bullishness_{i,t}\right)}{2 + M_{i,t}\left(1 - Bullishness_{\{i,t)}\right\}} \right] \tag{2}$$

The Bullishness variable shows a standardised net bullishness in the tweets posted from different senders in StockTwits. After building the Bullishness variable, this study can build the Agreement variable as follows:

$$Agreement_{i,t} = 1 - \sqrt{1 - Bullishness_{i,t}^{2}} \tag{3}$$

This set of an $Agreement_{i,t} \in [0,1]$. The agreement index is a proxy of agreement in daily sentiments on a particular stock in the StockTwits. The summary statistics of StockTwits are shown in 2.

3.4 Net Trade Option Volume Ratio

Inspired by Chan et al. (2002), we use the net trade options volume ratio as a proxy for signals variable from the options market. The net trade options volume ratio defines the signals variable as

$$N_{i,t}^{group} = \left(\frac{C_{i,t} - P_{i,t}}{C_{i,t} + P_{i,t}}\right)^{group} \tag{4}$$

where, on date *t* for stock i, $C_{i,t}$ and $P_{i,t}$ are volumes of puts and calls. If an informed investor with positive insider information on stock *i* acts on their information by trading “new” call options, then, this will add to $C_{i,t}$. In contrast, purchasing "new" put options on negative insider information adds to $P_{i,t}$. The $N_{i,t}^{group}$[4] is the net trade options volume ratio by group, given stock *i* and time *t.* The $N_{i,t}^{group}$ is formulated by volume of $C_{i,t}$ minus against volume of $P_{i,t}$ and divided by the total number of $C_{i,t}$ and $P_{i,t}$. According to Chan et al. (2002), the net trade options volume indicates volume of $C_{i,t}$ minus volume of $P_{i,t}$. The net trade option volume indicates a temporary order imbalance offering information to the market makers for market quote revision. The asymmetric information models indicate that market makers are uncertain of a specific buy or sell order from either an informed trader or liquidity trader. The market makers adopt a rational pricing strategy: revises the quotes upward (downward) when the net trade options volume is positive (negative). The net trade options volume can predict the quoted movement of options returns and stock returns (Admati & Pfleiderer, 1988; Kyle, 1985). The $N_{i,t}^{group}$ will increase if $C_{i,t}$ increases or $P_{i,t}$ decreases. The $N_{i,t}^{group}$ is partitioned by two main groups, maturity and moneyness. Moneyness measures the leverage of options trading. The options trading with leverage are options with OTM

[4] We use a proxy of the net trade option volume ratio because the ratio is parsimonious in merging the information in the put and call volumes into a single variable. Besides, it controls differences in options trading volume across stocks and over time.

and DOTM groups. The options maturity is further classified into short, medium, and long periods, while options moneyness is further classified into ATM, ITM, DITM, OTM, and DOTM.

3.5 Information from Options Market and Information from Social Media Platform.

Motivated by Leung and Ton (2015), we use multiple fixed effects regressions to test hypotheses. The fixed effects of regressions are based on stocks and time (month and year).

This section uses two regressions to test hypotheses relating to signals from options trading and activities of StockTwits. The test of the first regression examines the hypothesis that signals from options trading may have a significant association with sentiments on StockTwits. The test of the second regression investigates the hypothesis that signals from options market may improve the agreement on sentiments.

Motivated by Pan and Poteshman (2006), who include the liquidity underlying the options and stock market, we add two liquidity control variables of turnover and options spread (i.e., bid-ask options quotes) in regressions analysis. Turnover and options spread can affect returns of both stock and options markets, respectively (see, e.g., Chordia and Swaminathan (2000); Gervais et al. (2001)). The regressions are as follows:

$$B_{i,t} = \alpha + \beta^{group} N_{i,t}^{group} + \zeta\, \mathrm{t}_{i,t} + \gamma\, \mathrm{O}S_{i,t} + \epsilon_{i,t} \qquad (5)$$

$$A_{i,t} = \alpha + \beta^{group} N_{it}^{group} + \zeta\, \mathrm{t}_{i,t} + \gamma\, \mathrm{O}S_{i,t} + \epsilon_{i,t} \qquad (6)$$

The dependent variable is $B_{i,t}$ and $A_{i,t}$ which denote Bullishness and Agreement on stock *i* on date *t*, respectively. The main independent variable $N_{i,t}^{group}$ denotes the net trade options volume ratio on date *t* for stock *i* by different contract groups and two liquidity control variables (i.e., Turnover and options spread).

3.6 Information from Different Channels and Stock Returns

Motivated by Pan and Poteshman (2006), we examine the pooling equilibrium activities: that there may be a significant relationship between multiple information channels and the stock returns. I further analyse the hypothesis that agreement on sentiments improves the likelihood of moving a stock price to the perceived stock value.

As with Pan and Poteshman (2006), the main dependent variables are net trade options volume ratio. The independent variables are bullishness, agreement and two control variables (such as turnover and options spread). The regressions are as follows:

$$R_{i,t=0} = \alpha + \beta_1^{group} \mathrm{N}_{i,t=0}^{\mathrm{group}} + \beta_2\, B_{i,t=0} + \beta_3\, A_{i,t=0} + \beta_4\, \mathrm{t}_{i,t=0} + \beta_5 \mathrm{O}S_{i,t=0} + \epsilon_{i,t=0} \quad (7)$$

where, on the date t = 0 for stock i, the dependent variable $R_{i,t=0}$ denotes the stock returns for stock i. The $N_{i,t=0}^{group}$ denotes the day zero net trade options volume based on different options contract groups for stock i. $B_{i,t=0}$ denotes the day zero bullishness for stock i. $A_{i,t=0}$ refers to the day zero agreement of sentiments for stock i. The groups are the options contracts consisting of length of contracts (i.e., short-term, medium-term and long-term maturity) and moneyness of contract (i.e., ITM, ATM, DITM, OTM, and DOTM).

3.7 Predictive Power of Information on Future Stock Returns

We examine the hypothesis that information has significant predictive power on future stock returns. Besides, we also evaluate the hypothesis that agreement on sentiments may improve a positive relationship with current and future returns. The future returns are up to 20 days.

I only report the graphical coefficient of regressions to show the relationships between information from multiple channels (i.e., StockTwits and option market) and future stock returns.

$$R_{i,t=j} = \alpha + \beta^{OTM} N^{OTM}_{i,t=0} + \epsilon_{i,t=j} \tag{8}$$

$$R_{i,t=j} = \alpha + \beta^{DOTM} N^{DOTM}_{i,t=0} + \epsilon_{i,t=j} \tag{9}$$

$$R_{i,t=j} = \alpha + \beta\, B_{i,t=0} + \epsilon_{i,t=j} \tag{10}$$

$$R_{i,t=j} = \alpha + \beta\ \ A_{i,t=0} + \epsilon_{i,t=j} \tag{11}$$

Where we repeatedly perform regressions from dependent variable returns of stock i on *t* =0, $R_{i,t=0}$, up to returns stock i on *t* = 20, $R_{i,t=20}$. We repeatedly perform 21 regressions of each of Equations 8 – 9. However, Equation 8 and 9 use net trade options volume variables with OTM or DOTM, respectively. Equation 8 and 9 also measure the impact of signals from options trading with leverage on returns for 20 days. Equation 3.7 and 3.8 use Bullishness $B_{i,t=0}$ and Agreement $A_{i,t=0}$ on sentiments from StockTwits.

4 Results and Findings

4.1 Descriptive Summary

	Mean	Median	Min	Max	Skewness	Kurtosis
Stock (CRSP) Dataset:						
Returns	0.003	0.002	-0.788	3.010	5.599	274.1
Turnover	0.054	0.016	1.99e-6	11.34	17.021	536.5
Stocktwits Dataset:						
Bullishness	0.995	1.036	-5.030	7.748	-0.069	0.738
Agreement	0.855	1.000	0.000	1.000	-1.871	4.688
Option (OptionMetrics) Dataset:						
Option spread (bid-ask)	1.298	0.750	-0.0500	29.90	1.215	6.507
All:						
Net Vol. Ratio: Overall	.246	0.276	-1.000	1.000	-0.440	2.593
Maturity:						
Net Vol. Ratio: Short	0.034	0.000	-1.000	1.000	1.212	14.48
Net Vol. Ratio: Medium	0.064	0.000	-1.000	1.000	0.597	7.417
Net Vol. Ratio: Long	0.147	0.068	-1.000	1.000	0.051	3.673
Moneyness:						
Net Vol. Ratio: ATM	0.126	0.000	-1.000	1.000	-0.142	2.379
Net Vol. Ratio: ITM	0.080	0.000	-1.000	1.000	-0.136	1.737
Net Vol. Ratio: DITM	0.203	0.394	-1.000	1.000	-0.401	1.526
Net Vol. Ratio: OTM	0.166	0.000	-1.000	1.000	-0.244	2.204
Net Vol. Ratio: DOTM	0.054	0.000	-1.000	1.000	-0.101	1.398

This table shows returns, turnover, bullishness, agreement, options spread (bid-ask), net trade options volume ratio (for short maturity, medium and long maturity), and net trade options volume ratio (for ATM, ITM DITM, OTM and DOTM) variables. The returns variable indicates the daily change of stock prices. The turnover variable indicates the stock trading volume divided by shares outstanding. The bullishness variable indicates the daily net bullishness on the stock. The agreement variable indicates the daily agreed sentiments on the stock. The options spread indicates the closing bid options price minus closing ask options price. The net trade options volume ratio indicates the net daily trade option volume (daily numbers of calls − daily numbers of puts) divided by total daily numbers of options partitioned by different groups. There are two main groups: maturity and moneyness. The maturity group includes short, medium, and long while the moneyness group includes ATM, ITM, DITM, OTM, and DOTM.

Table 2 Descriptive Summary for Variables from Stock Market, Option Market and StockTwits

Table 2 shows the variables retrieved from three different datasets: CRSP, OptionMetrics and CRSP. For the stock dataset from CRSP, returns and turnover variables show positive skewed and leptokurtic distributions. The positively skews in the distributions of returns and turnover indicate the mean exceeding the median, and the distribution of returns and turnover implies fat tails; that is, a higher probability of extreme outliers.

For the StockTwits dataset, the distributions of both bullishness and agreement variables are negatively skewed. The kurtosis of these two variables exhibits different types of distribution: the agreement is leptokurtic, and the bullishness is platykurtic.

For the OptionMetrics dataset, the distribution of the options spread is positively skewed and leptokurtic. Distributions of net trade options volume ratio in the overall and moneyness groups are negative skewed and platykurtic. Among the moneyness groups, the net trade options volume ratio with DITM had the highest mean of 0.203.

However, distributions of the net trade options volume ratio in the maturity groups (i.e., short, medium, and long) are positively skewed and leptokurtic. Among maturity groups, the net trade options volume ratio with long maturity group shows the highest mean of 0.147.

4.2 Information from Options Market and Information from StockTwits

	(1) Bullishness Overall	**(2) Bullishness Group**	**(3) Agreement Overall**	**(4) Agreement Group**
Net Vol. Ratio:		0.1460***		-0.0027
Short		(0.0236)		(0.0054)
Net Vol. Ratio:		0.0209		-0.0014
Medium		(0.0167)		(0.0038)

Net Vol. Ratio:		0.0285**		-0.0053*
Long		(0.0131)		(0.0030)
Net Vol. Ratio:		0.0402***		0.0046**
ATM		(0.0087)		(0.0022)
Net Vol. Ratio:		0.0382***		0.0037*
ITM		(0.0078)		(0.0020)
Net Vol. Ratio:		0.0461***		0.0058***
DITM		(0.0080)		(0.0019)
Net Vol. Ratio:		0.0279***		0.0009
OTM		(0.0076)		(0.0020)
Net Vol. Ratio:		-0.0046		0.0056***
DOTM		(0.0087)		(0.0021)
Net Vol. Ratio:	0.0718***		0.0016	
Overall	(0.0090)		(0.0020)	
Constant	0.9800***	0.965***	0.853***	0.852***
	(0.0048)	(0.0050)	(0.0012)	(0.0013)
Observations	66,365	66,365	66,365	66,365
R-squared	0.338	0.340	0.300	0.300
Stock FE	YES	YES	YES	YES
Month-Year	YES	YES	YES	YES

Table shows a fixed effect regression with stock and time (month and year) for the period Oct 2012 to Feb 2018. Regressions (1) and (2) use bullishness as dependent variable. Regressions (3) and (4) use agreement as dependent variables. The independent variables in regression (2) and (4) are net trade options volume ratio partitioned by maturity (i.e., short, medium, and long period) and moneyness (i.e., ATM, ITM, DITM, OTM, DOTM). The independent variables in regression (1) and (3) are sum net trade options volume ratio of overall groups. The options volume ratio is expressed as the total daily volume of calls minus the daily volume of puts divided by the sum of daily volume of calls and puts. Standard deviation is reported in the brackets. *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Table 3 Regression for the Interrelationship between Signals from Options Trading and Activities of StockTwits

This section discusses the results that signals from options trading may have significant associations with sentiments on social media. Moreover, we show the results that signals from options market may improve the agreement on sentiments.

Table shows that net trade options volume for groups, such as overall, short, long, ATM, ITM, DITM, and OTM, has a positive and significant association with bullishness at the 1% significance level.

For regression (1), a unit increase in the net trade options volume for overall groups yields 0.0718 increase in the bullishness variable. For regression (2), a unit increase in the net trade options volume for short, long, ATM, ITM, DITM, and OTM groups yield 0.1460, 0.0285, 0.0402, 0.0382, 0.0461 and 0.2790 increase in bullishness variables, respectively. The positive relationships indicate that bullish information is shared between two information channels. The information shared across two information channels improve the likelihood of bullish stock returns. Because the sharing-information activities across two information channels improve the information diffusion power to those uninformed investors (such as retailed investors). Those uninformed investors may respond to the sentiments by spreading similar sentiments on the information channels and buying the stocks. However, the significant positive relationship between options trading with OTM group and bullish sentiments may imply a potential information manipulation. The significant positive relationship underpins Schmidt's (2020) argument that (long-term) investors can manipulate a stock price through an information transmission strategy. First, informed investors know the bullish fundamental of the stock, but they instead send bearish sentiments. The informed investors may invest a stock at lower stock price through the option and stock market. Thereafter, the stock price will increase with information revealed after a passage of time and the informed investors earn profit from this investment strategy.

The change of net trade options volume with long, ATM, ITM, DITM, and DOTM yield -0.0053, 0.0046, 0.0037, 0.0058, 0.0056 of agreements, respectively. The net trade options volumes of long, ATM, ITM, DITM, and DOTM have a positive and significant association with agreement at the 10%, 5%, 10%, 1%, and 1% significance levels, respectively. The positive and significant relationships between net trade volume and agreement exhibit that buy signals shared between the two information channels increase number of users in StockTwits who believe the bullish sentiment of the stocks. However, net trade options volume with long-term maturity group shows a significant and negative association with agreement because information from options trading with long-term group imply a signal of sentiments on the stock based on long-term investment prospective. Therefore, the users of StockTwits doubt that bullish sentiments from options with long-term group provides shorter-term stock price information on social media since most sentiments of social media may offer a relatively short-term stock information. Last, net trade options volume with DOTM shows limited evidence of a relationship with bullishness, but it shows significant and positive relationship with the agreement.

4.3 Information from Different Channels and Stock Returns

	(1) Return Overall	**(2) Return Group**
Net Vol. Ratio: Overall	0.0013***	
	(0.0004)	
Net Vol. Ratio: Short		0.0061***
		(0.0010)
Net Vol. Ratio: Medium		0.0027***
		(0.0008)
Net Vol. Ratio: Long		0.0002
		(0.0006)

Net Vol. Ratio: ATM		-0.0006
		(0.0004)
Net Vol. Ratio: ITM		-0.0001
		(0.0003)
Net Vol. Ratio: DITM		0.0024***
		(0.0004)
Net Vol. Ratio: OTM		-0.0003
		(0.0003)
Net Vol. Ratio: DOTM		-0.0020***
		(0.0004)
option spread	0.0002	0.0002
	(0.0002)	(0.0002)
Turnover	0.0340***	0.0334***
	(0.0014)	(0.0014)
Bullishness	0.0078***	0.0077***
	(0.0002)	(0.0002)
Agreement	0.0030***	0.0029***
	(0.0007)	(0.0007)
Constant	-0.0095***	-0.0098***
	(0.0007)	(0.0007)
Observations	66,365	66,365
R-squared	0.144	0.147
Stock FE	YES	YES
Month-Year	YES	YES

This table shows a fixed effect regression with stock and time (month and year) for the period Oct 2012 to Feb 2018. The dependent variables of regressions (1) and (2) are (stock) returns. There are two regressions: regression (1) uses the independent variables which comprise of net trade options volume ratio for overall groups + activities of social media + control variables; regression 2: uses the independent variables which comprise of net trade options volume ratio by groups + activities of social media + control variables. The net trade options volume ratio by groups are partitioned by maturity (short, medium, and long) and moneyness (ATM, ITM, DITM, OTM, DOTM). The activities of social media are bullishness and agreement variables. The control variables are options spread and turnover. The options spread and turnover variables measure the liquidity of options market and stock market, respectively. The options volume ratio is expressed as the total daily volume of calls minus daily number of puts divided by sum of volume of daily calls and puts. The standard deviation is reported in brackets. ∗, ∗∗, and *** describe significance at 10%, 5%, and 1%, respectively.

Table 4 Regression for the Activities from Multiple Information Channels and Stock Returns.

Table 4 shows the relationships between activities of both information channels and current returns. For regression (1), coefficients (0.0013) of net trade options volume of Overall groups combined, and coefficients (0.0078, and 0.0030) of bullishness and agreement show significant and positive association with current returns at the 0.1% level.

For regression (2), coefficients (0.0061, 0.0027, and 0.0024) of net trade options volume with short and medium and DITM groups, and coefficients (0.0077, and 0.0029) of bullishness and agreement show significant and positive association at the 0.1% level. These significant and positive coefficients show that there are significant and positive relationships between activities of information channels and current returns.

However, coefficients (-0.00201) of net trade options volume with DOTM groups show significant and negative association at the 0.1% level. Consistent with Pan and Poteshman (2006), signals from the option market with DOTM groups indicate that informed investors trade the options with deep leverage while the stock market only responds to the information later.

The agreement on sentiments remains significantly and positively associated with returns. This result indicates that more agreed messages improve current bullish returns. The turnover variable has positive and significant affiliation with the stock returns.

4.4 Predictive Power of Information on Future Stock Returns.

This section shows findings of relationships between activities from information channels and future returns.

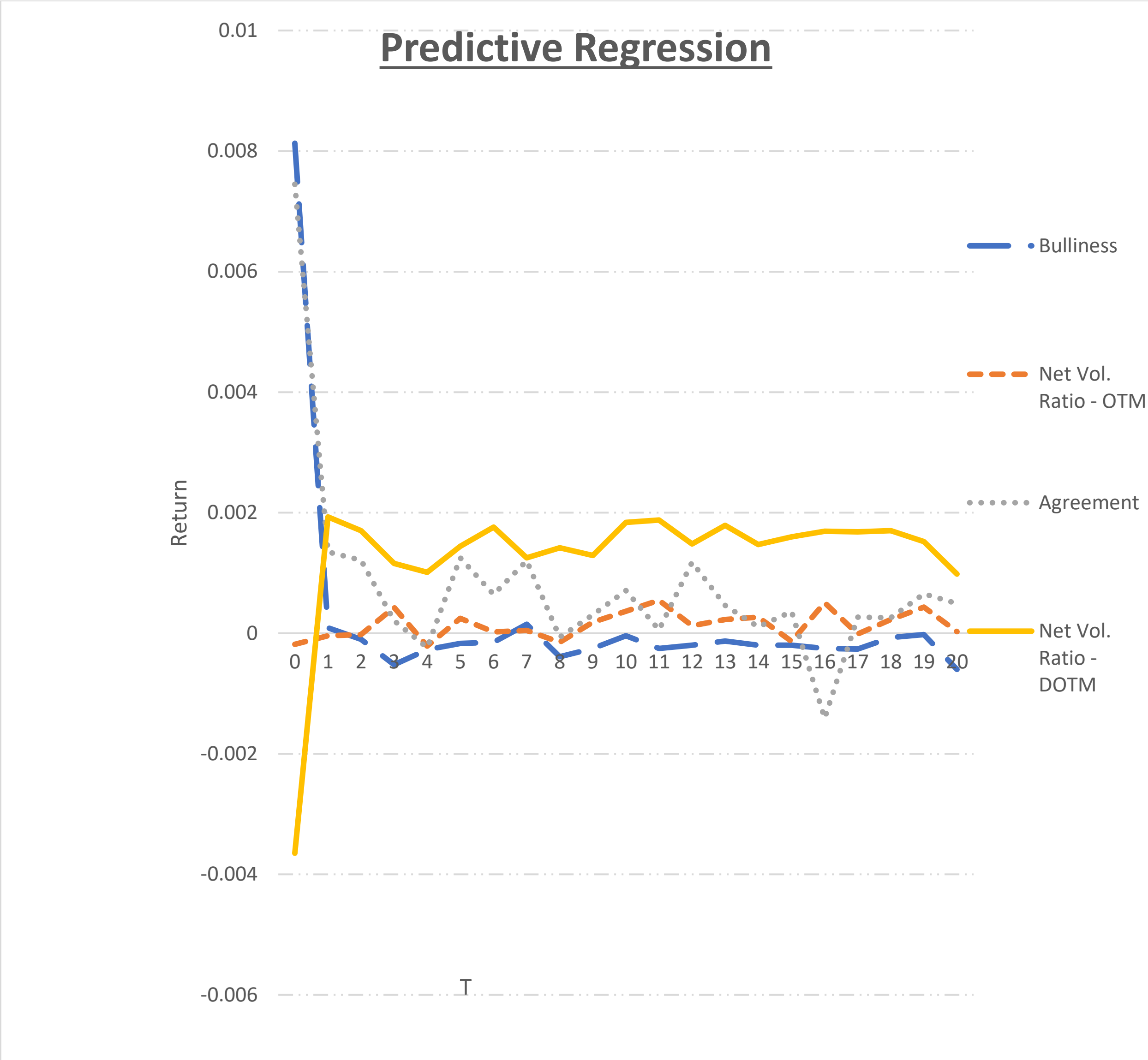

Figure 7 Predictive Power of Return: Coefficients of Information Activities

Figure 7 shows that an increase in a unit of net trade options volume with OTM has significant and positive future returns at t = 3, 10, 11, 16, and 19, while for the options with DOTM, an increase of a unit of net trade options volume will have positive and significant returns from t = 1 to t =19. Consistent with Pan and Poteshman (2006), trade in options market with more leverage have more significant and positive predictive power on future positive returns. As such, the options with DOTM have more predictive power than those of OTM. An option group with DOTM has more significant and longer positive economic returns than those options group with OTM.

In contrast, the result shows that negative coefficients trend of bullishness to future returns for future negative returns at t = 3, 4, 8, 9, 15, 16. The negative coefficient trend shows that bullish sentiments on StockTwits limited evidence of predictive power on future stock returns. However, the bullishness sentiment only shows a significant and positive association with the current returns at $t = 0$, indicating that the bullishness sentiments have a contemporaneous relationship to the stock returns.

Lastly, the agreement on sentiments shows that the agreed message may show a significant and positive association with future stock returns for most periods. The agreement on sentiments improves the strength of the information on the stock and maintains future returns over a longer period. The detailed coefficient results of regressions are available in appendix (see table A1).

4.5 Robustness

This section shows the robustness checks of overall testing on the hypothesis. We split our dataset into big and small market capitals (call big and small stocks henceforth). According to Fama and French (1993), they employed stock market capitalisation above the 90^{th} percentile as a 'big' stock for the North American market and quantified those stocks above the 70^{th} percentile as the 'big' stock for the other regions. For the moderation intuition, we select the stocks with market capital exceeding the 75^{th} percentile as big stocks; others are classified as small stocks.

Table 6 shows the robustness of our regression analysis in table 3. Regression in (1), (2), (5), and (6) shows significant and positive association to bullishness sentiments, except for net volume trading ratios with DOTM group for small stocks (shown in regression (6)), which shows a negative relationship to the bullishness sentiments. However, the net volume trading ratio with DOTM group for small stocks is an insignificant association with the Bullishness sentiments.

Table 3 also shows robust results of our regression analysis in Table 3. Regression in (3), (4), (7), and (8) shows the relationship between sentiments or signals from information channels and agreement on sentiments. Similarly, the regressions show most coefficients of the explanatory variable to the agreement are consistent results shown in Table 3, except for the net volume trading ratio with DOTM (in regression (7)) and Medium (in regression (8)) groups. However, the net volume trading ratio with DOTM (in regression (7)) and Medium (in regression (8)) groups show an insignificant coefficient to the agreement on sentiments.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bullishness Overall (Big)	***Bullishness Group (Big)***	***Agreement Overall (Big)***	***Agreement Group (Big)***	**Bullishness Overall (Small)**	**Bullishness Group (Small)**	**Agreement Overall (Small)**	**Agreement Group (Small)**
Net vol. ratio: Short		0.186***		0.0100		0.118***		-0.00770
		(0.0387)		(0.0110)		(0.0297)		(0.0064)
Net vol. ratio: Medium		0.0302		-0.0060		0.0100		0.00033
		(0.0268)		(0.0071)		(0.0216)		(0.0046)
Net vol. ratio: Long		0.0655***		-0.0087		0.0043		-0.0045
		(0.0212)		(0.00575)		(0.0167)		(0.0035)
Net vol. ratio: ATM		0.0313***		0.00114		0.0511***		0.0060*
		(0.0121)		(0.0035)		(0.0126)		(0.003)
Net vol. ratio: ITM		0.0382***		0.0062*		0.0482***		0.0019
		(0.0115)		(0.0032)		(0.0108)		(0.0026)
Net vol. ratio: DITM		0.00753		0.0050		0.0694***		0.0058**
		(0.0119)		(0.0034)		(0.0108)		(0.0024)
Net vol. ratio: OTM		0.0328***		0.0016		0.0219**		0.0007
94		(0.0105)		(0.0030)		(0.0111)		(0.002)
Net vol. ratio: DOTM		-0.0227*		0.0020		0.0011		0.0064**
		(0.0132)		(0.0037)		(0.0117)		(0.00256)
Net vol. ratio: Overall	0.0905***		-0.0020		0.0614***		0.0023	
	(0.0145)		(0.0039)		(0.0114)		(0.0024)	
Constant	0.793***	0.775***	0.817***	0.815***	1.1280***	1.1200***	0.8820***	0.8810***
	(0.0062)	(0.0069)	(0.0018)	(0.0020)	(0.0070)	(0.007)	(0.0016)	(0.0017)
Observations	29,089	29,089	29,089	29,089	37,189	37,189	37,189	37,189
R-squared	0.273	0.276	0.369	0.369	0.369	0.372	0.224	0.224
Ticker FE	YES	YES	YES	YES	YES	YES	YES	YES
Month_Year	YES	YES	YES	YES	YES	YES	YES	YES

This table shows a fixed effect regression with stock and time (month and year) for the period Oct 2012 to Feb 2018. The first four regressions are regressions result for big stocks and the last four regression are regressions results for small stocks. Regression (1), (2), (5), and (6) use bullishness as dependent variable. Regression (3) and (4), (7), and (8) use agreement as dependent variables. The independent variables in regression (2) and (4) are net trade option volume ratio partitioned by maturity (short, medium, and long period) and moneyness (ATM, ITM, DITM, OTM, DOTM). The independent variables in regression (1) and (5) are sum net trade option volume ratio of overall groups. The option volume ratio is expressed as the total daily volume of calls minus the daily volume of puts divided by the sum of daily volume of calls and puts. Standard deviation is reported in the brackets. ∗, ∗∗, and *** denote significance at 10%, 5% and 1%, respectively.

Table 5 Regression for the Interrelationship between Signals from Options Trading and Activities of StockTwits: Big and Small Stocks

Table 7 shows the robustness of our regression analysis in table 4. Consistently, table 7 shows that most of the coefficient’s signs are identical to our main result in 4. Regression in (1), (2), (5), and (6) shows significant and positive association to bullishness sentiments except for net volume trading ratios with DOTM group for small stocks (shown in regression (6)), which shows a negative relationship to the bullishness sentiments. However, the net volume trading ratio with DOTM group for small stocks is an insignificant association with the Bullishness sentiments.

Table 7 also shows robust result of our regression analysis in Table 5. Regression in (3), (4), (7), and (8) shows the relationship between sentiments or signals from information channels and agreement on sentiments. Similarly, the regressions show most coefficients of the explanatory variable to the agreement are consistent results shown in Table 5 except for net volume trading ratio with DOTM (in regression (7)) and Medium (in regression (8)) groups. However, the net volume trading ratio with DOTM (in regression (7)) and Medium (in regression (8)) groups show insignificant coefficient to the agreement on sentiments.

	(1) Ret=0 – Overall (Big)	(2) Ret_t=0 – Partition (Big)	(3) Ret_t=0 – Overall (Small)	(4) Ret_t=0 – Partition (Small)
Net vol. ratio: Short		0.00279***		0.00681***
		(0.000878)		(0.00158)
Net vol. ratio: Medium		0.000403		0.00336***
		(0.000595)		(0.00116)
Net vol. ratio: Long		0.000874*		0.000112
		(0.000474)		(0.000911)
Net vol. ratio: ATM		2.00e-06		-6.96e-05
		(0.000263)		(0.000668)
Net vol. ratio: ITM		0.000792***		0.000269
		(0.000247)		(0.000567)
Net vol. ratio: DITM		0.00105***		0.00278***
		(0.000254)		(0.000565)
Net vol. ratio: OTM		-2.16e-05		-0.000569
		(0.000219)		(0.000583)
Net vol. ratio: DOTM		-0.000458		-0.00289***
		(0.000285)		(0.000631)
Net vol. ratio: Overall	0.00104***		0.00149**	
	(0.000322)		(0.000619)	
Constant	-0.00304***	-0.00355***	-0.0153***	-0.0150***
	(0.000112)	(0.000112)	(0.000317)	(0.000316)
Turnover	-0.00183	0.00225	0.0344***	0.0336***
	(0.00662)	(0.00661)	(0.00184)	(0.00183)
Bullishness	0.00428***	0.00420***	0.0100***	0.00979***
	(0.000127)	(0.000127)	(0.000285)	(0.000285)
Agreement	0.00101**	0.000988**	0.00534***	0.00538***
	(0.000442)	(0.000441)	(0.00124)	(0.00124)
	(0.000447)	(0.000450)	(0.00123)	(0.00123)
Observations	29,089	29,089	37,189	37,189
R-squared	0.237	0.241	0.150	0.154
Ticker FE	YES	YES	YES	YES
Month_Year	Yes	Yes	Yes	Yes

This table shows a fixed effect regression with stock and time (month and year) for the period Oct 2012 to Feb 2018. The dependent variables of regressions are stock returns. There are four regressions: regression (1): uses the independent variables which comprise of net trade options volume ratio for Overall groups combined + activities of StockTwits + control variables for big stocks; regressions (2) uses the independent variables which comprise of net trade options volume ratio partitioned by groups + activities of StockTwits + control variables for big stocks; regressions (3) uses the independent variables which comprise of net trade options volume ratio for Overall groups combined + activities of StockTwits + control variables for small stocks; regression (4) uses the independent variables which comprise of net trade options volume ratio partitioned by group + activities of StockTwits + control variables for small stocks. The net trade options volume ratio by group is partitioned by maturity (short, medium, and long) and moneyness (ATM, ITM, DITM, OTM, DOTM). The activities of StockTwits are bullishness and agreement variables. The control variables are options spread and turnover. The options spread and turnover variables measure the liquidity of options market and stock market, respectively. The options volume ratio is expressed as the total daily volume of calls minus daily number of puts divided by sum of volume of daily calls and puts. The standard deviation is reported in brackets. *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Table 6 Regression for the Activities from Multiple Information Channels and Stock Returns: Big and Small Stocks

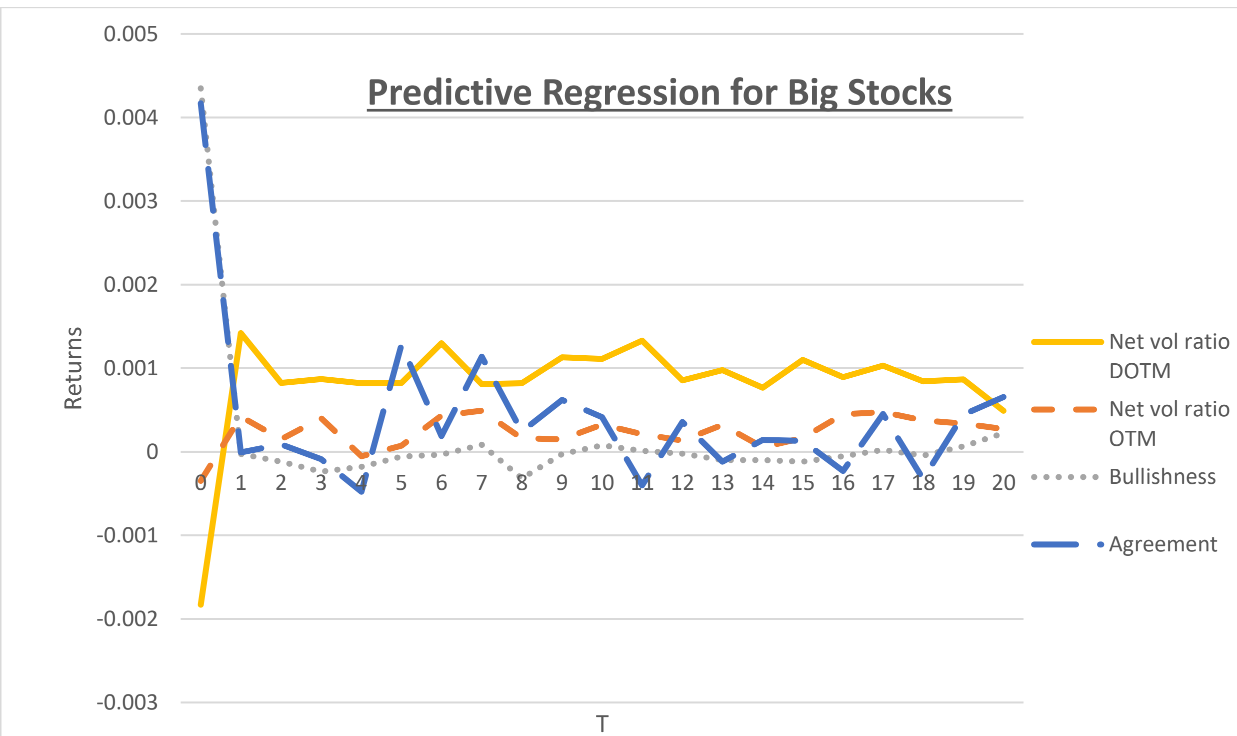

Figure 8 Predictive Power of Return: Coefficients of Information Activities: Big Stocks

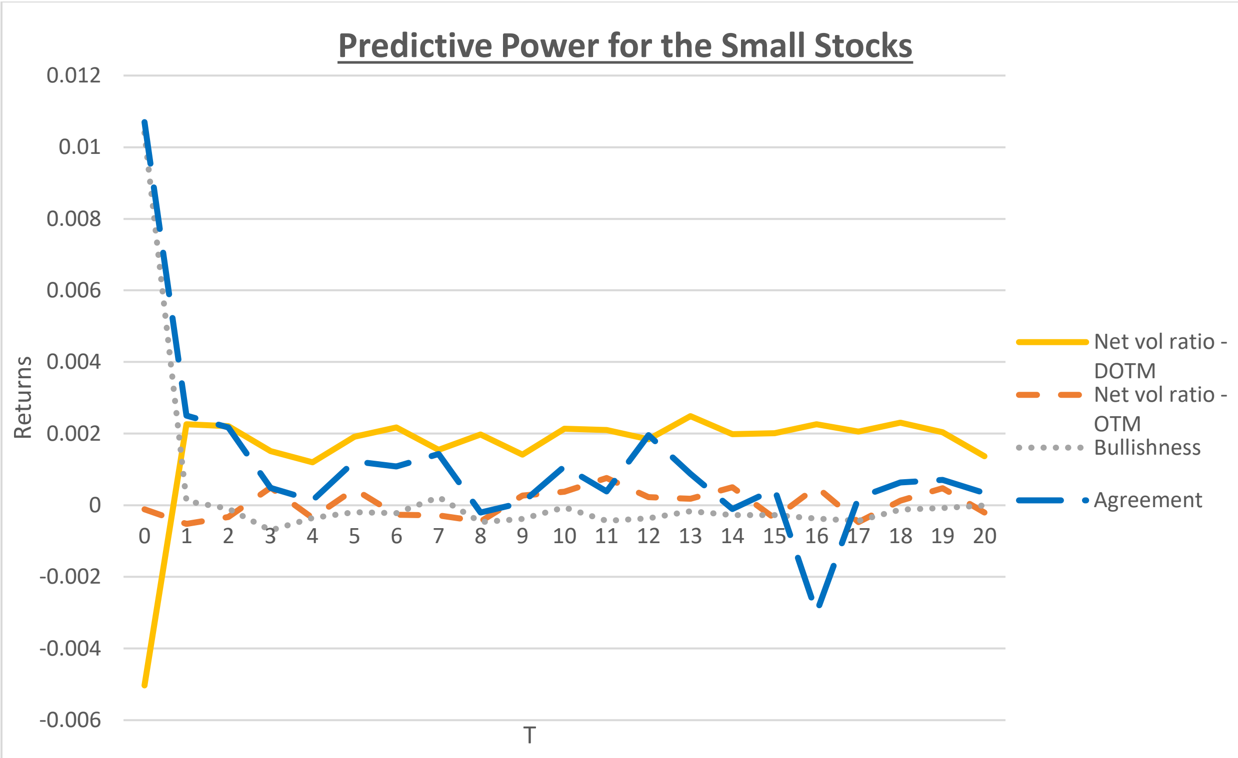

Figure 9 Predictive Power of Return: Coefficients of Information Activities: Small Stocks

Trends of predictive regression for both big and small stocks in Figure 8 and figures 9, respectively, show that robustness to trend of predictive regression in Figure 7. Although net volume trading ratio with DOTM group for big and small stocks show a negative return at t = 0, but those ratio with DOTM group shows the positive and significant future returns from t =1 until t =20. In contrast, the Bullish sentiments for big and small stocks show a positive return at t = 0, but the bullish sentiments demonstrate mostly insignificant and positive returns from t =1 until t =20 and the predictive returns are close to zero returns. Similarly, the net volume trading ratio with OTM group exhibits mostly insignificant and positive returns closest to zero from t = 0 to t = 20. Lastly, the agreement on sentiments reveals very high positive and significant returns at t = 0 and the agreement shows consistently positive returns from t = 1 to t = 20. The detailed results of the coefficients of regressions for big and small stocks are available in the appendix (see table A2 and table A3).

4.6 Discussion of Findings

We show possible significant relationships between signals from some options contract groups (i.e., All, ATM, ITM, DITM and OTM, long-term and short-term maturity groups) and bullish sentiments on StockTwits platforms. The sharing-information activities increase the likelihood of stock price movements to the perceived price target value (Chen et al., 2013; Dow & Gorton, 1994; Gray & Kern, 2011; Stein, 2008). Furthermore, the results show the signals from options trading (with ATM, ITM, DITM, and DOTM groups) have a significant and positive association with agreements on social media. The positive association indicates that investors improve their belief of bullish sentiments by observing bullish signals from the options market and sentiments on StockTwits.

Next, we show significant evidence of a pooling equilibrium between information channels and stock returns. Given the sharing-information activities, the signals of options trading and sentiments transmitted through social media have improved the positive association with the stock returns movement. As such, this pooling equilibrium condition increases the agreement on bullish sentiments. This agreement on sentiments may also has a positive association with the stock returns. Besides, signals from the options with deep leverage (i.e., DPTM) indicate that the informed investors trade the options with deep leverage while the stock market has lagged in response to the bullish agreement.

However, the significant positive relationship between options trading with OTM and bullish sentiments may be due to information manipulation. We underpin the argument that (long-term) investors can manipulate a stock price through fake news. Investors may send bearish sentiments even though the stocks have positive fundamentals. If bearish sentiments lower the stock price, the informed investors can buy the stock at a lower stock price. The stock price will then increase as information is revealed over the passage of time.

5 Conclusions

We demonstrate that there is a significant and positive relationship between signals from some options contract groups and bullish sentiments on StockTwits. The sharing-information activities improve the chance of stock price movements to the targeted price value (Chen et al., 2013; Dow & Gorton, 1994; Gray & Kern, 2011; Stein, 2008).

Furthermore, the results reported that the signals from options trading (with ATM, ITM, DITM, and DOTM groups) have significant and positive association with agreements of sentiments on StockTwits. The positive association indicates that investors improve their belief of bullish sentiments by observing bullish signals from the options market and sentiments on StockTwits.

We show that there is significant evidence of a pooling equilibrium between information channels and stock market. Given the sharing-information activities, the signals of some options groups and sentiments of social media have improved the positive association with the stock returns movements. As such, this pooling equilibrium condition increases the agreement on bullish sentiments. This agreement on sentiments may also has a positive association with the stock returns.

Therefore, this result shows that options with deep leverage (i.e., DOTM) on social media show possible significant prediction power on future stock returns. Consistent with Pan and Poteshman (2006), options trading with DOTM has a significant and positive association with future stock returns. Similarly, agreement on sentiments show a possible significant relationship with future stock returns. The agreement on sentiments assures investors that the stock returns align with the sentiments on StockTwits.

First, endogeneity problems may arise from the study of the association between activities of StockTwits and stock returns. Prior studies that use posting volume on the stock market are permeable to this problem as well (Antweiler & Frank, 2004; Leung & Ton, 2015; Wysocki, 1998). To the best of our knowledge, there are limited methods to tackle this problem, and its solution is left for future research.

Second, we focus on the signals transmitted from the general net trade volume position, since analysts attempt to send optimistic recommendations on StockTwits to convince naïve investors to join the investment bandwagon (Dechow et al., 2000; Griffin & Tang, 2012; Michaely & Womack, 1999). Future studies may consider net volume in call or put positions for the bullish or bearish conditions.

Third, we focus on a cross-sectional analysis of the interrelationship between communication channels and stock prices, and of the informational stock prediction. Future studies can be extended by using a time series analysis that can examine the causal effect between communication channels and stock prices.

Two policy implications of our analysis are as follows. First, regulators should monitor the intention of sentiments in social media and observe potential insider trading on options trading with deep leverage. Second, an educational policy targeting investors on social media and trading activities in the options market would help them interpret sentiments about stocks in a better way.

References

Admati, A. R., & Pfleiderer, P. (1988). A theory of intraday patterns: Volume and price variability. *The Review of Financial Studies*, *1*(1), 3-40.

Aggarwal, R. K., & Wu, G. (2006). Stock Market Manipulations. *The Journal of business (Chicago, Ill.)*, *79*(4), 1915-1953. https://doi.org/10.1086/503652

Alexa. (2022). *Competitive Analysis, Marketing Mix and Traffic*. Alexa Internet Retrieved 11 April from https://www.alexa.com/siteinfo/stocktwits.com

Antweiler, W., & Frank, M. Z. (2004). Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards. *The Journal of finance (New York)*, *59*(3), 1259-1294. https://doi.org/10.1111/j.1540-6261.2004.00662.x

Black, F. (1975). Fact and fantasy in the use of options. *Financial Analysts Journal*, *31*(4), 36-41.

Chakravarty, S., Gulen, H., & Mayhew, S. (2004). Informed trading in stock and option markets. *The Journal of Finance*, *59*(3), 1235-1257.

Chan, K., Chung, Y. P., & Fong, W.-M. (2002). The informational role of stock and option volume. *The Review of Financial Studies*, *15*(4), 1049-1075.

Chan, K., Ge, L., & Lin, T.-C. (2015). Informational content of options trading on acquirer announcement return. *Journal of Financial and Quantitative Analysis*, *50*(5), 1057-1082.

Chen, H., De, P., Hu, Y. J., & Hwang, B.-H. (2013). *Customers as advisors: The role of social media in financial markets*.

Chordia, T., & Swaminathan, B. (2000). Trading volume and cross‐autocorrelations in stock returns. *The Journal of Finance*, *55*(2), 913-935.

Cookson, J. A., & Niessner, M. (2020). Why don't we agree? Evidence from a social network of investors. *The Journal of Finance*, *75*(1), 173-228.

Dechow, P. M., Hutton, A. P., & Sloan, R. G. (2000). The relation between analysts' forecasts of long‐term earnings growth and stock price performance following equity offerings. *Contemporary Accounting Research*, *17*(1), 1-32.

Dow, J., & Gorton, G. (1994). Arbitrage chains. *The Journal of Finance*, *49*(3), 819-849.

Easley, D., O'hara, M., & Srinivas, P. S. (1998). Option volume and stock prices: Evidence on where informed traders trade. *The Journal of Finance*, *53*(2), 431-465.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of financial economics*, *49*(3), 283-306.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), 3-56.

Gan, B., Alexeev, V., Bird, R., & Yeung, D. (2020). Sensitivity to sentiment: News vs social media. *International review of financial analysis*, *67*, 101390.

Gervais, S., Kaniel, R., & Mingelgrin, D. H. (2001). The high‐volume return premium. *The Journal of Finance*, *56*(3), 877-919.

Gray, W. R., & Kern, A. E. (2011). Talking your book: Social networks and price discovery. *Available at SSRN 1767452*.

Griffin, J. M., & Tang, D. Y. (2012). Did subjectivity play a role in CDO credit ratings? *The Journal of Finance*, *67*(4), 1293-1328.

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *The Journal of Finance*, *50*(4), 1175-1199.

Hendershott, T., Livdan, D., & Schürhoff, N. (2015). Are institutions informed about news? *Journal of financial economics*, *117*(2), 249-287.
Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315-1335.
Leung, H., & Ton, T. (2015). The impact of internet stock message boards on cross-sectional returns of small-capitalization stocks. *Journal of Banking & Finance*, *55*, 37-55. https://doi.org/10.1016/j.jbankfin.2015.01.009
Manela, A. (2014). The value of diffusing information. *Journal of financial economics*, *111*(1), 181-199.
Michaely, R., & Womack, K. L. (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *The Review of Financial Studies*, *12*(4), 653-686.
Muhn, J. (2019). *StockTwits Launches Free Online Trading*. Finovate. Retrieved 25 August from https://finovate.com/category/stocktwits/
Pan, J., & Poteshman, A. M. (2006). The information in option volume for future stock prices. *The Review of Financial Studies*, *19*(3), 871-908.
Renault, T. (2017). Intraday online investor sentiment and return patterns in the US stock market. *Journal of Banking & Finance*, *84*, 25-40.
Stein, J. C. (2008). Conversations among competitors. *American Economic Review*, *98*(5), 2150-2162.
Stephan, J. A., & Whaley, R. E. (1990). Intraday price change and trading volume relations in the stock and stock option markets. *The Journal of Finance*, *45*(1), 191-220.
Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, *62*(3), 1139-1168.

6 Appendix A

Table A1, A2, A3 shows the coefficients results of the regression (the dependent is return =0) and predictive regressions (the dependent is returns are from t = 0 to t = +20). The coefficients of the regressions are: (1) Net Vol ratio with OTM groups; (2) Net Vol ratio with DOTM group; (3) Bullishness; (4) Agreement. The dependent variables of the regressions are returns from t = 0 to t = 20. Table A1, A2, and A3 show the coefficient results of regressions the Figure 7, 8, and 9, respectively.

	Net Vol ratio: OTM	**Net Vol ratio: DOTM**	**Bullishness**	**Agreement**
Return_t= 0	-0.0002	-0.0037***	0.0081***	0.0075***
Return_t=+1	-4.1E-05	0.0019***	0.0001	0.0014**
Return_t=+2	-2.2E-05	0.0017***	-0.0001	0.0012**
Return_t=+3	0.0004**	0.0012***	-0.0005***	0.0002
Return_t=+4	-0.0002	0.0010***	-0.0003*	-0.0002
Return_t=+5	0.0002	0.0014***	-0.0002	0.0013**
Return_t=+6	2.2E-05	0.0018***	-0.0002	0.0006
Return_t=+7	4.5E-05	0.0013***	0.0002	0.0012***
Return_t=+8	-0.0001	0.0014***	-0.0004***	-6.7E-05
Return_t=+9	0.0002	0.0013***	-0.0003*	0.0003
Return_t=+10	0.0004*	0.0018***	-0.4	0.0007
Return_t=+11	0.0005***	0.0019***	-0.0003	5.7E-05
Return_t=+12	0.0001	0.0015***	-0.0002	0.0012**
Return_t=+13	0.0002	0.0018***	-0.0001	0.0005
Return_t=+14	0.0003	0.0015***	-0.0002	0.0001
Return_t=+15	-0.0001	0.0016***	-0.0002*	0.0004
Return_t=+16	0.0005***	0.0017***	-0.0003*	-0.0014***
Return_t=+17	-1.0E-05	0.0017***	-0.0003	0.0003
Return_t=+18	0.0002	0.0017***	-0.0001	0.0003
Return_t=+19	0.0004**	0.0015***	-0.2 E-05	0.0007
Return_t=+20	0.2E-05	0.0010	-0.0006	0.0005

This table shows a fixed effect regression with stock and time (month and year) for the period Oct 2012 to Feb 2018. The dependent variables are return from t =0 until return t =20. The independent variables include net trade options volume ratio partitioned by maturity OTM in the first regression, net trade options volume ratio partitioned by DOTM in the second regression, bullishness for t = 0 in the third regression, and agreement for t = 0 in the fourth regression. The options volume ratio is formulated by total daily number of calls minus daily number of puts divided by the sum of daily calls and puts. The standard deviation is report in brackets. *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Table A1 Coefficient result for coefficients of predictive regression

	Net vol ratio - DOTM	Net vol ratio - OTM	Bullishness	Agreement
Return t= 0	-0.0018***	-0.0003*	0.0044***	0.0041***
Return_t=+1	0.0014***	0.0004**	-2.57E-05	-5.42E-06
Return_t=+2	0.0008***	0.0002	-0.0001	8.69E-05
Return_t=+3	0.0009***	0.0004**	-0.0002**	-8.83E-05
Return_t=+4	0.0008***	-5.36E-05	-0.0002*	-0.0005
Return_t=+5	0.0008***	7.46E-05	-5.75E-05	0.0013***
Return_t=+6	0.0013***	0.0004***	-3.24E-05	0.0002
Return_t=+7	0.0008***	0.0005***	8.46E-05	0.0011***
Return_t=+8	0.0008***	0.0002	-0.0003***	0.0002
Return_t=+9	0.0011***	0.0002	-2.82E-05	0.0006*
Return_t=+10	0.0011***	0.0003**	7.79E-05	0.0004
Return_t=+11	0.0013***	0.0002	1.08E-05	-0.0004
Return_t=+12	0.00085***	0.0001	-2.34E-05	0.0004
Return_t=+13	0.0010***	0.0003**	-9.89E-05	-0.0001
Return_t=+14	0.0008***	5.57E-05	-0.0001	0.0001
Return_t=+15	0.0011***	0.0002	-0.0001	0.0001
Return_t=+16	0.0009***	0.0005***	-5.17E-05	-0.0002
Return_t=+17	0.0010***	0.0005***	2.16E-05	0.0005
Return_t=+18	0.0008***	0.0004**	-4.58E-05	-0.0003
Return_t=+19	0.0009***	0.0003**	6.5E-05	0.0004
Return_t=+20	0.0005***	0.0003*	0.0002**	0.0007*

This table shows a fixed effect regression with stock and time (month and year) for the period Oct 2012 to Feb 2018. The dependent variables are return from t =0 until return t =20. The independent variables include net trade options volume ratio partitioned by maturity OTM in the first regression, net trade options volume ratio partitioned by DOTM in the second regression, bullishness for t = 0 in the third regression, and agreement for t = 0 in the fourth regression. The options volume ratio is formulated by total daily number of calls minus daily number of puts divided by the sum of daily calls and puts. The standard deviation is report in brackets. *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Table A2 Predictive Regression for Current and Future Returns: Big Stocks

	Net vol ratio - DOTM	Net vol ratio - OTM	Bullishness	Agreement
Return t= 0	-0.0050***	-0.0001	0.0104***	0.0107**
Return_t=+1	0.0023***	-0.0005	0.0001	0.0025**
Return_t=+2	0.0022***	-0.0003	-9.8E-05	0.0022**
Return_t=+3	0.0015***	0.00050	-0.0007***	0.00049
Return_t=+4	0.0012***	-0.00035	-0.0004	0.0001
Return_t=+5	0.0019***	0.0004	-0.0002	0.0012
Return_t=+6	0.0022***	-0.0003	-0.0002	0.0011
Return_t=+7	0.00155***	-0.0003	0.0002	0.0014*
Return_t=+8	0.0020***	-0.0005	-0.0005**	-0.0002
Return_t=+9	0.0014***	0.0003	-0.0004*	7.5E-05
Return_t=+10	0.0021***	0.0004	-5.6E-05	0.0011
Return_t=+11	0.0021***	0.0008**	-0.0004**	0.0004
Return_t=+12	0.0018***	0.0002	-0.0004*	0.0020**
Return_t=+13	0.0025***	0.0008	-0.0002	0.0009
Return_t=+14	0.0020***	0.0005	-0.0003	-0.0001
Return_t=+15	0.0020***	-0.0004	-0.0003	0.0005
Return_t=+16	0.0023***	0.0005	-0.0004*	-0.0030***
Return_t=+17	0.0021***	-0.0005	-0.0004*	0.0002
Return_t=+18	0.0023***	0.0001	-0.0001	0.0006
Return_t=+19	0.0020***	0.0005	-7.8E-05	0.0007
Return_t=+20	0.0014***	-0.0002	-3.3E-06	0.0003

This table shows a fixed effect regression with stock and time (month and year) for the period Oct 2012 to Feb 2018. The dependent variables are return from *t* =0 until return *t* =20. The independent variables include net trade options volume ratio partitioned by maturity OTM in the first regression, net trade options volume ratio partitioned by DOTM in the second regression, bullishness for *t* = 0 in the third regression, and agreement for *t* = 0 in the fourth regression. The options volume ratio is formulated by total daily number of calls minus daily number of puts divided by the sum of daily calls and puts. The standard deviation is report in brackets. *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Table A3 Predictive Regression for current and future return: Small Stocks