Biased information transmission in investor social networks: Evidence from professional traders*

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Abstract

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Abstract

Theoretical studies postulate that information transmission in investor social networks has important implications for diverse market phenomena, including trading volume, price informativeness, liquidity, volatility, and trading strategies. Yet, we have limited knowledge about the real-world links among information exchange, trading decisions, and performance in investor social networks. Using more than 1 million instant message communications and more than 2 million trading records of professional traders, we directly measure how information propagates through traders' strong and weak network ties and its effects on their trading decisions and performance. Our results suggest that investment information sharing is asymmetric: traders are more likely to exchange information on trading gains over losses, especially with their strong ties. However, message receivers are more likely to trade on information from strong ties when the information regards trading losses rather than trading gains, and only information about losses positively correlates with trading performance. Investigations of information propagation over the network indicate that neither the sender's performance nor the tie strength between the sender and receiver correlates with the receiver's propensity to forward information to third parties. Evidence suggests that the communication bias associated with the sender's performance and tie strength may weaken as the information travels away from the originating dyad in the network.

1. Introduction

Investors frequently make trading decisions based on information obtained from their social networks (e.g., Cohen et al. 2008, Ahern 2017). According to a 2015 interview with institutional investors, nearly one-third of these investors say that social media influenced their investment decisions (Connell 2015). Theoretical studies postulate that the way investment information is transmitted from one investor to another has important implications for diverse market phenomena, including trading volume, price informativeness, liquidity, volatility, and trading strategies (e.g., Colla and Mele 2010, Ozsoylev and Walden 2011, Han et al. 2019). Yet, we have limited knowledge about the links among real-world social network information exchange, trading decisions, and performance.

Existing studies show that investors are more likely to share illegal insider trading tips with strong social ties such as kin and close friends (Ahern 2017) and increase communication when trading performance is positive (Heimer and Simon 2015, Ammann and Schaub 2016). This suggests that communication exchange among investors is biased, creating asymmetry with respect to the information shared and who receives the information. These observations raise questions regarding the links among information propagation in investor social networks, tie strength between investors, and trading decisions and performance. Do investors selectively communicate information about their investments? Do they transmit different types of information to strong ties and weak ties? How do information exchanges relate to trading decisions and performance?

To answer these questions, it is crucial to consider what information an investor has and his social network contacts, what subset of information he shares and with whom, and how variation in information spreading relates to trading decisions and performance. Several studies examine investor communications in social networks.[1] However, their data chart the information an investor sends to another investor but do not contain information the sender kept private. Further, with an exception of Ahern (2017), they do not consider the sender's contacts who received no information. These issues suggest that our knowledge

[1] Ahern (2017), Heimer and Simon (2015), Ammann and Schaub (2016), Rantala (2019)

about informational and social selection biases in investors' social networks remains nascent (Granovetter 1973, Hansen 1999, Saavedra et al. 2001, Banerjee et al. 2013).

Our analysis uses a unique dataset comprised of the instant message communications and trades of 66 professional day traders at a proprietary trading firm from October 2007 to April 2009. During this period, traders executed over 2 million trades and exchanged over 1 million instant messages with their network contacts. Messages provide digital, timestamped records of the directionality and content and enable an identification of the information in communications, the relationship between contacts (strong vs weak ties), and information propagation through the social network. Our data also includes each trader's full book of trades of over 4,000 stocks. Thus, we can develop a comprehensive depiction of when traders share investment information on which stocks and with whom. Furthermore, the ability to observe how traders utilize and propagate the information they receive from their network contacts enables us to examine the relationship between traders' communication dynamics and their stock trades and performance.

First, we test if there is asymmetry in how traders communicate their stock information. Each time a trader sends a message about a stock he traded, we consider all stocks he had traded up to that point since the day's opening trade and estimate the trader's propensity to message about each of these stocks as a function of the trader's performance.[2] We find that traders are 13% (0.95%/7.37%=0.13) more likely to talk about the stocks they had gains on than the stocks they had losses on, suggesting a bias favoring the spread of gain information in his network. To the best of our knowledge, this is the first study to show that traders skew their communications towards the stocks in their portfolio based on the stock's performance.

Second, we examine how the strength of relationships among traders predicts who a trader shares investment information with, and how the message receiver uses the information in his subsequent

[2] This approach is analogous to the test of the disposition effect proposed by Odean (1998). Our methodology allows us to estimate a trader's propensity to send a message at the stock level as a function of his performance on the stock.

communications and trades. Social networks literature has long considered how differences in strong ties (e.g., frequent contacts) and weak ties (e.g., acquaintances) affect information propagation (e.g., Granovetter 1973, Uzzi 1997, Hansen 1999, Uzzi and Lancaster 2003). We measure the tie strength between traders based on their past instant message communications (Wuchty and Uzzi 2011), and find that traders show a stronger propensity to message about stocks with gains to their strong ties than to their weak ties. On the other hand, neither the sender's performance nor the tie strength between the sender and receiver correlates with the receiver's propensity to forward information to third parties.

Furthermore, message receivers are more likely to trade on information about their strong ties' losses than gains. This surprising result may suggest that some investors adjust for the bias in the sender's communication by attending disproportionately to the sender's loss information. We find that the asymmetry – the message receiver being more likely to trade on the information about his strong ties' losses than gains – is observed only in the subsample where the message sender exhibited in the past an above-median bias toward communicating his gains than his losses. This suggests that the asymmetry in the message receiver's trading decisions is at least partly due to his awareness of the bias in message senders' communications. Taken together, message receivers' subsequent communications and trading decisions suggest that the communication bias with respect to the sender's performance and tie strength is likely to be attenuated as the information flows further away from the original sender.

Last, we study the link between social network information and trading performance. We find that traders' stock returns are higher when they receive loss information from their strong ties. The result that one benefits more from messages about his strong ties' losses than gains may stem from the asymmetry in the way traders communicate about their gains and losses, especially with their strong ties. The asymmetry in communication implies that the information about other traders' losses is scarcer than the information about gains, and that the loss information is more trusted (Uzzi and Lancaster 2003). It may also explain why message recipients are more likely to trade on the stock information from their strong ties when it is about their losses than gains.

Our findings shed light on how social interactions among investors propagate investment information in social networks and how they correlate with trading decisions and performance. Most prior studies on investor social networks rely on indirect proxies of social bonds such as school ties, geographical and workplace proximity, and similar trading behavior to infer social networks,[3] rather than actual directed communications among investors. A few recent studies have used investor communication data from illegal insider trading (Ahern 2017), Ponzi schemes (Rantala 2019), and social trading platforms of retail investors (Heimer and Simon 2015, Ammann and Schaub 2016). In contrast, we study professional traders using data that permits direct measurement of person-to-person exchanges, message content, and stock trade. The study design permits a unique contribution to research on information spreading, trading decisions, and profitability in investor social networks.

First, we consider the social structure of relationships to identify how traders transmit information to their contacts with varying degrees of tie strength. Prior studies on investor communications seldom consider the role of tie strength, and none examines whether or not different types of information flow through strong versus weak ties. In the context of our proprietary trading firm, we have unique access to all e-communications among all traders in the firm. We find that traders are prone to share trading gain information with strong ties, yet strong ties are most likely to use rarer loss information in their trades. Furthermore, loss information from strong ties improves trading performance.

Second, we show that traders' choice of which stock to discuss in their communications depends on their performance on the stock. Our result supports the self-enhancing transmission bias, which skews information circulation, as investors tend to disproportionately broadcast their successes while downplaying failures (Han et al. 2019). Heimer and Simon (2015) and Ammann and Schaub (2016) also provide supporting evidence of the self-enhancing bias that a trader's overall performance is positively related to his communication intensity. However, it is possible that such a behavior arises due to other

[3] E.g., Hong et al. (2005), Ivković and Weisbenner (2007), Brown et al. (2008), Cohen et al. (2008, 2010), Kaustia and Knüpfer (2011), Ozsoylev et al. (2014), Hvide and Östberg (2015), Pool et al. (2015), Dimmock et al. (2018), Maturana and Nickerson (2019), Ouimet and Tate (2020)

effects than the self-enhancing bias. For example, performance can affect a trader's arousal level, which is also associated with information transmission (Berger 2011, Liu et al. 2016). We focus on which stock a trader mentions in his message out of all the stocks he has traded, controlling for his overall performance. By doing so, we observe if and when traders pass along information about their trading decisions, and disentangle the effects of confounding factors that may affect a trader's overall tendency to communicate at that moment.

Third, we contribute to the literature on how information from social networks and trading performance are related by directly examining the content of information exchanged (withheld) and the nature of the relationship between the sender and receiver. This information helps advance research that has shown a relation between social networks and investment performance (e.g., Cohen et al. 2008, Hochberg et al. 2007, Ozsoylev et al. 2014, Hvide and Östberg 2015, Pool et al. 2015). Our paper identifies stock information an investor transfers to another investor, and shows that information investors obtain from their social networks has different effects on their trading performance depending on the type of information and the channels of information transfer. We find that receiving stock information has no effect by itself, rather information from close contacts about their losses significantly improves performance. Our results suggest that it is important to identify the type of the information and the relationship between the sender and the receiver of the message when we examine how information from social networks affects trading performance.

2. Data

We use instant message communication exchanges and intra-day trades of 66 professional traders at an anonymous day trading firm from October 1, 2007 to April 30, 2009. Day traders keep short-term positions and typically do not hold inventories of stocks overnight; they enter and exit positions each day, normally between 9:30 AM and 4:00 PM. The firm's trading platform automatically captured all communication and trade data. In the firm, traders predominately use instant messages to converse with each other, which permits them to simultaneously follow the market and communicate. Over the time period, traders traded about 4,500 different stocks over various exchanges, made over 2 million stock trades, and exchanged over 1 million instant messages. Intraday stock price data are from the Trade and Quote (TAQ) and daily stock return data are from the Center for Research in Security Prices (CRSP).

We use a variant of the popular normalization method in Wuchty and Uzzi (2011) to measure the tie strength between the trader *i* and trader *j* as follows:

$$Tie_{i,j} = \frac{1}{2}\left(\frac{\#\,Msg_{i\to j}}{\max\limits_{m\in\Gamma_i}\#\,Msg_{i\to m}} + \frac{\#\,Msg_{j\to i}}{\max\limits_{m\in\Gamma_i}\#\,Msg_{m\to i}}\right). \tag{1}$$

Γ_i is the set of contacts of Trader *i*, and $\#\,Msg_{i\to j}$ is the number of instant messages from Trader *i* to Trader *j*. This method normalizes the strength of the connections relative to the strongest link such that the value of *Tie* ranges from 0 to 1.

We compute two measures of tie strength: *Tie* uses all messages and *Tie_Fin* uses messages that are likely to contain financial information. Following prior work (e.g., Loughran and McDonald 2016), we use a dictionary classification method to identify messages that are likely to contain financial information. We developed a custom dictionary comprised of terms from the NASDAQ stock exchange[4] and IG trading glossary[5] to capture trading related terms. A message is considered to be a finance message if it contains at least one word from our custom dictionary.

Figure 1 illustrates an example of how stock information is passed from one trader to another in traders' social network. It shows Trader 7, Trader 50, and Trader 55 who sent or received a message about stock KED on February 17, 2009, and the contacts of those three traders. The thickness of the edge connecting two traders corresponds to the tie strength between the two traders. At 9:55:38am, Trader 7 had a positive return on KED and sent a message about KED ("ked steps") to Trader 50. At 10:18:30am, Trader 50 sent a message about KED to Trader 55 ("ked"), although he did not trade KED on that day.

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[4] https://www.nasdaq.com/glossary

[5] https://www.ig.com/uk/glossary-trading-terms/

Table 1 shows summary statistics. Traders hold a stock position for a relatively short period -- 58 minutes on average, with a median of 12 minutes. On average, traders hold 19 positions daily over 13 stocks, execute 144 trades a day, and earn 0.21% on a round-trip trade.[6] Traders send 31.3 and receive 33.3 messages daily on average. The average length of a message is a little below 6 words and the median is 4 words. The average tie strength between two traders based on their instant message communications over past 7 days is 0.264 using all messages and 0.270 using finance messages.

3. Results

3.1. Asymmetry in Trader's Propensity to Send Message about Stock

To identify messages a trader sent about stocks he traded, we parse all messages sent by the trader during the day and check if he mentions in the message a stock he has traded on that day up to the time he sent the message. To minimize possible errors in identifying messages mentioning stock, we go through all the tickers symbols in the data and exclude those with a generic meaning such as “AT”, “HE”, and “CAR” in our analysis.[7] After parsing messages, we obtain a list of messages a trader sent about the stocks he traded on that day, and which stock(s) are mentioned in each of those messages.

When a trader sends a message about stock he traded, we consider all stocks he has traded up to that time since the beginning of the day. We examine if the trader's trading profit on each of those stocks as of the message time is related to the propensity he mentions the stock in his message. For example, suppose a trader has traded five stocks (A,B,C,D,E) when he sends a message about Stock A at 11:15am. At 11:15am, he has gains (positive returns) on A, B, and C and losses (zero or negative returns) on D and E. For this message time, we have five observations for this trader on the five stocks he has traded. For each of the five stocks, we estimate the propensity the trader talks about the stock as a function of his trading performance on that stock using the following regression model:

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[6] We winsorize returns at the 1% and 99% levels to minimize the influence of outliers.

[7] A total of 82 tickers out of 4,854 tickers (1.69%) are excluded. The results are qualitatively the same when we include those tickers (results available upon request).

$$Prob\left(Msg_{i,k,t} = 1\right) = \beta_0 + \beta_1 \cdot Gain_{i,k,t} + \sum \boldsymbol{X}_{i,k,t} \cdot \boldsymbol{\beta} + \varepsilon_{i,k,t}. \tag{2}$$

$Msg_{i,k,t}$ is an indicator variable equal to 1 if trader *i* sends a message about stock *k* at time *t*, $Gain_{i,k,t}$ is an indicator variable equal to 1 if trader *i* has a positive return on stock *k* at time *t* and zero otherwise. In the aforementioned example, $Msg_{i,k,t}$ is equal to 1 for *k*=A and 0 for *k*=B, C, D, and E, and $Gain_{i,k,t}$ is equal to 1 for *k*=A, B, and C and 0 for *k*=D and E. $\boldsymbol{X}_{i,k,t}$ is a vector of control variables such as minutes passed since the last trade of the stock (*Delay*), the trader's overall return across all stocks for the day (*RetDay*), dollar value of the position on the stock as a percentage of the trader's total portfolio value (*%Pos*), volatility index (*VIX*), market return (*MktRet*), and return of the stock during the day (*StockRet*). For short positions, we reverse the sign of *StockRet* and *MktRet*. We also include month, day of week, and trader fixed effects, and estimate robust standard errors clustered at the day level.

Trader *i* 's return on stock *k* at time *t* is computed as follows.

$$R_{i,k,t} = \log\left(\frac{VS_{i,k,t}}{VB_{i,k,t}}\right), \tag{3}$$

where $VB_{i,k,t}$ is the total dollar value of the shares of stock *k* purchased by trader *i* from the opening the position up to time *t*, and $VS_{i,k,t}$ is the total dollar value of the shares of stock *k* sold by trader *i* up to time *t*. If the position is currently open at time *t* (# shares purchased > # shares sold for an open long position, # shares purchased < # shares sold for an open short position), we use the current market price of the stock at time *t* to compute the value of the open position.

Panel A of Table 2 shows the percentage of stocks mentioned in traders' messages out of all stocks they have traded up to the message time, separately for stocks with gains and with losses. This percentage can be interpreted as the probability a trader mentions a stock with a gain/loss in his communication. Our approach is analogous to the PGR and PLR ratios in the test of the disposition effect proposed by Odean (1998). It computes the proportion of stocks with gains mentioned in messages out of all stocks with gains, and the proportion of stocks with losses mentioned in messages out of all stocks with losses. The difference between the two proportions can be interpreted as the extent of bias toward communicating stocks with gains rather than those with losses. By doing so, we control for the possibility that traders message more about gains than losses simply because their portfolio have more gain than loss stocks. Traders are 13% more likely to share information about their gains than losses.[8] The probability a trader talks about a stock he traded is 8.32% if he had a gain on the stock and 7.37% if he had a loss on the stock, a small absolute difference of 0.95% but consequential when compounded over the high volume of stock transactions.

Panel B of Table 2 shows the results of probit regressions in Equation (2) that estimate the propensity of a trader to send a message about a stock he has traded. For ease of interpretation, we report the average marginal probability of each variable as its coefficient. We find that traders are more likely to mention stocks with positive returns in their messages, as the coefficient of *Gain* is positive and significant at the 1% level. The effect is also economically sizable. In Column (2), for example, having a gain on the stock increases the probability of sending a message by 0.71% based on the estimated average marginal probability of *Gain*. This is a 9.6% increase in the probability of sending a message relative to the probability of sending a message for a loss stock reported in Panel A (0.71%/7.37%=0.096), after controlling for the effects of the control variables and fixed effects.

Among the control variables, *RetDay* and *%Pos* are positive and significant at the 1% level while *Delay* is negative and significant at the 1% level. The results suggest that a trader is more likely to send a message about a stock he traded when his overall performance for the day is good, when the stock represents a larger portion of his portfolio, and is less likely to send a message about a stock when more time passes since he traded the stock. The asymmetry in the trader's propensity to talk about a stock remains the same when we include additional controls in Columns (3) and (4) such as the number of messages sent by the trader during the day (*#Messages*) and the number of people the trader sent messages to over days [-7,0] (*#Contacts*), where day 0 is the current day.

[8] 0.95%/7.37%=0.13

Note that having a gain on a stock has a significant positive effect on the trader's propensity to send a message about the stock after we control for the trader's overall performance across all stocks (*RetDay*). This suggests that our results are not driven by traders' sentiments, confidence, or arousal level related to their overall performance. For instance, there is a relation between traders' performance and their emotions (Liu et al. 2016), and emotional arousal is positively related to the social transmission of information (Berger 2011). Thus, it is important to control for the effect of overall performance on the propensity to talk about a stock when we test if traders selectively communicate their investment performances. Our results show that a trader shows asymmetry toward different stocks within his portfolio, controlling for the effect of his overall portfolio return on his communication behavior.

3.2 Variations in the Asymmetry to Talk about Stock

We examine when traders' are more likely to show an asymmetry in their propensity to talk about a stock with a gain compared to a stock with a loss. The incentive for traders to selectively communicate about their investments may vary with trader or stock characteristics, and identifying factors that lead to greater or lesser asymmetry can help us better understand the potential biases in information propagation in traders' social networks. In Table 3, we include interaction terms of *Gain* with *RetDay* (Column 1), with *Delay* (Column 2), with *%Pos* (Column 3), and with *#Contacts* (Column 4). We find that the trader's performance for the day (*RetDay*) and how many minutes passed since the last trade of the stock (*Delay*) do not affect the asymmetry, as both *Gain×%Pos* and *Gain×%Pos* are insignificant in Columns (1) and (2). On the other hand, the coefficients of the interaction terms *Gain×%Pos* and *Gain×#Contacts* are negative and significant at the 1% level in Columns (3) and (4), respectively.

Table 3 results indicate that the asymmetry in traders' propensity to talk about their gains rather than their losses is weaker for stocks that represent larger portions of the trader's portfolio and for traders who have a larger number of contacts. One possible interpretation of the results is that a trader is less likely to selectively communicate their gains more than their losses when his communication about the stock is more important: when he talks about a stock that represents a larger portion of his portfolio, or when he has a larger number of contacts, a possible indicator of how much he values communications with others.

3.3 Choice of Message Receiver

Next we examine to whom a trader chooses to send a message about a stock he traded. In particular, we focus on the effect of tie strength between the trader and his contact on his choice of whom to send the message to and how such an effect varies with the trader's performance on the stock.

Panel A of Table 4 compares the tie strength between the sender and the receiver of a message about stock traded, separately for messages about stock the sender had a gain on and for messages about stock the sender had a loss on. It shows that the tie strength between the sender and the receiver is stronger when the message is about gains than losses: the average value of *Tie* is 0.618 when the message mentions a stock the sender had a gain on, and 0.602 when it mentions a stock with a loss. The difference, 0.016, is statistically significant at the 5% level. The results are similar when we use a measure of tie strength using finance messages (*Tie_Fin*). The results suggests that traders are more likely to send messages about their gains to their strong ties compared to messages about their losses.

However, Panel A of Table 4 provides a preliminary and incomplete picture as it ignores the set of potential message receivers the sender could have sent the message to. Without considering counterfactuals, we cannot tell if traders show an asymmetry in their choice of whom to talk to about stocks they traded. For example, suppose traders do not show any preference regarding whom to talk to among their contacts when they send messages about stocks they traded. In this scenario, we may still observe higher values of tie strength for messages about gains than those about losses if traders who have gains happen to have stronger ties with their contacts compared to traders who have losses.

To address this issue, we conduct the following analysis that considers counterfactual message receivers. When a trader sends a message about a stock he traded, we consider all contacts of the trader and test to whom among these contacts the trader actually sends the message. For example, in Figure 1, Trader 7 has three contacts (Trader 40, Trader 48, and Trader 50) when he sends a message about KED.

For each of the three contacts, we examine whether or not Trader 7 sends the message about KED to the contact as a function of the tie strength between him and the contact and Trader 7's performance on KED. We define a trader's contacts as those who received any message from the trader during days [-7,0], where day 0 is the day that the message about the stock was sent. With these observations of all contacts of the trader, we estimate the following regression model and show the results in Panel B of Table 4:

$$Prob\left(IM_{i,j,k,t} = 1\right)$$
$$= \beta_0 + \beta_1 \cdot Gain_{i,k,t} + \beta_2 \cdot Tie_{i,j,t} + \beta_3 \cdot Gain_{i,k,t} \cdot Tie_{i,j,t} + Controls + \varepsilon_{i,j,k,t}. \qquad (4)$$

$IM_{i,j,k,t}$ is an indicator variable equal to 1 if trader *i* sends a message to trader *j* about stock *k* at time *t*. For example, suppose Trader 1 has four contacts (Trader 2 ~ Trader 5) and he sent a message about stock *k* to Trader 2 at time *t*. We then have four observations for this case, with $IM_{1,j,k,} = 1$ for *j*=2 and $IM_{1,j,k,} = 0$ for *j*=3~5. $Tie_{i,j,t}$ is a measure of the strength of tie between the trader *i* and trader *j* as of the message time *t* based on the messages to and from Trader *i* over days [-*7*,-*1*] using Equation (1). [9] $Tie\_Fin_{i,j,t}$ is defined the same way as $Tie_{i,j,t}$ using finance messages only. A message is considered to be a finance message if it contains at least one word from our custom dictionary of finance trading terms as explained in Section 2.

We find that a trader is more likely to send a message about a stock he traded to a contact with whom he has a stronger tie, as evidenced by a positive and significant coefficient of *Tie* in Panel B of Table 4. The result is consistent with the prior findings that people are more likely to communicate important information with their strong ties as they are more familiar with one another and have greater trust embedded in their relationship (e.g., Uzzi 1997, Hansen 1999).

Interestingly, traders' preferences over conversation partners change when they talk about their gains as opposed to their losses; the interaction term $Gain \times Tie$ is positive and significant at the 5% level,

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[9] While we define a trader's contacts as those who received any message from the trader during days [-7,0], we compute the tie strength between the trader and his contact based on their past communications over days [-7,-1]. Thus a contact whom the trader first communicated with in day 0 is assigned a tie strength of 0.

indicating that having a positive return on the stock increases the propensity of the trader to send a message about the stock to his strong-tie contact. In other words, a trader's communication with his strong tie is more biased toward his gains than losses compared to his communication with his weak tie. Because traders have a stronger tendency to pass on the information about their gains to their close contacts compared to their tendency to pass on the information about their losses, strong ties are more likely to be sources of propagating gain information than weak ties.

Our results contribute to the literature on "the strength of weak ties" (Granovetter 1973). Granovetter (1973) argues that information we receive through our weak ties is more novel than information through strong ties because the information our close contacts receive overlaps considerably with what we already know due to similar friendship circles. The tendency for traders to talk about their gains rather than losses suggests that information about losses is more novel to the receiver than information about gains. Our results suggest that people may choose different information from their available information sets to pass onto their strong versus weak ties. The implication, however, is that weak ties are more likely to gain access to novel information about losses, and are thereby have more opportunities to learn from the information obtained from their networks (Romero et al. 2016).

3.4 Message Receivers' Communication about Stock

To further study how information about a stock propagates through a social network, we examine the message receiver's subsequent communications. Figure 1 shows an example: Trader 50 receives a message about stock KED at 9:55am, and sends a message about the same stock to Trader 55 at 10:18am. We examine how the likelihood that a message receiver propagates information about the stock through his social network is related to the type of the information (whether it is about a stock the sender had a gain on or about a stock with a loss) and the relationship between the sender and the receiver.

Columns (1) through (3) in Table 5 show the results of probit regressions where the dependent variable, *MsgSent*, is equal to one if the message receiver sent a message about the same stock after the receipt of the original message. We find that the coefficient estimates for *Tie* and *%Pos* are positive while that for *Delay* is negative. The results suggest that the receiver is more likely to send a message about the same stock when the sender of the original message is a close contact, when it is about a stock that represents a larger proportion of the sender's portfolio, and when the original message was sent shortly after the sender traded the stock. Interestingly, the sender's performance on the stock, *SenderGain*, has a negative effect on the propensity of the message receiver to send a message about the same stock. The interaction term, $SenderGain \times Tie$, is not significant in Column (3),[10] indicating that the effect of the sender's gain on the message receiver's subsequent communication does not differ with the tie strength between the sender and the receiver.

Possibly, the message receiver is simply replying to the sender of the original message rather than spreading the information to another trader. Thus, we examine the propensity of the message receiver to spread the information to a third party in Column (4) through Column (6) of Table 5. The dependent variable, *Msg sent to third party*, is equal to one if the message receiver sends a message about the same stock to another trader who is not the sender of the original message. The only significant predictor of the information about a stock being spread along the network is the value of the stock as a percentage of the sender's portfolio (*%Pos*), which may indicate the significance of the stock for the sender's investment. In contrast, we find that all other independent variables have insignificant effects on the propensity of the message receiver to spread the information to another trader. Neither the sender's performance on the stock nor the strength of the relation between the message sender and receiver has a significant effect on the probability that the information is passed onto a third trader. The results in Table 5 suggest that the bias in information propagation occurs primarily at the first stage, when a sender initially decides whether or not to share information about his gains or losses.

[10] The results are similar using *Tie_Fin*.

3.5 Message Receivers' Trades of the Stock

Trades by the message receiver can provide insights into how he processes the information about the stock mentioned in the messages he receives. In Table 6, we examine 1) the propensity the message receiver trades the stock mentioned in the message he received, and 2) the direction of the message receiver's trades compared to the sender's trades. Columns (1) through (3) of Table 6 show the results of probit regressions that estimate the propensity that the receiver trades the stock mentioned in the message he received. Columns (4) through (6) show the propensity that the sender and the receiver trade the stock in the same direction (both the sender and the receiver buy the stock or both sell the stock) after the receiver receives a message about the stock from the sender.

Column (1) of Table 6 shows that message sender's gain on the stock (*SenderGain*) and the tie strength between the sender and the receiver (*Tie*) do not have significant effects on the receiver's trade on average. When we interact *SenderGain* and *Tie* in Column (2), the coefficient estimate of the interaction term of *SenderGain* and *Tie* is negative and is slightly bigger in magnitude than the coefficient estimate of *Tie*. The results indicate that the receiver is more likely to respond to their close ties' messages in his trading decision when the sender has a loss on the stock compared to a gain, suggesting that the message receiver discounts the information about his strong tie's gain relative to the information about his strong tie's loss. The results are similar using a tie measure constructed from finance messages (*Tie_Fin*) in Column (3).

The results are qualitatively similar but weaker when we examine the propensity of the sender and the receiver of a message to trade in the same direction after the message in Columns (4) through (6). The sender and the receiver with a stronger tie are more likely to trade in the same direction after the message when the sender had a loss on the stock rather than a gain, but the effect is marginally significant at the 10% level in Column (5) and insignificant in Column (6). Similar to the effect on the message receiver's communications in Table 5, *%Pos* has a positive and significant effect in all columns, suggesting that the message receiver is more likely to trade the stock when the stock represents a larger portion of the sender's portfolio.

The results in Table 6 suggest that the message receiver is more likely to incorporate the information about the stock from his strong tie in his trading decisions when the sender had a loss on the stock. Such a tendency may be related to loss aversion that people are more sensitive to losses than gains (Kahneman and Tversky 1979) or to the negativity bias that people are more sensitive to and learn more from negative information than positive information (e.g., Rozin and Royzman 2001, Baumeister et al. 2001, Kuhnen 2015). However, *SenderGain* does not have a significant effect on the receiver's trading decisions in Columns (1) and (4) and has a positive effect in other columns. The results suggest that loss aversion or negativity bias by itself does not offer a full explanation of the receiver's trading decisions.

Our earlier results show that traders are more likely to send messages about their gains than losses, especially to their strong ties. If the message receiver is aware of such a bias in his strong ties' communications, he may try to adjust to the bias by incorporating the information about his strong ties' losses more than the information about their gains in his trading decisions. Thus, one possible explanation of the results in Table 6 is that the receiver is adjusting his trades in response to the sender's biased communications. If the receiver's awareness of the sender's communication bias is one of the drivers of his tendency to trade more based on the information about his strong tie's loss rather than gain, such an effect should be stronger when the sender's past communications are more biased toward gains than losses. To test this conjecture, we measure the extent to which the sender is biased toward his gains than losses in his past communications and examine the receiver's trade responses to the messages from more vs. less biased senders in Table 7.

We define *SenderBias* as the difference between the message sender's propensity to send a message about his gain stock and his propensity to send a message about his loss stock, computed in the same manner as *Diff* in Panel A of Table 2. The propensity to send a message for gain (loss) stock is defined as the fraction of the gain (loss) stocks the sender mentioned in his messages during the past three months.[11]

[11] We require at least 5 gain (loss) stock observations to compute the propensity to send a message about gain (loss) stock.

We split the sample based on the median *SenderBias*, and estimate the probability the message receiver trades the stock (*Trade*) and trades in the same direction as the sender (*Same*) for each subsample.

Table 7 shows that the interaction term of *SenderGain* and *Tie* (*Tie_Fin)* is significant only in the subsample with above-median *SenderBias*. The results support our conjecture that message receivers' asymmetric trading responses to their strong ties' gains versus losses in Table 6 are at least partly due to their awareness of the bias in sender communications.

Taken together, the message receivers' subsequent communications (Table 5) and trading decisions (Tables 6 and 7) suggest that the initial bias in investors' communications toward their gains than losses is likely to be attenuated as the information travels further away from the sender of the original message.

3.6 Trading Performance

Although the tendency to share positive events with others is natural, and often associated with increased positive affect and well-being (Gable et al. 2004, Reis et al. 2010), it can create an asymmetry in learning from the investment decisions of others. If the information about others' losses is scarce because people tend to talk about their gains rather than losses, it may be more novel and valuable to the traders than the information about others' gains. To test the idea, we examine the effect of receiving a message about other traders' investments on the performance.

Table 8 shows the results of the OLS regression of a trader's return on a round-trip trade of a stock on other traders' performance on the same stock on the same day, and on whether or not the trader received a message about the stock from another trader who traded the same stock. Column (1) shows that whether or not the trader received a message about the stock from other trader who traded the same stock (*MsgReceived*) does not affect the return regardless of other traders' performance, as all terms with *MsgReceived* are insignificant. Not surprisingly, a trader's return on a stock is higher when other traders have gains on the same stock and is lower when other traders have losses on the same stock. The return on a stock is positively related to the trader's overall return for the day (*RetDay*) and the stock's return (*StockRet*).

An interesting pattern emerges when we interact *MsgReceived* with the tie strength between the trader and the message sender.[12] The interaction term $Loss^{O}\times MsgReceived\times Tie$ is positive and significant at the 5% level, indicating that receiving a message about other trader's loss on a stock has a positive effect on the trader's return on the same stock when the message is from his strong tie. On the other hand, $Gain^{O}\times MsgReceived\times Tie$ is not significant, suggesting that receiving a message from a strong tie about his gain does not significantly affect one's performance. The result is similar when we use a tie measure constructed from finance messages (*Tie_Fin*) and when we add *Log(PositionSize)* as an additional control.

The asymmetry appears to be closely related to our earlier findings that traders are more likely to talk about their gains than losses, especially with their strong ties, while the message receivers appear to discount the information about their strong ties' gains in their trading decisions. The fact that the message receiver incorporates the information about his strong ties' losses in his trading decisions more than the information about their gains (Table 6) may be closely related to the performance implications of messages about their strong ties' gains and losses in Table 8. It is possible that the message receiver is more likely to incorporate the information about his strong ties' losses in his trading decisions because it has a positive impact on his trading performance.

4. Conclusion

We find that professional traders show an asymmetry when they communicate with other traders about their investments. They are more likely to talk about their gains than losses, especially when they talk to their close contacts with strong ties. The message recipients' subsequent communications and trading decisions suggest that they are aware of such a bias in senders' communications to some extent. The message receivers are more likely to trade based the information from their strong ties when it is about the

[12] Tie is defined only if MsgReceived is equal to one. Thus, a double interaction $Gain^{O}\times Tie$ is dropped as it is perfectly correlated with $Gain^{O}\times MsgrRceived\times Tie$. Similarly $Loss^{O}\times Tie$ and Tie are dropped due to $Loss^{O}\times MsgReceived\times Tie$ and $MsgReceived\times Tie$.

sender's loss than gain, and traders earn higher returns on a stock when they receive a message about their strong tie's loss on the same stock.

Our results indicate that investment information propagates in investor social networks asymmetrically with respect to the type of the information and selectively along connections with different tie strengths. Nevertheless, message receivers appear to make some adjustment for the asymmetry in the messages they receive, suggesting that the bias in the initial communication may get weaker as the information travels along the social network.

Our paper contributes to the emerging literature on the social transmission of financial information by utilizing a rich dataset on professional traders' communications and trading records, which have not been available in the existing studies. Our data allows us to identify a bias in the choice of information an investor transmits to another investor and in the choice of the message recipient. The existing finance research has largely ignored the role of tie strength between investors, yet our results show that it plays a key role in the transmission of investment information and in the way the message receivers respond to and learn from the information in their own investment decisions. Our results suggest that further investigation of the role of tie strength in investor social networks can be fruitful.

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Table 1: Summary Statistics

This table reports summary statistics on trades, instant messages, and tie strengths of 66 day traders from 10/1/2007 to 4/30/2009. Return is the log return on a round-trip trade on a stock, defined as the natural logarithm of the total value of the shares sold divided by the total value of the shares purchased. Position duration is the duration of a round-trip trade on a stock (in minutes), and # positions/day is the number of round-trip trades by the trader on a day. Tie is the strength of tie between the trader and each of his contacts, as defined in Equation (1) using messages during the last 7 days. A trader's contacts are defined as other traders the trader has sent a message to during the last 7 days. Tie_Fin is defined similarly using messages that contain a word in our custom dictionary comprised of NASDAQ Glossary of financial and investing terms and IG Glossary of trading terms. STD is the standard deviation, Q1 is the first quartile, and Q3 is the third quartile.

	Mean	Q1	Median	Q3	STD	# Obs
Position duration (minutes)	57.8	4	12	43	108.5	297,693
Position size ($)	29,675	4,865	11,404	29,400	67,631	297,693
# positions/day	18.9	9	15	24	16.2	15,759
# stocks traded/day	13.0	6	10	15	11.9	15,759
Trade size ($)	7,341	1,711	3,550	7,743	13,499	2,268,641
# trades/day	144	46	89	176	166	15,759
Return (%)	0.21	-0.38	0.10	0.73	2.04	297,693
# Messages sent/day	31.3	0	9	41	50.8	15,759
# Messages received/day	33.3	0	9	44	54.0	15,759
# words per message	5.88	2	4	7	10.26	1,008,177
Tie	0.264	0.031	0.099	0.359	0.334	25,989
Tie_Fin	0.270	0.024	0.115	0.404	0.323	25,758

Table 2: Trader's propensity to send message about stock

Table 2 estimates the propensity of a trader to send a message about a stock he traded. The unit of observation is trader-day-time-stock, where time is when the trader sends a message about a stock he traded on that day. For each trader-day-time, we consider all stocks the trader has traded from the beginning of the day up to the time of message and estimate the probability that the trader sends a message about each of those stocks. Panel A shows the result of the univariate analysis where we compute the fraction of the stocks for which message was sent out of all stocks traded, separately for stocks with gains and those with losses. Panel B shows the results of the multivariate probit regressions that estimate the propensity of a trader to send a message about a stock he traded. The dependent variable, MsgSent, is equal to 1 if the trader sent a message about the stock. The coefficient represents the average marginal probability. The coefficient estimates for Delay, VIX, and #Messages are multiplied by 100. See Appendix for variable definitions. Standard errors are clustered by day and robust z-statistics are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Panel A: Univariate result

	#obs	Prob(Message)
Gain	118,081	8.32%
Loss	101,132	7.37%
Diff		0.95%
t-stat		8.31
p-value		<0.001

Panel B: Multivariate results

	(1) MsgSent	(2) MsgSent	(3) MsgSent	(4) MsgSent
Gain	0.0060***	0.0071***	0.0071***	0.0071***
	(3.53)	(5.04)	(5.04)	(5.02)
RetDay		0.1387***	0.1359***	0.1379***
		(2.91)	(2.79)	(2.91)
Delay (×100)		-0.0419***	-0.0419***	-0.0419***
		(-37.20)	(-37.18)	(-37.23)
%Pos		0.1953***	0.1953***	0.1953***
		(49.52)	(49.56)	(49.60)
VIX (×100)		-0.0050	-0.0044	-0.0071
		(-0.95)	(-0.82)	(-1.29)
MktRet		0.0021	0.0020	0.0027
		(0.10)	(0.10)	(0.13)
StockRet		-0.0043	-0.0043	-0.0045
		(-0.37)	(-0.37)	(-0.38)
#Messages (×100)			-0.0006	
			(-1.14)	
#Contacts				-0.0003**
				(-1.96)
Trader FE	Y	Y	Y	Y
Month and Day of Week FE	Y	Y	Y	Y
Observations	219,213	215,413	215,413	215,413
Pseudo R2	5.94%	18.2%	18.2%	18.2%

Table 3: Variation in asymmetric propensity to send message about stock

Table 3 examines the variation in the asymmetry between gain and loss in traders' propensity to send a message about a stock. The unit of observation is trader-day-time-stock, where time is when the trader sends a message about any stock he traded on that day. For each trader-day-time, we consider all stocks the trader has traded from the beginning of the day up to the time of message and estimate the probability that the trader sends a message about each of those stocks. The average marginal probability is reported as the coefficient. See Appendix for variable definitions. The coefficient estimates for Delay, VIX, and Gain×Delay are multiplied by 100. Standard errors are clustered by day and robust z-statistics are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

	(1) MsgSent	(2) MsgSent	(3) MsgSent	(4) MsgSent
Gain	0.0070***	0.0072***	0.0090***	0.0120***
	(4.95)	(4.10)	(5.59)	(5.43)
Gain×RetDay	0.1238			
	(1.31)			
Gain×Delay (×100)		-0.0002		
		(-0.09)		
Gain×%Pos			-0.0147***	
			(-2.76)	
Gain×#Contacts				-0.0362***
				(-2.73)
RetDay	0.0712	0.1388***	0.1408***	0.1384***
	(1.21)	(2.92)	(2.96)	(2.91)
Delay (×100)	-0.0419***	-0.0418***	-0.0419***	-0.0418***
	(-37.22)	(-29.21)	(-37.22)	(-37.25)
%Pos	0.1953***	0.1953***	0.2035***	0.1954***
	(49.51)	(49.50)	(41.60)	(49.52)
VIX (×100)	-0.0051	-0.0050	-0.0050	-0.0072
	(-0.96)	(-0.95)	(-0.94)	(-1.32)
MktRet	0.0021	0.0021	0.0022	0.0029
	(0.10)	(0.10)	(0.11)	(0.14)
StockRet	-0.0043	-0.0042	-0.0047	-0.0035
	(-0.37)	(-0.37)	(-0.41)	(-0.31)
#Contacts				-0.0101
				(-0.60)
Trader FE	Y	Y	Y	Y
Month and Day of Week FE	Y	Y	Y	Y
Observations	215,413	215,413	215,413	215,413
Pseudo R2	18.2%	18.2%	18.2%	18.2%

Table 4: Trader's choice of receiver when sending message about stock

Panel A of Table 4 compares the tie strength between the sender and the receiver when the message is about a stock the sender had a gain on and when it is about a stock the sender had a loss on. Panel B shows the results of probit regressions that estimate the probability that a trader's contact receives a message from the trader about a stock the trader has traded. The unit of observation is trader-day-time-stock-contact, where time is when the trader sends a message about a stock he traded. For each trader-day-time-stock, contacts are those who received a message from the trader during days [-7,0], where day 0 is when the message was sent. The dependent variable, MsgSent, is equal to 1 for the actual receiver of the message, and 0 for other contacts who did not receive the message. The coefficient represents the average marginal probability. The coefficient estimates for Delay and VIX are multiplied by 100. See Appendix for variable definitions. Standard errors are cluster by day and robust z-statistics are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Panel A: Tie strength between the sender and the receiver of stock message

	#obs	Tie	Tie_Fin
Gain	9,827	0.618	0.624
Loss	7,451	0.602	0.609
Diff		0.016	0.015
t-stat		2.54	2.41
p-value		0.011	0.016

Panel B: Multivariate results

	(1) MsgSent	(2) MsgSent	(3) MsgSent	(4) MsgSent
Gain	-0.0006	-0.0036**	-0.0006	-0.0029**
	(-1.46)	(-2.39)	(-1.54)	(-2.02)
Tie	0.1789***	0.1744***		
	(42.81)	(37.84)		
Gain×Tie		0.0080**		
		(2.21)		
Tie_Fin			0.1935***	0.1899***
			(49.66)	(43.70)
Gain×Tie_Fin				0.0063*
				(1.77)
MktRet	0.0051	0.0051	0.0026	0.0027
	(0.64)	(0.64)	(0.31)	(0.32)
StockRet	-0.0025	-0.0025	-0.0022	-0.0022
	(-0.72)	(-0.73)	(-0.71)	(-0.71)
VIX (×100)	0.0104**	0.0104**	0.0132***	0.0132***
	(2.56)	(2.56)	(2.76)	(2.76)
#Contacts	-0.0023***	-0.0023***	-0.0023***	-0.0023***
	(-22.65)	(-22.64)	(-25.86)	(-25.85)
%Pos	-0.0008	-0.0008	-0.0011*	-0.0011
	(-1.29)	(-1.28)	(-1.66)	(-1.64)
Delay (×100)	-0.0006**	-0.0006**	-0.0004	-0.0004
	(-2.15)	(-2.17)	(-1.33)	(-1.34)
Trader FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y
Observations	209,221	209,221	209,221	209,221
Pseudo R2	23.9%	23.9%	27.3%	27.3%

Table 5: Message receiver's propensity to send message about the same stock

Table 5 shows the results of probit regressions that estimate the propensity of the message receiver to send a message about the same stock afterward the receipt of the original message. MsgSent is equal to one if the receiver sends a message about a stock after receiving a message about the stock. Msg sent to third party is equal to one if the receiver sends a message about the stock to another trader who is not the sender of the message he received. See Appendix for variable definitions. The coefficient represents the average marginal probability. Standard errors are clustered by day and robust z-statistics are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

	(1) MsgSent	(2) MsgSent	(3) MsgSent	(4) Msg sent to third party	(5) Msg sent to third party	(6) Msg sent to third party
SenderGain	-0.0217***	-0.0213***	-0.0019	-0.0060	-0.0060	-0.0101
	(-2.21)	(-2.17)	(-0.09)	(-1.33)	(-1.32)	(-1.20)
Tie	0.0817***		0.0962***	0.0005		-0.0027
	(4.37)		(4.14)	(0.06)		(-0.27)
Tie_Fin		0.0894***			0.0061	
		(4.57)			(0.80)	
SenderGain×Tie			-0.0266			0.0063
			(-1.06)			(0.56)
MktRet	0.0986	0.1018	0.0959	-0.1317	-0.1324	-0.1318
	(0.61)	(0.63)	(0.59)	(-1.54)	(-1.55)	(-1.54)
StockRet	0.0075	0.0062	0.0063	-0.0134	-0.0141	-0.0129
	(0.11)	(0.09)	(0.09)	(-0.40)	(-0.42)	(-0.38)
VIX (×100)	0.0822	0.0869	0.0834	-0.0314	-0.0319	-0.0316
	(1.36)	(1.44)	(1.38)	(-1.23)	(-1.25)	(-1.23)
%Pos	0.0334**	0.0337**	0.0340**	0.0171**	0.0169**	0.0171**
	(2.12)	(2.14)	(2.16)	(2.56)	(2.53)	(2.55)
Delay (×100)	-0.0204**	-0.0206**	-0.0206**	-0.0016	-0.0017	-0.0016
	(-2.34)	(-2.35)	(-2.36)	(-0.49)	(-0.51)	(-0.47)
Trader FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y
Observations	8,314	8,314	8,314	7,610	7,610	7,610
Pseudo R2	10.9%	11.0%	11.0%	8.0%	8.1%	8.1%

Table 6: Message receiver's trades of the stock

Table 6 shows the results of probit regressions that estimate the propensity that the receiver trades the stock mentioned in the message he received (Columns (1)-(3)) and the propensity that the sender and the receiver trade the stock in same direction (Columns (4)-(6)) after receiving a message about the stock. Trade is equal to one if the receiver trades the stock after receiving message about the stock, and Same is equal to one if the sender and the receiver trade the stock in the same direction (both buy/both sell) after the message. See Appendix for variable definitions. The coefficient represents the average marginal probability. Standard errors are clustered by day and robust z-statistics are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

	(1) Trade	(2) Trade	(3) Trade	(4) Same	(5) Same	(6) Same
SenderGain	-0.0027	0.0389*	0.0365*	0.0146	0.0407**	0.0330*
	(-0.23)	(1.83)	(1.66)	(1.61)	(2.32)	(1.81)
Tie	0.0222	0.0562**		0.0224	0.0439**	
	(1.05)	(2.23)		(1.37)	(2.20)	
SenderGain×Tie		-0.0598**			-0.0373*	
		(-2.12)			(-1.71)	
Tie_Fin			0.0591**			0.0452**
			(2.31)			(2.27)
SenderGain×Tie_Fin			-0.0550*			-0.0255
			(-1.86)			(-1.12)
MktRet	-0.0023	-0.0058	-0.0059	-0.0126	-0.0155	-0.0148
	(-0.01)	(-0.03)	(-0.03)	(-0.09)	(-0.12)	(-0.11)
StockRet	0.1079	0.1032	0.1032	-0.0283	-0.0308	-0.0302
	(1.24)	(1.18)	(1.18)	(-0.45)	(-0.48)	(-0.47)
VIX (×100)	0.0817	0.0847	0.0854	0.1301***	0.1319***	0.1327***
	(1.40)	(1.45)	(1.47)	(2.99)	(3.03)	(3.05)
%Pos	0.1050***	0.1062***	0.1060***	0.0843***	0.0850***	0.0848***
	(6.55)	(6.62)	(6.60)	(6.91)	(6.93)	(6.91)
Delay (×100)	-0.0222**	-0.0227**	-0.0228**	-0.0156	-0.0159	-0.0159
	(-2.11)	(-2.17)	(-2.17)	(-1.56)	(-1.60)	(-1.60)
Trader FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y
Observations	8,241	8,241	8,241	8,183	8,183	8,183
Pseudo R2	7.3%	7.4%	7.4%	5.1%	5.1%	5.1%

Table 7: Message receiver's trades conditional on sender bias

We split the sample based on the sender's bias toward sending message about his gains than losses. For each subsample, we estimate the propensity that the receiver trades the stock mentioned in the message (Trade) and the propensity that the sender and the receiver trade the stock in same direction (Same). The average marginal probability is reported as the coefficient. Trade is equal to one if the receiver trades the stock after receiving message about the stock, and Same is equal to one if the sender and the receiver trade in the same direction (both buy/both sell) after the message. SenderBias is defined as the difference between the sender's propensity to send a message about a gain stock and the propensity to send a message about a loss stock, computed in an analogous manner as Diff in Panel A of Table 2, based on the trading and message records of the sender during the past three months. The coefficient represents the average marginal probability. See Appendix for variable definitions. Standard errors are clustered by day and robust z-statistics are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

	SenderBias above median: More biased toward sending message about gain stock than loss stock			SenderBias at or below median: Less biased toward sending message about gain stock than loss stock		
	(1)	(2)	(3)	(4)	(5)	(6)
	Trade	Trade	Same	Trade	Trade	Same
SenderGain	0.0740*	0.0870*	0.0588*	0.0160	0.0076	0.0323
	(1.68)	(1.95)	(1.72)	(0.61)	(0.27)	(1.46)
Tie	0.0548		0.0231	0.0467		0.0408
	(1.18)		(0.63)	(1.41)		(1.44)
SenderGain×Tie	-0.0895*		-0.0546	-0.0254		-0.0257
	(-1.75)		(-1.35)	(-0.71)		(-0.90)
Tie_Fin		0.0575			0.0524	
		(1.23)			(1.57)	
SenderGain×Tie_Fin		-0.1051**			-0.0102	
		(-2.04)			(-0.27)	
MktRet	0.5982*	0.6045*	0.0119	-0.3627	-0.3628*	-0.0223
	(1.82)	(1.85)	(0.05)	(-1.64)	(-1.64)	(-0.15)
StockRet	-0.0744	-0.0735	-0.1491	0.2614**	0.2628**	0.0982
	(-0.51)	(-0.50)	(-1.36)	(2.41)	(2.43)	(1.24)
VIX (×100)	-0.1055	-0.1038	0.2129**	0.2270**	0.2306**	0.2387***
	(-0.92)	(-0.90)	(2.50)	(2.16)	(2.22)	(3.47)
%Pos	0.1143***	0.1141***	0.0975***	0.0705***	0.0703***	0.0600***
	(4.29)	(4.27)	(4.97)	(3.09)	(3.07)	(3.39)
Delay (×100)	-0.0330**	-0.0333**	-0.0187*	-0.0219	-0.0217	-0.0226
	(-2.48)	(-2.51)	(-1.73)	(-1.47)	(-1.45)	(-1.50)
Trader FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y
Observations	3,672	3,672	3,576	3,960	3,960	3,957
Pseudo R2	8.9%	8.9%	5.9%	9.5%	9.5%	7.1%

Table 8: Trading performance as a function of other traders' performance and message about the stock

Table 8 shows the results of OLS regressions of the log return (in %) on a round-trip transaction on a stock (Ret) on other traders' performance on the same stock ($Gain^O$ and $Loss^O$) and whether or not the trader received a message about the stock before closing the position from another trader who traded the same stock (MsgReceived). Variable definitions are in Appendix. Standard errors are clustered by day and robust t-statistics are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

	(1) Ret	(2) Ret	(3) Ret	(4) Ret	(5) Ret	(6) Ret
$Gain^O$	0.693^{***}	0.693^{***}	0.693^{***}	0.701^{***}	0.701^{***}	0.701^{***}
	(25.03)	(25.03)	(25.03)	(25.23)	(25.24)	(25.24)
$Loss^O$	-0.642^{***}	-0.642^{***}	-0.642^{***}	-0.627^{***}	-0.627^{***}	-0.627^{***}
	(-21.66)	(-21.66)	(-21.66)	(-21.43)	(-21.43)	(-21.43)
MsgReceived	-0.024	0.169	0.221	-0.005	0.175	0.234
	(-0.18)	(0.66)	(0.84)	(-0.04)	(0.69)	(0.90)
$Gain^O$×MsgReceived	-0.146	-0.160	-0.154	-0.151	-0.143	-0.142
	(-1.24)	(-0.71)	(-0.66)	(-1.29)	(-0.64)	(-0.61)
$Loss^O$×MsgReceived	0.156	-0.202	-0.247	0.141	-0.203	-0.250
	(1.47)	(-1.08)	(-1.29)	(1.33)	(-1.10)	(-1.32)
$Gain^O$×MsgReceived×Tie		0.059			0.023	
		(0.19)			(0.07)	
$Loss^O$×MsgReceived×Tie		0.570^{**}			0.546^{**}	
		(2.36)			(2.26)	
MsgReceived×Tie		-0.332			-0.309	
		(-0.96)			(-0.89)	
$Gain^O$×MsgReceived×Tie_Fin			0.049			0.019
			(0.15)			(0.06)
$Loss^O$×MsgReceived×Tie_Fin			0.621^{**}			0.600^{**}
			(2.57)			(2.49)
MsgReceived×Tie_Fin			-0.399			-0.386
			(-1.15)			(-1.12)
RetDay	46.090^{***}	46.084^{***}	46.084^{***}	45.568^{***}	45.562^{***}	45.563^{***}
	(25.04)	(25.06)	(25.06)	(24.91)	(24.93)	(24.94)
StockRet	3.642^{***}	3.642^{***}	3.642^{***}	3.605^{***}	3.606^{***}	3.606^{***}
	(31.11)	(31.12)	(31.12)	(30.85)	(30.86)	(30.86)
MktRet	-0.081	-0.081	-0.081	0.082	0.083	0.083
	(-0.52)	(-0.52)	(-0.52)	(0.54)	(0.55)	(0.55)
VIX	0.002^{***}	0.002^{***}	0.002^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(5.42)	(5.42)	(5.43)	(2.69)	(2.69)	(2.69)
Log(PositionSize)				-0.088^{***}	-0.088^{***}	-0.088^{***}
				(-15.27)	(-15.26)	(-15.26)
Trader FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y
Observations	297,638	297,638	297,638	294,762	294,762	294,762
Adj. R-squared	9.3%	9.3%	9.3%	9.5%	9.5%	9.5%

Figure 1: Example of trader communication

Figure 1 shows a message sent from Trader 7 to Trader 50 at 9:55:38am on February 17, 2009 about a stock with a ticker symbol "KED" and a message from Trader 50 to Trader 55 at 10:18:30am about the same stock. The contacts of Trader 7, Trader 50, and Trader 55 are shown, and the thickness of an edge connecting two traders corresponds to the tie strength between the two traders.

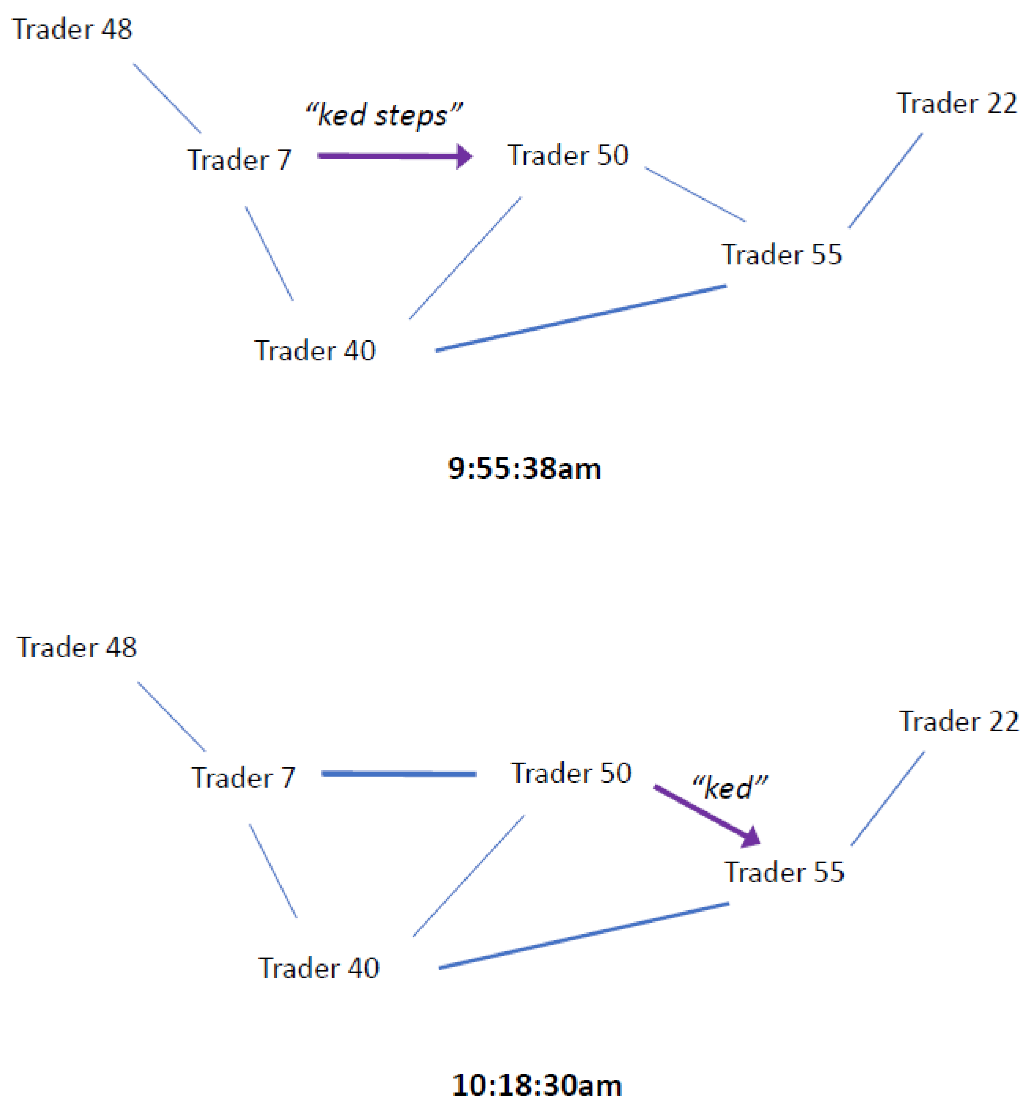
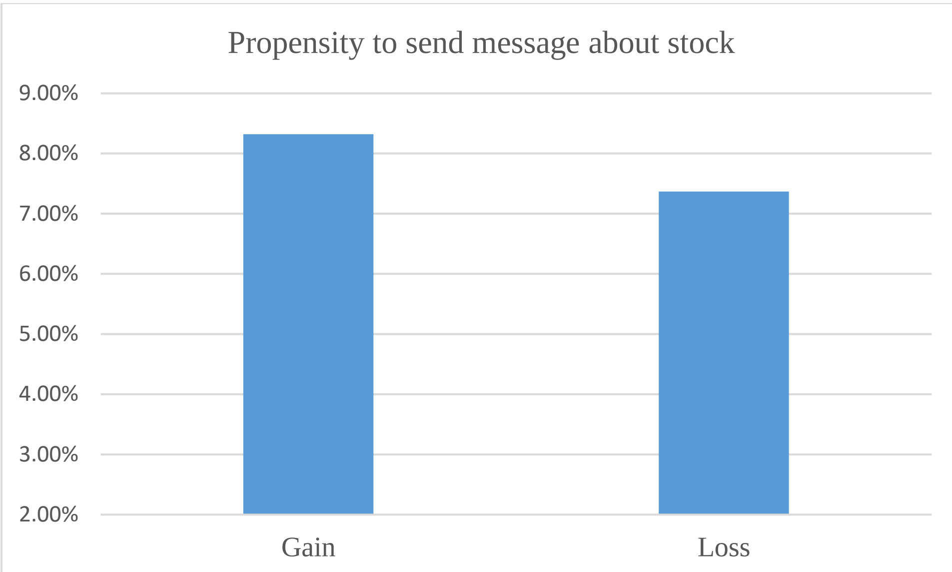


Figure 2: Propensity to send message about stock

Figure 2 shows the fraction of the stocks mentioned in instant messages out of all stocks traded, separately for stocks with gains and losses, as reported in Panel A of Table 2.



Appendix: Variable definitions

This appendix provides the descriptions of the variables used in our analyses.

Variable	Definition
Delay	Time since the last trade of the stock (in minutes)
Gain	Indicator variable equal to 1 if the trader's return on the stock when he sent a message about the stock is positive. Return on the stock is computed according to Equation (3)
$Gain^{O}$	Equal to 1 if another trader had a gain on the same stock
MsgReceived	Equal to 1 if the trader received a message about the stock before closing the position on the stock
MsgSent	Indicator variable equal to 1 if the trader sent a message about the stock
Msg sent to third party	Indicator variable equal to 1 if the message receiver sends a message about the same stock to another trader who is not the sender of the original message
Log(PositionSize)	Natural logarithm of the total dollar value of the shares purchased for the stock
$Loss^{O}$	Equal to 1 if another trader had a loss on the same stock
MktRet	Return of SP500 index for the day (sign reversed for short position)
Ret	Return on a round-trip trade of a stock, defined as the natural logarithm of the total dollar value of the shares of the stock sold divided by the total dollar value of the shares of the stock purchased.
RetDay	Trader's overall return for the day, defined as the natural logarithm of the total dollar value of all stock sales divided by the total dollar value of all stock purchases during the day.
SenderGain	Equal to 1 if the sender had a positive return on the stock mentioned in his message
StockRet	Stock's return for the day from CRSP (sign reversed for short position)
Tie	The strength of tie between the trader and his contact, using messages during the last 7 days in Equation (1)
Tie_Fin	The strength of tie between the trader and his contact, using finance messages during the last 7 days in Equation (1)
VIX	CBOE volatility index
#Contacts	Number of people the trader sent a message to during days [-7,0]
#Messages	Number of messages sent by trader during the day
%Pos	Dollar value of the position on the stock as a percentage of the trader's total portfolio value