Why Don't We Agree? Evidence from a Social Network of Investors*

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Abstract

We develop a new measure of disagreement based on the sentiment expressed by investors on a social network investing platform. Changes in our measure of disagreement robustly forecast abnormal trading volume, even though it is unlikely that investor trades from those on the investing platform move the market. Using information on the investment philosophies of the investors (e.g., technical, fundamental, short term, long term), we test existing theories that suggest that differing investment philosophies are an important source of disagreement. Although we also find significant scope for disagreement among investors with the same investment philosophy, our findings suggest that investment approaches matter fundamentally to disagreement. Therefore, even with perfectly informationally efficient markets, investor disagreement, and thus high trading volume and volatility, would likely persist.

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1 Introduction

Disagreement among investors is central to trading in financial markets. Indeed, it is difficult to motivate why investors would trade at all without some source of disagreement (Milgrom and Stokey, 1982; Karpoff, 1986). Motivated partly by this observation, a growing literature evaluates the effects of investor disagreement on financial market outcomes (e.g., Varian, 1985; Nagel, 2005; Banerjee and Kremer, 2010; Carlin et al., 2014). Research has linked disagreement to trading volume and stock returns, and has studied its dynamic effects (Ajinkya et al., 1991; Diether et al., 2002; Banerjee and Kremer, 2010).

Despite the breadth of work on the consequences of investor disagreement, much less is known empirically about the *sources* of disagreement. That is, why do investors disagree in the first place? Leading theories have identified different investment philosophies and different information sets as the most important sources of disagreement (Hong and Stein, 2007). In this paper, we document that differences in investment philosophies contribute significantly to overall investor disagreement by studying a setting in which individual investment philosophies are explicitly reported.

In most existing data sets on trading, it is impossible to distinguish different investment approaches from different information because investors' opinions and trading approaches must be inferred from observed trading behavior (e.g., see Rothschild and Sethi (2014) and Baldauf and Mollner (2015)). We overcome this challenge by studying disagreement among investors on a social investing platform (called StockTwits), in which many investors report their opinions about same stocks on the same date directly as bullish or bearish. This feature of the data allows us to treat dispersion of opinions at the firm-date level as a measure of disagreement. In addition, individual profile information on StockTwits *explicitly* conveys the user's experience level and investment approach. We use stated investment philosophies and experience levels to compute within-group disagreement measures that focus on the difference of opinions among *ex ante* similar individuals. We find that there is significant disagreement among traders who adopt the same broad investment approach. Moreover, we show that existing disagreement measures do not correlate strongly with our measure, which further supports the novelty of our measurement and approach.

Our disagreement measure has three major advantages over existing broad-market disagreement measures. First, our measure directly measures dispersion of investor opinions, whereas leading alternative disagreement measures rely on indirect information, either observed trading patterns (i.e., volatility measures) or opinions of third parties (i.e., analyst forecast dispersion). Second, our measure can be reliably computed at the daily level, whereas alternative measures need to be measured at lower frequencies (typically, monthly or quarterly). Third, our measure is novel because it can be computed for sub-groups of investors at the firm-date level, just by restricting attention to the stated opinions of those investors, which helps compare the amount of disagreement across groups versus within groups.

To evaluate the usefulness of our measure more generally, we empirically evaluate how within-group disagreement relates to trading outcomes in the market. Our tests show that within-group differences of opinion are an important predictor for trading volume, both for contemporaneous volume and for forecasting future volume, and that these correlations do not arise because of an investor reaction to market outcomes. Moreover, variation in our within-group disagreement measure can explain one third of the spike in volume around earnings announcements, which provides empirical evidence for emerging theories that argue for why disagreement rises precisely when information arrives to the market (Kondor, 2012; Banerjee et al., 2015).

Digging deeper, we use investors' stated investment strategies and differences of opinion within and across groups to evaluate the sources of market-wide disagreement. Specifically, knowing each investor's approach *ex ante* enables us to quantify the importance of cross-group disagreement (i.e., disagreement among investors with different investment philosophies), versus within-group disagreement (disagreement among individuals with the same investment strategy). When we decompose the relationship of disagreement to trading volume into cross-group and within-group components, we find that cross-group disagreement explains two thirds of the trading volume that within-group disagreement explains. The significant explanatory power of cross-group disagreement for trading volume provides corroborative evidence that investment models are an important contributor to market-wide disagreement. On this basis, our findings suggest that the disagreement and high trading volume observed in financial markets would persist even as markets became more informationally efficient.

Our results, measure of disagreement, and approach should be of broad interest to scholars studying individual investing behavior and market microstructure, as well as policy makers more generally. First, although there has been significant inquiry into the consequences of disagreement for financial market outcomes, we are the first to empirically study the sources of disagreement. In so doing, we provide empirical evidence of both channels posited theoretically in Hong and Stein (2007). This is an important step forward because showing that a substantial component of disagreement arises from differing approaches to investment implies that enriching the information environment will not fully alleviate disagreement in financial markets, and in fact, as recent theoretical contributions have highlighted, disagreement may rise (Kondor, 2012; Banerjee et al., 2015).

We also contribute to the disagreement literature by innovating a useful measure of disagreement among individual investors. Although the consequences of disagreement are well studied, the extant measures of disagreement have notable weaknesses. For example, some of these measures measure dispersion of opinion indirectly (e.g., volatility of accounting performance, historical trading volume, firm age, return volatility), and the most prominent measure of analyst forecast dispersion measures the stated opinions of analysts, which has been questioned as a reliable measure of market-wide disagreement (Ataise and Bamber, 1994; Bamber et al., 2011). We fill this gap by combining our setting – which yields daily measures of sentiment at the individual firm $\times$ approach level – with a theoretically grounded measure of disagreement from Antweiler and Frank (2004). Taken together, our disagreement measure can be computed at a higher frequency than most other measures of disagreement (analyst dispersion is usually computed monthly or quarterly), and because it is a direct sentiment measure, it is less likely to proxy for other market forces that are unrelated to disagreement, such as liquidity needs of investors.

Our results on abnormal trading and disagreement also relate to the literature on the abnormal trading of individual investors (Barber and Odean, 2000). In particular, this literature has identified numerous behavioral rationales for over-trading, including entertainment (Dorn and Sengmueller, 2009), sensation seeking (Barber and Odean, 2008; Grinblatt and Keloharju, 2009), gambling (Kumar, 2009; Cookson, 2016), and learning by doing (Linnainmaa, 2011). We contribute to this stream of research by showing clean evidence that model disagreement is an additional reason for the abnormal trading volume of individual investors. It is notable that model disagreement is not well aligned with entertainment motives, nor learning by doing motives for trading, and thus, is a theoretically distinct rationale for additional trading.

Our research complements recent work on the micro-level determinants and consequences of investor disagreement (e.g., Carlin et al., 2014). In this literature, the most closely related paper to ours is Giannini et al. (2015). Both our paper and Giannini et al. (2015) use data from StockTwits, but our analyses are distinct along at least two dimensions. First, our analysis makes use of information on investor types – not utilized in Giannini et al. (2015) – to study the *sources* of disagreement. Second, our measure of disagreement captures the degree to which individual investors on the social network disagree with one another, whereas Giannini et al. (2015) captures the disagreement between the average social network investor and the typical media article.[1]

In the end, understanding the cause of investor disagreement has important policy implications. Regulators put substantial effort into trying to minimize information asymmetry among investors (e.g., see the analysis in Rogers et al., 2015). Abstracting from any notion of fairness, it is important to understand whether and by how much these policies could actually decrease disagreement among investors, and therefore trading volume and volatility in the stock market. For these reasons, it is natural that Hong and Stein (2007) pose the key question, "what are underlying mechanisms, either at the level of market structure or individual cognition, that give rise to disagreement among traders and hence to trading volume?" Our results suggest that different investment philosophies are partly responsible for the high trading volume because two investors reading the same piece of information likely draw different conclusions about the report's implications for a proper trading position.[2] Therefore, new information might not decrease volatility, but in fact, volatility may increase.

2 Data

2.1 The Ideal Data Set

Separating the roles of information asymmetry and heterogeneous models in investor disagreement is empirically challenging, given the typical data limitations. First, disagreement refers to differences in investors' opinions, which are difficult to observe. Even if a researcher had individual-level trading data (which itself is hard to come by), it is difficult to impute investors' opinions from the trading data, as investors can trade for reasons unrelated to their opinion - like liquidity. Second, as

[1] We conduct an exercise that explicitly compares our measure and Giannini et al.'s in Section 4.3. The takeaway is that both measures are a significant improvement over other disagreement measures, but that our measure exhibits a stronger correlation with abnormal trading volume.

[2] A recent article by the Economist mentioned "This week a report showing a slump in China's imports and exports in November was read differently by bulls and bears" (The Economist, "In a hole", December 12, 2015)

Rothschild and Sethi (2014) and Baron et al. (2012) point out, in order to separate whether the differences in investor opinions are due to differences in information sets or differences in investors' models, ideally the researches would observe investors trading strategies – not just the executed trades – in an asset market. Motivated by the theories mentioned in the previous section, the ideal dataset would provide information on the approach, holding period, and sentiment of investors toward particular tradable assets.

2.2 StockTwits Data

Our data set comes from a company called StockTwits. StockTwits was founded in 2008 as a social networking platform for investors to share their opinions about stocks. The website has Twitter-like format, where participants post messages of up to 140 characters, and use "cashtags" with the stock ticker symbol (example $AAPL), to index ideas to a particular company. Although the website does not explicitly integrate with other social media websites, users can share content to their personal Twitter, LinkedIn, and Facebook accounts. According to a website analytics tool, Alexa, StockTwits was ranked as the 2,004th most popular website in the US as of May, 2015. The users are predominantly male and the number of users with a graduate school degree is over-represented relative to other websites on the internet that Alexa tracks.

Our original dataset spans from 1 January, 2010 until 30 September, 2014. In total, there are 18,361,214 messages by 107,920 unique users mentioning 9,755 tickers. For each message, we observe a user identifier and the message content. We also observe indicators for sentiment (bullish, bearish, or unclassified), and "cashtags" that link the message to particular stocks.

For most users, we observe a self-reported investment philosophy that can vary along two dimensions: (1) Approach – technical, fundamental, momentum, value, growth, and global macro, or (2) Investment Horizon (or Holding Period) – day trader, swing trader, position trader, and long term investor. Users of the site also self-report their experience level as either novice, intermediate, or professional. This user-specific information about the style and investment model employed is useful to distinguish the role of investment philosophies from features of the informational environment.

We restrict our sample to cover the time period between January 2013 and September 2014 because the number of messages posted to StockTwits has grown substantially over time and the best quality data come from more recent years. As can be seen in Table 1, this restriction leaves us with 75% of messages. To focus on sentiment that can be directly linked to particular stocks, we restrict attention to messages that only mention one ticker. We also focus on the sample of messages by users who have indicated their approach, holding period, and experience. To link with earnings announcements information, we focus on firms that are headquartered in the United States, and thus, have regular filings with the SEC. It would be ideal to observe investors' opinions about individual firms every day for constructing a daily measure of disagreement. Thus, we concentrate on firms for which there is a high amount of StockTwits coverage. The top 100 firms mentioned comprise 60% of the overall number of messages in our sample. This leaves us with 1,460,349 messages by 11,874 unique users.[3] We present the names of the 100 firms and the frequency of messages about these firms in Table 2. Not surprisingly, many of the most discussed firms are in technology and pharmaceutical industries.

Note that some users joined StockTwits after January 1, 2013. We control for the growing nature of our sample by including time fixed effects in our analysis. Out of 11,874 users, 4,566 joined before January 1, 2013.[4] Figure 2 portrays the number of messages over time in our data, indicating no dramatic changes over time aside from steady growth in the number of users and messages posted.

Table 3 presents summary statistics of the sample coverage. The median number of messages per firm per day is 10, with as many as 5,000 messages on some days for some firms. More generally, this feature of the sample is useful because the typical firm has multiple messages per trading day in the data, which enables calculating useful measures of disagreement at the day-firm level.

2.3 StockTwits Users

To register with StockTwits, a user reports via an online form his or her investment approach (Fundamental, Technical, Momentum, Global Macro, Growth, or Value), investment horizon (Day Trader, Swing Trader, Position Trader, or Long Term Investor), and experience level (Novice, Intermediate,

[3] To ensure that the cutoff of 100 firms does not arbitrarily influence our results, we reproduce our main findings in Table 12 using the sample of the 150 most talked-about firms, obtaining similar results. When we replicate our main results using the top 50 firms and the top 51-100 firms, the results are not driven by just the top stocks. Indeed, our measure of disagreement exhibits somewhat better properties for firms 51-100 than for the top 50 firms.

[4] In the Appendix, we conduct an robustness test to ensure that the potentially changing composition of the investors is not affecting our results by repeating the analysis using just users who joined Stocktwits before January 1, 2013. As can be seen in table 12, the results are very similar.

or Professional). In Table 3 Panel B, we present the breakdown of users by approach, holding period, and experience. On StockTwits, the most common approach is Technical, representing 38% of users and also posting about 38% of messages. Momentum and Growth investors represent the next two most common investment philosophies (20% and 18% of investors, respectively), followed by Fundamental and Value investors. Although some groups of investors post more than their fair share (Momentum investors) and some less (Value investors) the posting frequencies across investor groups is similar. To the best of our knowledge this is the first paper to directly measure investor approaches, and therefore, we cannot compare whether this breakdown representative of other samples in the market.

Next, we examine the holding horizons of investors. A plurality of investors (44%) are swing traders, who tend to have an investment horizon from a couple of days to a couple of weeks. The next biggest group is position traders, whose investment horizon is usually several months. The day traders and long term investors each makeup about 15% of the investors.

It is important to evaluate the representativeness of the opinions on the platform if we hope to speak to broad-market disagreement using the unique features of StockTwits. Validating the empirical measures from StockTwits is especially important for self-reported measures, such as approach. Both the distribution across approaches and the posting behavior within approaches suggest that StockTwits data provides broader, useful insight into investor opinions. Specifically, according to the self-reported experience measure, approximately half of the investors report an intermediate experience level. About 20% are professional and about 30% are novices. Consistent with likely trading behaviors, professionals post disproportionately more messages than novices or intermediates.

In addition, we hand-checked a number of user profiles using identifying information when available. In the cases we checked by hand, this self-reported experience appears to be a reliable indicator of the user's experience. Figure 1 presents three examples of user profiles, one for each experience level in the data, to give a sense for this comparison. The *novice* investor is a student, who is mostly trading for fun, the *intermediate* investor reports real life trading experience, but seems to be less active. Finally, the *professional* investor has over 30 years of trading experience and has worked in the IBM PIT.

We also examine when investors post the messages. We are interested to know whether they post the messages as news occur and investors update their beliefs, or in the evening after work, when they have more free time. In figures 3 and 4 we plot the distribution of messages by the day of the week and by the hour of the day. It is evident that investors predominantly post messages when the markets are open (Monday-Friday and between 9am and 4pm). This is consistent with investors updating their messages in real time as financial events unfold.

2.4 Why do users post messages?

For constructing a measure of disagreement, it is essential that the sentiment expressed on StockTwits reveals the true opinions of investors. Thus, before using the data, it is useful to rule out that users are trying to manipulate the stock market by posting fake opinions. For example, if a user thinks the stock price will go down and thus wants to sell the stock, she could post really positive messages, in an attempt to increase the price temporarily, which would allow her to sell at a higher price. This would invalidate our measure, as we would capture her opinion as bullish, even though she is bearish on the stock. This does not appear to be an important concern in our data for several reasons. First, there is anecdotal evidence that investors post on the social networks to attract followers, and gain internet fame or a job.[5] In all those cases, it is in their best interest to provide their best forecast of the future stock performance, and thus their honest opinion about the stock. Second, these firms have large market caps, and therefore it is very unlikely that individual investors think they can move prices.

3 Sentiment

3.1 Sentiment measure

When using StockTwits, users can post a message (limited to 140 characters) and indicate their sentiment as bullish, bearish, or unclassified (the default option). The following figure presents an image of the interface.

[5]For example, here is an article on the fame motive for posting to investment social networks (article here).

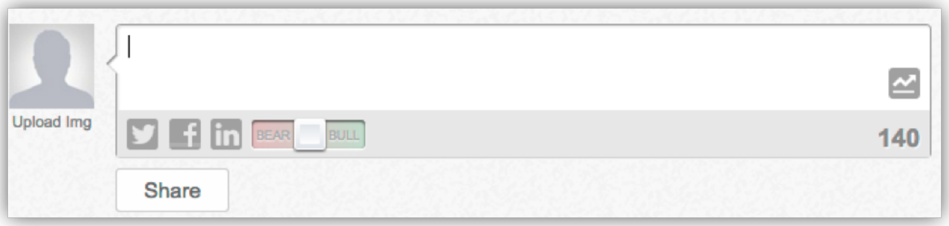


Table 4 Panel A shows the distribution of sentiment across messages. According to these summary statistics, 5.97 percent of messages are bearish, 26.58 percent are bullish, and 67.45 percent are unclassified. Even though the setting and timeframe are different, our classifications give similar relative frequencies to the distribution reported in Antweiler and Frank (2004) who hand classify individual trader messages on an Internet message board.

From reading the unclassified messages, it is clear that most of them are quite bullish or quite bearish, but the user did not select the option. To incorporate this information into the analysis, we follow prior literature and use natural language methods to classify the unclassified messages into bearish and bullish ones. Prior papers that use message data (e.g., Antweiler and Frank (2004), Giannini et al. (2015)) must construct a training dataset (usually ~1,000 messages) by classifying the messages by hand, calibrating a classification model (usually based on maximum-entropy methods) to this self-constructed training set of messages, and then using the calibrated model to classify the rest of the data. In our setting, we avoid the subjectivity of hand classification because 475,303 messages were pre-classified by the users as bullish or bearish. This training sample is both larger and more accurate because the users report their sentiment directly to StockTwits. On this large training sample, we use a maximum entropy-based method (described in the appendix) to classify the rest of the messages to be either bearish or bullish. Furthermore, we train our algorithm and use it to classify messages separately by investment approach to account for the possibility that investors with different approaches use different terminology to describe positive or negative sentiment. Table 4 Panel B shows the distribution of sentiment in the final dataset. We have 458,218 bearish and 1,001,788 bullish messages.

We conduct a cross-validation exercise to examine whether investors are more certain of their sentiment when they click select the option than when they leave sentiment unclassified. For users who classify at least one message in the data set, we randomly select 100,000 pre-classified messages to train the maximum entropy algorithm. Then we randomly draw another set of 100,000 messages, where users expressed their sentiment, and 100,000 messages that were left unclassified, and apply the maximum entropy algorithm to those messages. The algorithm assigns the probability that each message is bullish or bearish such that a higher probability of a message being bullish means that more words that are usually associated with bullish sentiment were used in the message. We examine whether the unclassified messages differ in their likelihood of being bullish or bearish from the pre-classified ones. The two distributions are almost identical with the mean probability being 0.958 for unclassified and 0.959 for pre-classified messages, and the standard deviation being 0.104 and 0.105, respectively. This confirms our impression that the unclassified messages are very similar in nature to the pre-classified ones.[6]

Figure 4 presents the frequency distribution of messages posted by hour of day. Most messages are posted during trading hours, but there are also a significant fraction of messages posted after the market closes. We account for these off-market messages in our analysis by calculating sentiment and disagreement measures for day t from messages posted between the market close of day $t-1$ to the market close of day t. Figure 5 presents the timing of our measurement as it corresponds to these measures. For some tests that disentangle the timing of message posting and market outcomes, we focus on messages that occur between the close of the prior day and the open of the present day (labeled as "Before Market Opens").

From reading the messages, many investors post new messages as their sentiment changes. They might not necessarily go from being bullish to bearing bearish, but they might feel more or less strongly about a given stock. Therefore, the sentiment expressed by the users is a useful measure of how the average investor changes or updates sentiment, rather than the overall level of sentiment. This is appropriate because changes in sentiment more naturally lead to trading than the overall level of sentiment.

We follow Antweiler and Frank (2004) to combine these ratings into one measure of change in sentiment, we code each bearish message as -1, and each bullish message as 1, and take the arithmetic average of these classifications at the $firm \times day \times group$ level:

[6]In the Appendix, we replicate our main findings in Table 12 using only messages that were classified by the investors themselves (user-classified messages), and we obtain qualitatively similar results.

$$AvgSentiment_{itg} = \frac{N_{itg}^{bullish} - N_{itg}^{bearish}}{N_{itg}^{bullish} + N_{itg}^{bearish}}. \tag{1}$$

The $AvgSentiment_{itg}$ measure ranges from -1 (all bearish) to $+1$ (all bullish). If no messages were posted for a given firm/day/group, we set the average sentiment measure equal to 0, as we assume that no change in sentiment occurred from the last time the users posted. Table 4, Panel C displays the summary statistics of average sentiment change in messages for all users, and then broken down by investment philosophy, experience, and holding period. As seen with the distribution of bullish and bearish messages, investors tend to express more bullish sentiment, on average. Therefore, it is not surprising that the average sentiment for all users is 0.372. Interestingly, investors who self-report to follow a Growth investment philosophy are the most likely to post bullish messages, whereas fundamental investors are the most likely to post bearish messages. Novice investors are more likely to post bullish messages than professional investors, and longer-term investors are more likely to post bullish messages than day traders.

For our main measure, the sentiment of each message is given equal weight, but not all messages are created equally when some users have greater status than others. Thus, as a robustness to our main measure of sentiment, we also calculate a weighted average sentiment measure by weighting by the number of followers. As we show in the Appendix, our broad findings are not sensitive to using the weighted average sentiment versus average sentiment (see Table 12).

3.2 Validating the Sentiment Measure

We validate the sentiment measure in three ways. First, we utilize the entropy-based cross validation method while classifying the messages that were not self-classified by the users. Second, we show that the measure correlates sensibly with proxies for investor short sale constraints. Third, we examine whether sentiment is related to future stock performance.

3.2.1 Cross Validating the Sentiment Classification

Using most of the original classified data for training the model and a small subset to test the algorithm, we are able to comment on the accuracy of our classification method. On average, the overall accuracy rate is 83%. This high degree of accuracy enhances our confidence in using the classification scheme on unclassified messages. Indeed, when we extend the classification to the unclassified messages, we find that the distribution of messages is similar.

3.2.2 Expressed Sentiment versus Trading

One potential concern with an expressed sentiment measure like ours is that expressed opinions might reflect the investor's true beliefs about the investment, but reflect a behavioral bias toward broadcasting positive information. We address this concern in two complementary ways: (1) later in the paper, we evaluate whether these expressed opinions correlate with observed trading outcomes (returns, volume, etc.) in a manner consistent with theory, and (2) we relate the propensity to report positive news to the likelihood that an investor without an inventory of the stock cannot trade because of short selling constraints. If negative investor sentiment is unlikely to be expressed when investors face greater short-selling constraints, it would enhance confidence that our measure of sentiment is representative of investor beliefs.

Indeed, the raw summary statistics confirm this pattern because sentiment tends to be relatively bullish. Given that many investors face short selling constraints (as in Hong and Stein (2003), Engelberg et al. (2014)), this tilt toward bullish sentiment is natural. A bearish investor with a strict short sale constraint can only sell the stock until her inventory is zero. Retail investors with limited attention tend to neglect information on stocks for which they have zero inventory (see Davies, 2015). Zero inventory stocks are likely to be the stocks for which investors are bearish, and because these stocks get less investor attention, bearish messages are reported less frequently.

The correlation with short selling constraints further suggests that this underlying mechanism behind the bullish-bearish imbalance is important. Using percent of institutional ownership of a firm as a proxy for shorting constraints (as in Nagel, 2005) on the view that short selling tends to be easier for stocks with high institutional ownership, we find that the the fraction of bullish of messages for companies in the top quartile of institutional holdings is 0.54, compared with 0.28 for companies in the bottom quartile. This evidence suggests that our sentiment measure reflects true investor opinion because, in theory, short sale constraints should be related to the imbalance between bullish and bearish trades (Hong and Stein, 2003).

3.3 Sentiment and Stock Returns

To further evaluate our sentiment measure, we evaluate whether sentiment forecasts stock returns by analyzing the abnormal cumulative returns of portfolios formed using the frequency of bullish and bearish messages. Specifically, we evaluate the performance two portfolios based on the sentiment of StockTwits users: a bullish portfolio and a bearish portfolio. We use the bullish or bearish message frequencies as portfolio weights for each portfolio. To be concrete, consider an example where there are two potential firms (A and B) and 20 bullish messages were posted in total. In this scenario, if firm A had 15 bullish messages and firm B had 5 bullish messages then firm A will get a weight of 0.75 and firm B a weight of 0.25 in the "bullish portfolio". We construct cumulative returns over the following 60 days for each of the two portfolios and subtract out the value-weighted market index. We rebalance the portfolios daily.

Figure 6 (a) presents a graph of the cumulative abnormal returns for the bullish and bearish portfolios for the overall sample. The cumulative returns for each portfolio are flat initially, and then increase over the coming months. Firms for which investors are bullish exhibit similar stock market performance as firms for which investors are bearish. This finding is consistent with prior findings that investors, especially retail investors, cannot predict returns, on average. Despite this average finding, it is possible that some subsets of investors have skill at predicting returns. We present separate bearish and bullish portfolios by experience level (i.e., novice, intermediate and professionals) to shed light on this question in Figure 6 (b) - (d). The portfolios that follow novice recommendations exhibit very poor performance. A bullish recommendation from a novice tends to forecast *lower* return than a bearish recommendation from a novice. This is in line with prior research that individual investors lose money in the market, even before accounting for transaction costs (Barber and Odean, 2000). The portfolios following recommendations of intermediate investors on the platform also do poorly, but not as poorly as the novice portfolios. Interestingly, a portfolio that follows the recommendations of StockTwits professionals yields positive abnormal returns, suggesting that experienced investors have some ability to forecast returns (either by taking priced risks, or by identifying mispricing). A bullish recommendation of a stock from a professional investor forecasts positive abnormal return, whereas a bearish recommendation forecasts negative abnormal return. Professionals appear to do quite well, outperforming by almost 2% over a 60 trading-day period.

4 Within-Group Disagreement

4.1 Measuring Disagreement within Groups

Our primary measure of disagreement follows the disagreement measure developed in Antweiler and Frank (2004). We have also constructed an alternative measure to evaluate the robustness of our findings to our measurement choices. In particular, the Appendix discusses a linear measure related to Antewiller and Frank's proxy.

We define the disagreement measure for a group of users who express sentiment or a trading disposition (e.g., the level at which we measure disagreement is $firm \times day \times group$, where "group" can represent all investors, or only investors with a given investment approach, experience, or investment horizon). First, we calculate the average sentiment measure at the $firm \times day \times group$ level

$$AvgSentiment = \frac{N^{bullish} - N^{bearish}}{N^{bullish} + N^{bearish}}. \tag{2}$$

Using the fact that sentiment opinions are expressed as a binary variable (-1/1), Antweiler and Frank show that the variance of the sentiment measure during a time period t can be calculated as $1 - AvgSentiment^2$. We follow their logic and define a disagreement measure as

$$Disagreeement = \sqrt{1 - AvgSentiment^2} \tag{3}$$

As the *AvgSentiment* measure captures changes in sentiment (as discussed above), the disagreement measure captures changes in disagreement. This disagreement measure ranges from 0 to 1, with 0 being no change in disagreement and 1 being maximum change in disagreement. To illustrate the properties of the disagreement measure consider the following example. Assume that there are 10 messages by fundamental investors about Apple on a given day. In Figure 7, we show how the disagreement measure changes as the number of bearish messages goes from 0 (all bullish messages) to 10 (all bearish messages). There is no change in disagreement if everyone's opinion changes in the same direction – all messages are either bearish or bullish, and the change in disagreement is maximized at 1, when investors' opinions change in opposite directions - when there are 5 bullish and 5 bearish messages. Since the measure is a square root function, the disagreement measure changes the most when there are few bullish or few bearish messages (the measure has the largest slope). As these recent changes in sentiment are most relevant to trading behavior, we expect that this change-in-disagreement measure captures recent disagreement over sentiment. Hereafter, we refer to the measure as "disagreement," though by our measure and interpretation, it is appropriate to think of the measure as capturing changes in how investors disagree. In the Appendix, we also discuss a measure that is a linear function of the number of bullish/bearish messages. Using this linear measure, we obtain very similar results.

We deviate from the Antweiler-Frank measure in one respect. If there are no messages by a given group in a given time period, they set disagreement for that time period to be 1, and justify it by saying that no information came out during that time period, and thus there is latent disagreement. Because we expect people to be most likely to post when their sentiment about a firm changes, we set the our disagreement measure for the given group and time period to be 0 if no messages were posted that day. For example, if disagreement for fundamental investors about Apple on a Monday was 0.6, and we don't observe any messages by fundamental investors about Apple on Tuesday, we set the disagreement measure for fundamental investors about Apple on Tuesday to 0. Intuitively, if no information came out that fundamental investors viewed as informative, we assume that their opinions about the firm (and thus their disagreement) have not changed.

4.2 Disagreement and Investor Groups

In Table 5 Panel A, we summarize the disagreement measure. The average for our main disagreement measure is 0.47, and the median is 0.637. The linear measure described in the appendix portrays a similar picture, with the correlation between the two measures being 0.956.

Using the self-reported investment approaches from investor profiles, we break down our main disagreement measure by the approach of investors. To do this, we construct the disagreement measure separately for messages about the same firm on the same day by investors of the same approach type. In so doing, we are able to measure investor disagreement among investors who report having the same investment philosophy. We also perform the same exercise for different experience levels and holding periods. These disagreement measures are also presented in Panel A of Table 5. By comparison to overall disagreement (an average of 0.469), these within-group disagreement measures are uniformly smaller (ranging from 0.066 to 0.360 across investor approaches). This finding implies that some fraction of overall disagreement comes from cross-group differences –

i.e., differing investment philosophies contribute to market-wide disagreement.

The patterns of within-group disagreement are interesting as well. Technical investors disagree the most, whereas value, fundamental, and growth investors disagree much less with investors of the same investment philosophy. This finding resonates with the fact that there are many ways to be a technical investor, but much more standardization in what value, fundamental, and growth investing means. Turning to investor experience, intermediate and professional investors disagree more with one another than novices who may be more prone to herding or reacting to media sentiment than those with greater experience. Finally, within-group disagreement does not vary systematically with investment horizon.

4.3 Comparing Disagreement Measures

In this section, we examine how well our disagreement measure correlates with alternative measures of disagreement (e.g., analyst dispersion as in Diether et al. (2002), and return volatility), and with abnormal trading volume. Broadly, we find a weak correlation between our measure and existing measures of disagreement, but a strong correlation between our measure and abnormal trading volume, which enhances confidence that the measure is a useful proxy for disagreement.

First, we evaluate the correlation between our disagreement measure and analyst dispersion. Following prior literature, we calculate a monthly measure of analyst dispersion using the standard deviation of analyst earnings forecasts made in a given month. To compare our measure to this monthly measure of analyst dispersion, we compute the average of our measure over the month, then calculate its correlation with analyst dispersion. As can be seen in Table 5, Panel C, column (1) the two measures do not correlate with one another significantly. On some level, this low correlation between our measure and analyst dispersion is to be expected. Our measure captures high-frequency and recent disagreement about the prospects of a stock based on the sentiment of actual traders, whereas analyst dispersion is much lower frequency and is issued by analysts rather than traders.

We further evaluate the performance of disagreement measures by examining their correlation with abnormal trading volume. Aside from being a useful way to evaluate a measure of disagreement, explaining trading volume is interesting unto itself. What exactly drives trading volume and why it varies so much over time is still subject to much debate in the finance literature (e.g., see pages 111-112 of Hong and Stein, 2007). Relevant to our tests, one theory is that trading volume reflects differences in investors' opinions about the prospects of a stock. Despite the compelling logic, there is not much empirical support for a correlation between existing measures of disagreement and abnormal trading volume. Consistent with this body of evidence, when we correlate analyst dispersion at the monthly level with abnormal trading volume, there is a weak and insignificant correlation (0.0388). In contrast, our measure of disagreement correlates much more strongly with abnormal trading volume. Specifically, in Table 5, Panel C, column (2), we present the correlations between daily abnormal log trading volume and our daily measures of investor disagreement. We find that the correlation of market-wide disagreement and the abnormal log trading volume is 0.117. This represents a substantial improvement in the ability to explain abnormal trading volume. Examining this correlation group-by-group, the abnormal trading volume is slightly more correlated with within-professional-investor disagreement and within-momentum-investor disagreement than with within-group disagreement for other groups of investors.

Another recent disagreement measure is provided by Giannini et al. (2015) who also use StockTwits messages, but construct a substantially different measure of disagreement from ours. Given the similarity of the setting, it is important to contrast our measure with theirs. Specifically, Giannini et al. (2015) measure the divergence between investor sentiment on StockTwits and the sentiment of breaking news articles and firm press releases. Their measure is akin to a cross-group disagreement measure where one group is all StockTwits users, and the other group is whomever posts in the media. Unlike our analysis, Giannini et al. (2015) do not evaluate how different groups of StockTwits investors disagree with one another. To quantitatively evaluate how their style of measuring disagreement contrasts with ours, we reproduce an alternative measure that – like Giannini et al. (2015) – contrasts investor sentiment on StockTwits with media sentiment as reported in the Ravenpack database. Appendix 8.3 presents precise details on how we construct this alternative measure of disagreement, but our goal is to stay as close as possible to the Giannini et al. (2015) measure in an out-of-sample replication of their proxy for disagreement. To contrast our disagreement measure with disagreement between StockTwits investors and media, we correlate abnormal trading volume with each of the two measures. As can be seen in Table 6 column (1), both measures correlate significantly with abnormal trading volume, but the correlation is significantly stronger for our within-group measure of disagreement. In fact, the correlation is twice as strong with our within-group measure of disagreement. In addition, we repeat the same analysis, concentrating only on the two weeks before and after the earnings announcement (following the sampling frame of Giannini et al. (2015) paper), and as can be seen in Table 6 column (2), the difference in correlations is even more striking.

4.4 Disagreement, Volume, and Returns

In the previous section, we showed that within-group disagreement has a relatively strong correlation with trading volume in comparison to alternatives. Nevertheless, because disagreement is measured for the same time period as abnormal trading volume, a potential concern of reverse causality remains that any changes in the disagreement of StockTwits investors are purely a reaction to the trading volume in the stock market. We alleviate this concern by examining whether disagreement predicts future changes in trading volume.

To examine whether our disagreement measure forecasts future trading volume, we estimate the following regression specification:

$$\begin{aligned} AbLogVol_{i,t} = \alpha + \beta Disagreement_{i,t} + \gamma AbLogVol_{i,t-1} \\ + TimeFEs + FirmFEs + \varepsilon_{it} \end{aligned} \tag{4}$$

where $Disagreement_{i,t}$ is our disagreement measure for firm i in time period t. For ease of interpretation, we standardize the measure by subtracting the mean and dividing by the standard deviation, over the entire sample period. *AbLogVol* is the difference between log volume in timer period t and the average log volume from $t-140$ to $t-20$ trading days (6-month period, skipping a month). Since trading volume tends to be autocorrelated, we also control for abnormal trading volume on day $t-1$. We include year, month, day-of-the-week, and firm fixed effects. The standard errors are clustered at the date and firm levels.

The results from estimating equation (4) are presented in Table 7. In column (1) we examine whether market-wide disagreement on day $t-1$ forecast abnormal trading volume on day t for stock of firm i. We find that the coefficient is statistically insignificant, which is consistent with the idea that changes in disagreement are reflected in trading volume the same day. In column (2) we regress abnormal trading volume on day t on changes in disagreement on the same day. The coefficient estimate is statistically significant and suggests that a one standard deviation larger change in disagreement is associated with 1.1% increase in trading volume.

To alleviate the concern that disagreement among investors merely reflects changes in trading activity, in column (3), we regress abnormal trading volume on day t on disagreement among messages that were posted before the market opened on day t, as illustrated in Figure 5. In this case, the disagreement measure clearly leads the trading volume measure in time, but the connection between the two is more immediate than in column (1). To account for autocorrelation among trading volume, we also control for abnormal trading volume on day $t-1$. As can be seen in column (3), one standard deviation higher change in disagreement overnight (before the market opens on day t) is associated with a 0.54% increase in abnormal trading volume after the market opens on day t. This suggests that our disagreement measure is not fully driven by changes in trading volume. In fact, approximately half of the effect of contemporaneous disagreement (0.054 versus 0.110) can be attributed to messages that were posted before the trading volume is observed.

Finally, we also examine the relationship between investor disagreement and subsequent stock returns. In theory, greater disagreement could forecast either higher or lower future returns. Theories based on disagreement among optimists and pessimists suggest that greater disagreement should forecast negative returns (Hong and Stein, 1999), whereas other theories where disagreement is a priced risk factor suggest a positive return premium when there is more disagreement (Carlin et al., 2014). To evaluate this tension empirically, we estimate the following regression specification for abnormal stock returns on day $t+1$ and cumulative abnormal returns over days $t+1$ to $t+5$:

$$\begin{aligned} Abret_{i,t+1} &= \alpha + \beta DisMeasure_{it} + \nu AvgSentiment_{it} + \phi Abret_{it} \\ &\quad + \gamma AbLogVol_{it} + \delta LogME_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

where $Abret_{i,t+1}$ is the abnormal return (minus the value-weighted market index) for firm i on day $t+1$, $DisMeasure_{it}$ is our disagreement measure on day t. Some specifications also control for $AvgSentiment_{it}$ to alleviate the concern that the result arises from a mechanical correlation of our disagreement measure with sentiment. Moreover, we examine the stock market response starting the following day, which alleviates the concern of reverse causality (disagreement reacting to returns) .

Table 8 presents the results from estimating equation (5), with and without controlling for average sentiment. In column (1) we see that a standard deviation increase in disagreement is associated with a 6 basis points decrease in next business day's returns. The estimates in column (2), which also control for average sentiment, show that this relationship is not mechanically due to the relationship between our disagreement measure and sentiment, but arises from disagreement, conditional on sentiment.

In columns (3) and (4), we predict cumulative abnormal returns for days $t+1$ to $t+5$ ($CAR[1,5]$) using our measure of disagreement. According to these specifications, a one standard deviation increase in disagreement is associated with a 12 basis point decrease in returns over the following week. Moreover, this effect is not due to a mechanical relationship to investor sentiment as the effect of disagreement is a very similar magnitude when controlling for sentiment.

5 Disagreement and Trading around Earnings Announcements

We now turn to examine the relationship between within-group disagreement and the well-known spike in volume around earnings announcements. On its face, that trading volume increases after earnings announcements is puzzling because firms release important financial information to the market during this time, which would tend to resolve uncertainty. Nonetheless, it is a robust feature of the market that volume goes up after earnings announcements, and remains high for several weeks (Drake et al., 2012; Kaniel et al., 2012). Recent theoretical work on this phenomenon points to a role for disagreement to resolve the puzzle (Banerjee et al., 2015). However, without a reliably high-frequency measure of disagreement like our measure, it is difficult to provide evidence for this conjecture. Thus, our setting and measurement positions us to provide one of the first empirical tests of the role of disagreement in explaining volume changes around earnings announcements.

To examine whether greater disagreement can explain the spike in volume around earnings announcements, we use our within-group measure of disagreement to examine how volume changes around earnings announcements in the following regression:

$$\begin{gathered}AbLogVol_{it} = \alpha + \beta_1 1WeekBeforeEA_{it} + \beta_2 EA_{it} + \beta_3 1WeekAfterEA_{it} \\ +\beta_4 2WeekAfterEA_{it} + \beta_5 3WeekAfterEA_{it} + \beta_6 Dis_{it} + SUE_{iq} + \Gamma' \mathbf{X} + TimeFEs + FirmFEs + \varepsilon_{it}\end{gathered} \tag{6}$$

where $AbLogVol_{it}$ is the abnormal log trading volume on day t for firm i, $1WeekBeforeEA$ is a dummy variable equal to 1 if day t for firm i happens to be a week before an earnings announcement for that firm, EA_{it} is a dummy variable equal one if firm i announces earnings on day t, $1WeekAfterEA_{it}$, $2WeekAfterEA_{it}$, $3WeekAfterEA_{it}$ are dummy variables for whether day t for firm i falls in week 1, week 2, or week 3 after an earnings announcement, respectively. SUE_{iq} is the earnings surprise for firm i in quarter q defined as the difference in reported earnings minus the median analyst forecast. Finally, in some specifications, we control for the amount of disagreement Dis_{it} at the firm-day level, and include interactions between disagreement and the timing dummy variables (captured in $\Gamma'\mathbf{X}$).

The results from estimating equation (6) are presented in Table 9. Column (1) replicates the existing finding in the literature that volume spikes on the earnings announcement date, and remains high for three weeks after the earnings announcement. The coefficients on the 1 week before the earnings announcement, the day of the earnings announcement, and 1, 2, or 3 weeks after the earnings announcement are relative to the time outside of these weeks. Based on the coefficient estimate on $WeekBeforeEA_{it}$, the trading volume before an EA is approximately the same as it is during the time outside of the earnings announcement period. On the day of the announcement, trading volume increases by 67%, and stays high (39% higher) for one week and then slowly decreases over time. Note that abnormal trading volume is still 5% higher than normal three weeks after the earnings announcement.

Columns (2) and (3) of Table 9 present a test of the role of disagreement as measured by our measure of disagreement. If greater disagreement among investors can explain some of the spike in volume, controlling for it will reduce the coefficient estimate on the spike. To the extent that our measure of disagreement captures this spike in disagreement, we should expect the coefficient on EA_{ti} to diminish as we control for our disagreement measure. Indeed, we find that controlling for disagreement can explain approximately one eighth of the spike in abnormal volume around the earnings announcement (0.572 versus 0.670 on the earnings announcement date). Controlling for interactive effects of disagreement allows for the effect of disagreement to be different by date relative to the earnings announcement. In this specification, we observe that our within-group measure of disagreement can explain up to 26 percent of the spike in abnormal volume on the earning announcement day. These findings are important, especially because there are very few predictors that well explain changes in abnormal volume.

In columns (4) through (7), we estimate the model on subsamples, split by whether the earnings surprise was positive (columns (4) and (5)) or negative (columns (6) and (7)). In either case, controlling for our measure of disagreement explains a significant fraction of the volume spike on the earnings announcement day, but the explanatory power is better for negative earnings surprises than positive earnings surprises (40% vs. 20%).

6 Cross-Group Disagreement

6.1 Investment Philosophies and Variation in Sentiment

The fact that we observe sentiment for the same firm separately for distinct groups of investors allows us to construct a direct test for whether adherence to a particular group of investors (i.e., a particular approach, holding period philosophy, or experience level) is a source of disagreement in the market. Taking it one step further, we are able to evaluate how important these investment philosophy affiliations are to overall disagreement. When investors disagree, there will be variation in the sentiment expressed for the same firm on the same day. One test for whether differing investment philosophies lead to disagreement is to evaluate whether these affiliations explain variation in expressed sentiment. If investment philosophy exhibits an association with expressed sentiment, differing investment philosophies contribute to market-wide changes in disagreement. Moreover, the amount of variation that is explained by accounting for investment philosophies can help quantify the extent to which these philosophies matter to overall changes in disagreement.

To test for this, we estimate the following regression specification of sentiment by group, date, and firm:

$$AvgSentiment_{itg} \quad = \quad FirmFEs + TimeFEs + GroupFEs + \varepsilon_{itg} \tag{7}$$

where $AvgSentiment_{itg}$ is the average expressed sentiment on date t for firm i by investors of group g (groups can be different approaches, experience levels, or horizon – i.e., holding period philosophies). Specifications that include firm, time (month, year, and day-of-week), and approach fixed effects enable an explicit comparison of the explanatory power of different investment models to the amount of variation in sentiment captured by differences across firms and across time.

Table 10 presents the analysis of variance (ANOVA) decomposition from specifications that estimate equation (7). In columns (1) through (3), we evaluate the importance of different investment approaches to explaining the amount of disagreement in the market (i.e., variation in sentiment). Including approach fixed effects is rather important to explaining variation in sentiment. Firm and time dummies alone explain 10.1 percent of the variation in sentiment changes. Adding the approach fixed effects explains an additional percentage point of variation in sentiment. To put the importance of approach styles in context, differing approaches explain approximately 9.9 percent of the changes in disagreement (variation in sentiment) that is explained using firm and time fixed effects. The F-statistics indicate that all types of categories (approach, experience and horizon) are statistically significant, and thus, are sources of model disagreement. Yet, horizon and experience explain much less variation in sentiment – approximately 0.7 percent of firm fixed effects for experience and approximately 2.3 percent of firm fixed effects for horizon.

If differing investment philosophies are important for disagreement, they should also be important for trends in how sentiment is expressed over time. For example, if fundamental investors and technical investors respond to the same information differently, accounting for approach fixed effects should explain different trends in expressed sentiment. To test for this, we estimate the following regression specification of first-differenced sentiment by group, date, and firm:

$$\Delta AvgSentiment_{itg} = FirmFEs + TimeFEs + GroupFEs + \varepsilon_{itg} \tag{8}$$

where $\Delta AvgSentiment_{itg}$ is first-differenced average expressed sentiment on date t for firm i by investors of group g (groups can be different approaches, experience levels, or horizon – i.e., holding period philosophies).

In Panel (b) of Table 10, we present the ANOVA decomposition of sentiment trends from estimating equation (8). Similar to the regressions of average sentiment, differing approaches explains 0.8% of the variation in first-differenced average sentiment. In contrast to the regressions of average sentiment, time and firm fixed effects explains little of the variation in first-differenced average sentiment, only explaining 0.5%. That is, differing investment philosophies is as important for explaining sentiment trends as changes in sentiment, despite these trends being more difficult to explain using firm and time fixed effects. Indeed, the F-statistics on approach, experience, and horizon indicate that these differing philosophies are significant sources of model disagreement that explain differing trends in sentiment. As above, approach is a much more important factor than experience and investment horizon. In the following section, we more explicitly consider how differing investment philosophies contribute to disagreement.

6.2 Trading Volume and Cross-Group Disagreement

To quantify the effect of cross-group disagreement in comparison to within-group disagreement, we construct a pairwise cross-group disagreement measure that captures how close the average sentiment measure is for two groups. For example, the cross-group disagreement between fundamental and technical investors about firm i on day t is

$$Disagreement_{it,ft} = |AvgSentiment_{it,f} - AvgSentiment_{it,t}| \tag{9}$$

We construct similar cross-group measures for any pair of groups. To understand the rationale behind this measure, suppose the $AvgSentiment$ for fundamental investors is -1 and the $AvgSentiment$ for technical investors is +1. This means that fundamental investors became more bearish and technical investors became more bullish on a given date. Because most disagreement is across groups, trade will occur across groups.

To examine how the cross-group disagreement measure is related to the abnormal trading volume, we estimate the following regression specification:

$$\begin{aligned} AbLogVol_{it} &= \alpha + \beta_1 Disagreement_{it,g_1} + \beta_2 Disagreeemnt_{it,g_2} \\ &+ \beta_3 Disagreement_{it,g1g2} + AbLogVol_{it-1} \\ &+ TimeFEs + FirmFEs + \varepsilon_{it} \end{aligned} \tag{10}$$

where $AbLogVol_{it}$ is the abnormal log trading volume on day t for firm i, $Disagreement_{itg_k}$ is our within-group measure of investor disagreement about stock i, for group k (e.g., Fundamental, Technical, etc.) on day t. $Disagreement_{itg_kg_s}$ is the cross-group disagreement measure across groups k and s, defined as the absolute value of the difference in average sentiment between groups k and s about firm i on day t. We also control for trading volume on day $t-1$ to account for persistence in abnormal trading volume. As in our other specifications, we include year, month, day-of-the-week, and firm fixed effects, and cluster the standard errors at the day and firm levels.

The results from estimating equation (10) for differing pairs of investment philosophies are presented in Table 11, columns (1)-(10). As in our within-group tests, a standard deviation increase in cross group disagreement is associated with more abnormal trading volume, and the association is statistically significant. These specifications also allow us to quantify the effect of cross-group disagreement relative to within-group disagreement. Even though these groups are coarsely defined, the effect of cross-group of a similar magnitude to the effect of within-group disagreement. Specifically, from column (1), cross-group disagreement between fundamental and technical investors has approximately 65 percent the effect on abnormal trading volume as within-group disagreement among fundamental investors (0.036 versus 0.055). Because the differing groups are coarsely defined and some within-group disagreement likely still arises from differing investment models, these relative magnitudes are likely a lower bound on the importance of model disagreement to abnormal trading volume.

In column (11) we construct a joint cross-group disagreement measure (Across-Group Disagreement), defined as the standard deviation of the average sentiment measures ($AvgSentiment_{itg}$) for all groups (fundamental, technical, momentum, growth, and value investors) on day t for firm i. This measure is similar in spirit to our within-group disagreement measure, as we are capturing the standard deviation of changes in sentiment. In column (11), we regress abnormal log volume on all within-group disagreement measures for the different groups, and also on the cross-group disagreement measure. Since all the measures are standardized, the results suggest that controlling for within-group changes in disagreement, one standard deviation increase in the across-group disagreement is associated with a 0.5 percent increase in abnormal trading volume. As in the other specifications, this magnitude is comparable to the effects of within-group disagreement measures, and is a lower bound for the relative influence of model disagreement to abnormal trading volume.

In conjunction with our findings in the variation of sentiment specifications in Table 10, these findings suggest that the models investors use to interpret information matter for the extent of disagreement among investors in the marketplace. Because we document that models matter significantly, we expect that improvements to the informational efficiency of markets will not completely erode volatility, nor the spike in volume around earnings announcements.

7 Conclusion

In this paper, we utilize the unique features of a dataset of messages posted by individual investors on a social investing network to construct a novel and theoretically-grounded measure of disagreement within investor groups across different investment approaches. We exploit the fact that users frequently self-classify their sentiment about a given firm as bullish or bearish, and that we also observe their self-reported investment philosophy, experience level, and investment horizon, to study causes of disagreement among investors. So far there has been very scant empirical research in the area of investor disagreement, mainly due to data limitations.

We find that our measure of disagreement correlates strongly with abnormal trading volume, as predicted by seminal underlying theories of disagreement and trading. We furthermore find that disagreement is negatively related to stock returns. Our measure has predictive power for abnormal trading volume, and importantly, can explain much of the spike in abnormal volume around earnings announcements.

Furthermore, we find strong support for the idea, developed in theoretical literature on investor disagreement, that much of disagreement in financial markets is driven by differences in investment philosophies, rather than just reflecting different information sets. These findings have important implications for policy makers, among others, as they suggest that even with perfectly informationally efficient markets, investor disagreement, and thus high trading volume and volatility, would likely persist.

References

Ajinkya, B. B., R. K. Atiase, and M. J. Gift (1991). Volume of Trading and the Dispersion in Financial Analysts' Earnings Forecasts. *The Accounting Review*.

Antweiler, W. and M. Z. Frank (2004). Is all that talk just noise? the information content of internet stock message boards. *The Journal of Finance 59*(3), 1259–1294.

Ataise, R. K. and L. S. Bamber (1994). Trading volume reactions to annual accounting earnings aannouncement: the incremental role of predisclosure information asymmetry. *Journal of Accounting and Economics*.

Baldauf, M. and J. Mollner (2015). Fast Traders Make a Quick Buck: The Role of Speed in Liquidity Provision. *Working Paper*.

Bamber, L. S., O. E. Barron, and D. E. Stevens (2011). Trading Volume around Earnings Announcements and Other Financial Reports: Theory, Research Design, Empirical Evidence, and Directions for Future Research. *Contemporary Accounting Research*.

Banerjee, S., J. Davis, and N. Gondhi (2015). When transparency improves, must prices reflect fundamentals better? *Working Paper*.

Banerjee, S. and I. Kremer (2010). Disagreement and Learning: Dynamic Patterns of Trade. *Journal of Finance*.

Barber, B. M. and T. Odean (2000). Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. *The Journal of Finance*.

Barber, B. M. and T. Odean (2008). All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies 21*(2), 785–818.

Baron, M., J. Brogaard, and A. Kirilenko (2012). The trading profits of high frequency traders. *Unpublished Manuscript*.

Carlin, B. I., F. A. Longstaff, and K. Matoba (2014). Disagreement and asset prices. *Journal of Financial Economics 114*(2), 226–238.

Cookson, J. A. (2016). When Saving Is Gambling. *SSRN Working Paper 2517126*.

Davies, S. W. (2015). Retail Traders and the Competitive Allocation of Attention. *Working Paper*.

Diether, K. B., C. J. Malloy, and A. Scherbina (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance 57*(5), 2113–2141.

Dorn, D. and P. Sengmueller (2009). Trading as Entertainment? *Management Science*.

Drake, M. S., D. T. Roulstone, and J. R. Thornock (2012, September). Investor Information Demand: Evidence from Google Searches Around Earnings Announcements. *Journal of Accounting Research 50*(4), 1001–1040.

Engelberg, J., A. V. Reed, and M. Ringgenberg (2014). Short selling risk. *Working Paper, University of California, San Diego, University of North Carolina, and Washington University in St. Louis.*.

Giannini, R. C., P. J. Irvine, and T. Shu (2015). The convergence and divergence of investors? opinions around earnings news: Evidence from a social network. *Available at SSRN 2017748*.

Grinblatt, M. and M. Keloharju (2009). Sensation Seeking, Overconfidence and Trading Activity. *The Journal of Finance*.

Hong, H. and J. C. Stein (1999). A Unified Theory of Underraction, Momentum Trading, and Overaction in Asset Markets. *The Journal of Finance*.

Hong, H. and J. C. Stein (2003). Differences of opinion, short-sales constraints, and market crashes. *Review of financial studies 16*(2), 487–525.

Hong, H. and J. C. Stein (2007). Disagreement and the stock market. *The Journal of Economic Perspectives*, 109–128.

Kaniel, R., S. Liu, G. Saar, and S. Titman (2012). Individual Investor Trading and Return Patterns around Earnings Announcements. *Journal of Finance 67*(2), 639–680.

Karpoff, J. M. (1986). A Theory of Trading Volume. *Journal of Finance*.

Kondor, P. (2012). The more we know about the fundamental, the less we agree on the price. *The Review of Economic Studies 79*(3), 1175–1207.

Kumar, A. (2009). Who Gambles in the Stock Market? *The Journal of Finance*.

Linnainmaa, J. (2011). Why do (some) households trade so much? *Review of Financial Studies*.

Milgrom, P. and N. Stokey (1982). Information, Trade, and Common Knowledge. *Journal of Economic Theory*.

Nagel, S. (2005). Short sales, institutional investors and the cross-section of stock returns. *Journal of Financial Economics 78*(2), 277–309.

Nigam, K., J. Lafferty, and A. McCallum (1999). Using maximum entropy for text classification. In *IJCAI-99 workshop on machine learning for information filtering*, Volume 1, pp. 61–67.

Rogers, J. L., D. J. Skinner, and S. L. C. Zechman (2015). Run EDGAR Run: SEC Dissemination in a High-Frequency World. *Chicago Booth Research Paper No. 14-36*.

Rothschild, D. M. and R. Sethi (2014). Trading strategies and market microstructure: Evidence from a prediction market. *Available at SSRN 2322420*.

Varian, H. R. (1985). Divergence of Opinion in Complete Markets: A Note. *Journal of Finance*.

8 Appendix

8.1 Alternative Disagreement Measure

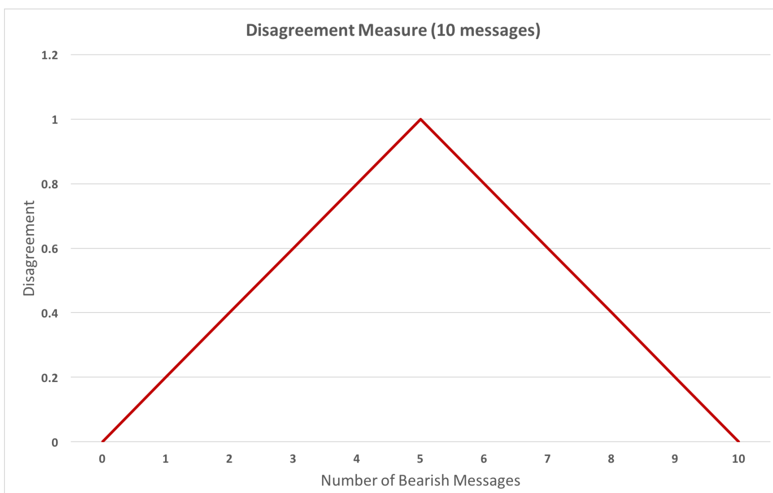
As mentioned in Section 4, the Antweiler-Frank disagreement measure is calculated as

$$D = \sqrt{1 - AvgSentiment^2}$$

Since it's a square-root function, it has the largest slope (changes in disagreement) if there are very few bullish or very few bearish messages. We follow that method in our main analysis. However, as a robustness test, we also use a function that is liner in the average sentiment measure.

$$D^* = 1 - |AvgSentiment|$$

The disagreement measure for an example with 10 messages is depicted in the figure below.



Using this measure the slope of the disagreement function remains the same as the fraction of bearish messages increases in the market. In Table 12 we rerun our analysis using this measure of disagreement and get qualitatively similar results as our main disagreement measure.

8.2 Maximum Entropy Method

There are a plethora of text and document learning algorithms that have been shown (empirically and theoretically) to yield desirable misclassification rates. Some of the more popular methods are maximum entropy, naive Bayes, k-nearest neighbor, and support vector machines. Here, we give a brief outline of the maximum entropy approach.

Excluding neutral opinions, “sentiment" is a binary variable and therefore a standard logistic regression model can be used to estimate the proportion of bullish investors. Classification can be done by thresholding these probabilities. This technique, also known as a maximum entropy classifier, uses labeled training data to fix a collection of constraints for the model that define the class-specific averages. We will use training data to fix constraints on the conditional distributions of the learned distribution (the condition probability of bullish or bearish classification given a particular message). The goal is to find the distribution $p^\star$, satisfying these constraints, that maximizes the entropy quantity

$$H(p) = \sum_{x \in \mathscr{X}} p(x) \log\left(\frac{1}{p(x)}\right),$$

where p is a probability mass function that belongs to a collection of mass functions $\mathscr{C}$ satisfying the constraint. That is,

$$p^\star = \text{argmax}_{p \in \mathscr{C}} H(p).$$

Let $\mathscr{M}$ denote our dataset. Let $m \in \mathscr{M}$ denote a message and define $f_w(m, c(m))$ to be equal to the proportion of times the word w appears in the message m when it is classified as $c(m)$. Here, $c(m)$ can be either “bearish" or “bullish". We explicitly write $c(m)$ to emphasize the dependence of the class on the message m. We stipulate that the conditional distribution of the class given the message $p(c|m)$ satisfy

$$\frac{1}{|\mathscr{M}|} \sum_{m \in \mathscr{M}} f_w(m, c(m)) = \frac{1}{|\mathscr{M}|} \sum_{m \in \mathscr{M}} \sum_{c} p(c|m) f_w(m, c),$$

for all words w we consider informative. In the above notation, $\mathscr{C}$ is the collection of all probabilities $p(c|m)$ satisfying the above constraints. Then we choose

$$p^\star(c|m) = \text{argmax}_{p(c|m) \in \mathscr{C}} H(p(c|m)).$$

Using the concavity of the logarithm, it can be shown that

$$p^{\star}(c|m) = \frac{\exp\{\sum_w \lambda_w f_w(m,c)\}}{\sum_c \exp\{\sum_w \lambda_w f_w(m,c)\}},$$

where the λ_w are estimated from the data. We classify a message m as bearish or bullish according to a 0.5 threshold for $p^{\star}(c|m)$. For more details on this method, we refer the reader to Nigam et al. (1999). We performed the maximum entropy algorithm separately within the six types of investment approach: growth, technical, value, momentum, fundamental, and global macro.

8.3 Producing a Disagreement Measure in the Spirit of Giannini et al. (2015)

In Giannini et al. (2015), the authors download all breaking news and company press releases that mention the company name or the company ticker from PR News Wire, Dow Jones News Wire, and Reuters News Wire from Factiva news database. They then use the maximum entropy approach to estimate the sentiment of every news article. We adopt a conceptually-similar approach that is more easily replicable by turning to Ravenpack - a news database that collects and classifies news articles and company press releases, as that is much more readily available. The advantage of using Ravenpack is that Ravenpack produces a standardized classification methodology for sentiment of articles about firms, which avoids the need to replicate the time-intensive maximum entropy approach in constructing a measure analogous to Giannini et al. (2015). Further, the advantages extend to other researchers and practitioners, who can adopt a similar methodology to construct a Giannini et al. (2015)-like measure of disagreement.

Using Ravenpack, we collect company press releases from PR News Wire and Dow Jones News Wire. Ravenpack uses proprietary methods to assign a sentiment score to every article, which we use to classify articles into “bearish” and “bullish” categories. We then follow Giannini et al. (2015) in constructing the IMPACT and the NEWS measures, where the former measures the StockTwits sentiment and the later captures the news media sentiment. We calculate these measures at the firm-day level.

To calculate the IMACT measure at the daily level, we first assign each StockTwits message a -1 or 1, based on whether the message was bearish or bullish, and then weigh each message by 1 plus the number of followers the author of the message has. In other words, for an individual message

$IMPACT = (1 + Followers) \times Sentiment$. We then add the IMPACT score for every message to the firm-day level.

We repeat the above procedure with press releases, by assigning -1 or 1 to each article, based on it's sentiment, and then add up those sentiment scores for each firm to the daily level. To calculate the final disagreement measure, at the firm-day level, we follow Giannini et al. (2015) and define disagreement (DIVOP) to be 0 if both IMPACT and NEWS are either positive or both are negative (there is agreement), and 1 otherwise (there is disagreement).

Note that our reproduction of the Giannini et al. (2015) measure is not an exact replication of their original measure, as we use the Ravenpack data instead of manually downloading the Factiva articles. However, the replicated measure has the same concept - difference in sentiment between the media and the StockTwits messages, and we believe that this is a reasonable approach to take for someone who wants to replicate the original measure.

9 Tables and Figures

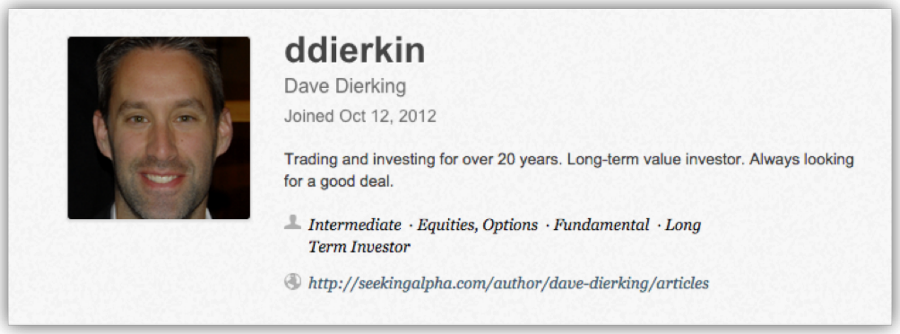
9.1 Figures

Figure 1: Examples of StockTwits User Profiles

Note: This figure presents screenshots of representative user profiles from StockTwits, illustrating the difference between novice, intermediate and professional StockTwits users.

(a) Novice Trader Profile

(b) Intermediate Trader Profile



(c) Professional Trader Profile

Figure 2: Monthly Time Series of Messages Posted to StockTwits

Note: This figure portrays the aggregate number of messages posted to StockTwits for each month in our 21-month sample (from January 2013 to September 2014).

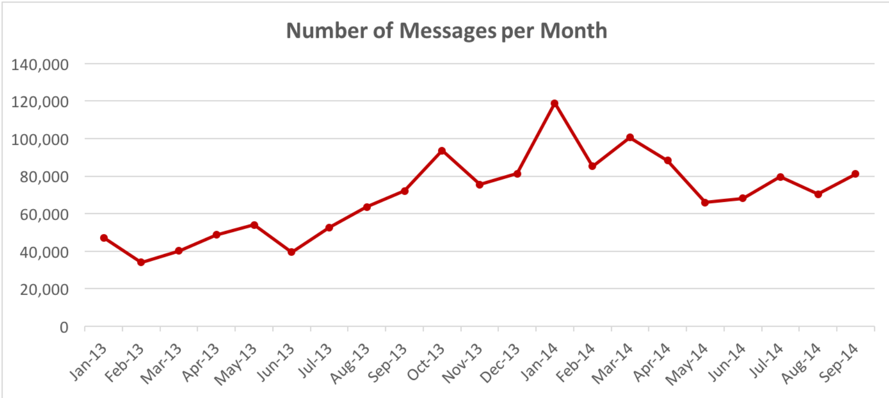


Figure 3: Day-of-Week Frequency Distribution of Messages Posted

Note: This figure presents a frequency distribution of the days of the week that messages are posted to StockTwits.

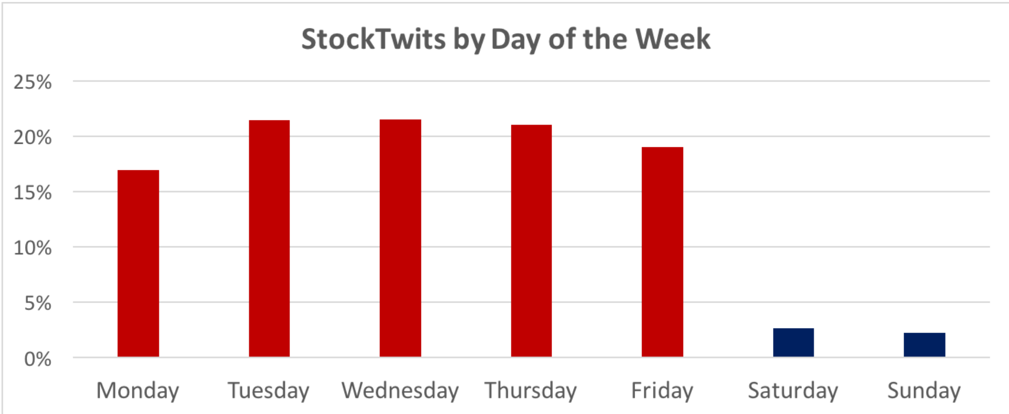


Figure 4: Hour-of-Day Frequency Distribution of Messages Posted

Note: This figure presents a frequency distribution across the hour of the day (Eastern Standard Time) at which messages are posted to StockTwits. Trading hours are plotted in red, whereas non-trading hours are plotted as blue bars.

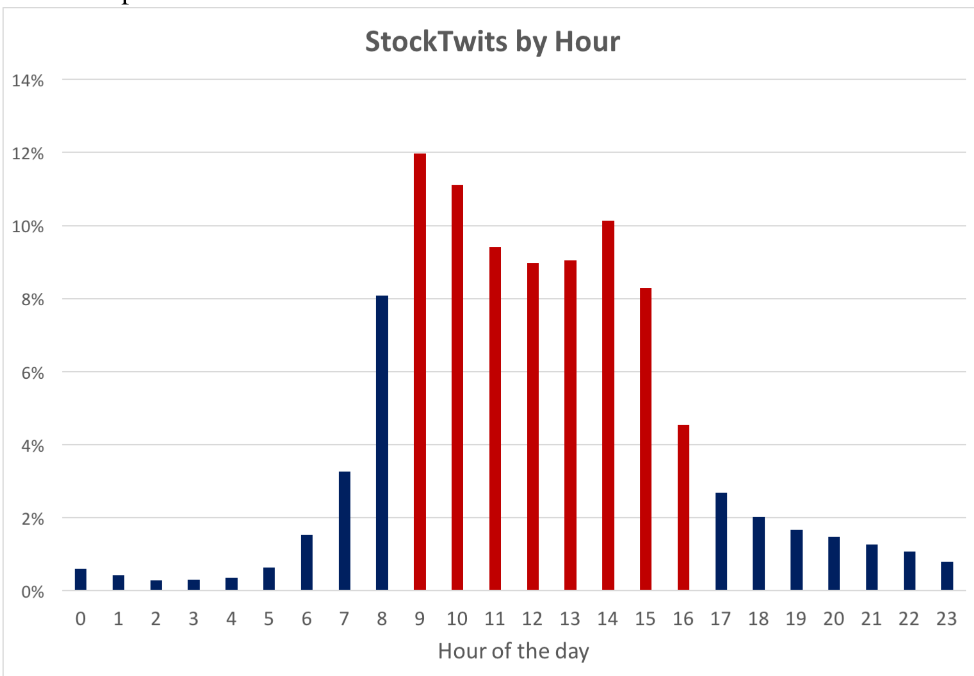


Figure 5: Timeline for Calculating Disagreement

Note: This figure presents how we calculate changes in disagreement. Since trading stops at 4pm on day $t-1$, we assign any messages that are posted on day $t-1$ after 4pm to trading day t. The same way we assign any messages posted after 4pm on day t to day $t+1$. To calculate "overnight" changes in disagreement, before the market opens (BMO) on day t, we include messages that are posted after 4pm on the previous day until 9am on day t.

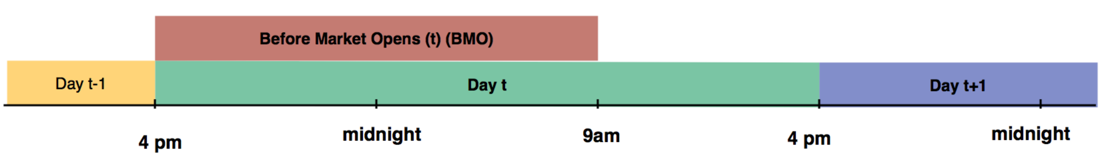
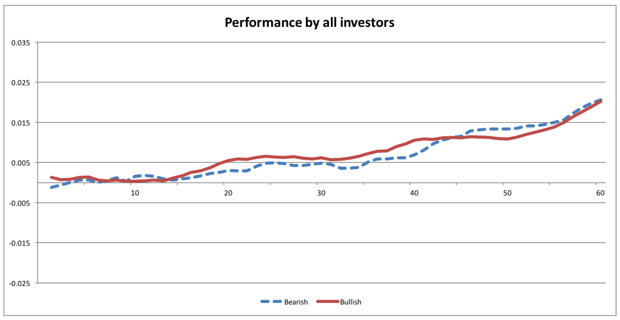


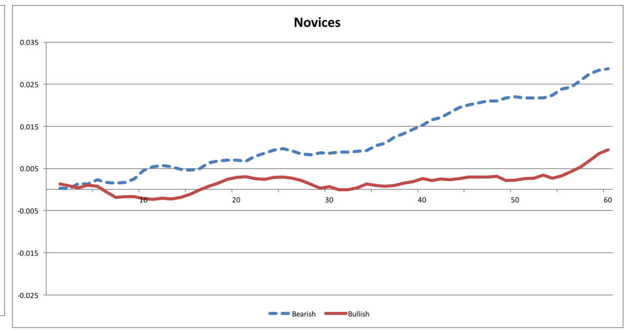
Figure 6: Performance of StockTwits Sentiment Strategies

Note: This figure presents the cumulative abnormal returns of strategies that buy when sentiment is bullish and sell when sentiment is bearish for several sentiment classifications: (a) the sentiment of all StockTwits users ("All Investors"), (b) the sentiment of Novices, (c) the sentiment of Intermediates, and (d) the sentiment of Professionals.

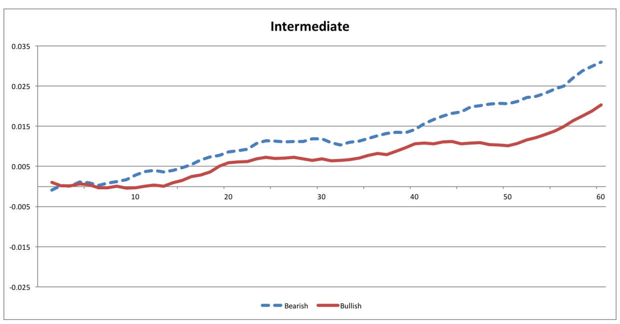
(a) All Investors



(b) Novices



(c) Intermediate



(d) Professionals

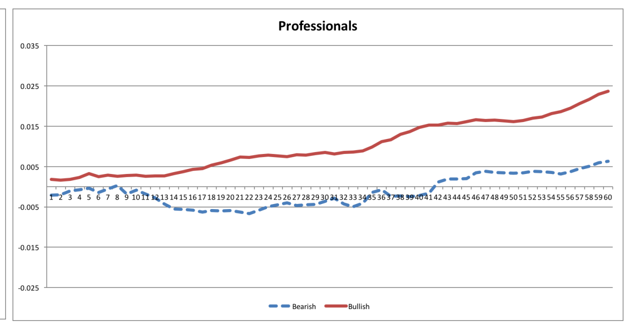
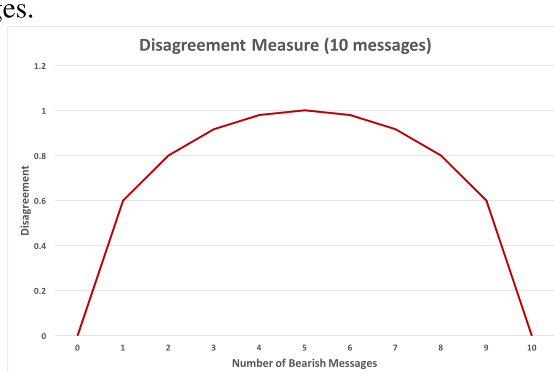


Figure 7: An Example of the Disagreement Measure

Note: This figure portrays how our main disagreement measure depends on the average sentiment of the underlying messages.



10 Tables

Table 1: Sampling Restrictions and the Size of the Analysis Sample

Note: In this table, we present the number of messages, number of unique StockTwits users, and number of company tickers covered as we clean the full sample to our final analysis sample.

Messages	Users	Tickers	Action
18,361,214	107,920	9,755	Original Sample
13,763,653	73,964	9,137	Years 2013 and 2014
7,315,198	56,551	8,558	Keep messages with 1 ticker per message
4,550,746	27,369	8,055	User must have non-missing approach and holding period and experience
3,928,842	25,109	6,326	Merge on CRSP
2,870,856	22,669	3,708	Stocks with at least one earnings announement
1,460,349	11,874	100	Keep top 100 firms

Table 2: 100 Most Discussed Firms

Note: In this table, we present tickers, names, and number of messages of the top 100 firms ranked by the number of messages posted to StockTwits that reference the firm's ticker.

Ticker	Name	Messages	Frequency	Ticker	Name	Messages	Frequency
AAPL	Apple Inc.	331,212	18.8%	ICPT	Intercept Pharmaceuticals Inc	6,045	0.34%
FB	Facebook Inc	140,258	7.96%	QCOR	Questcor Pharmaceuticals Inc	5,989	0.34%
TSLA	Tesla Motors Inc	109,200	6.2%	FCEL	FuelCell Energy Inc	5,897	0.33%
PLUG	Plug Power Inc	95,565	5.43%	CHTP	Chelsea Therapeutics International	5,876	0.33%
VRNG	Vringo, Inc	62,890	3.57%	TTWO	Take-Two Interactive Software	5,760	0.33%
TWTR	Twitter Inc	48,953	2.78%	GS	Goldman Sachs Group Inc	5,644	0.32%
NFLX	Netflix, Inc	38,572	2.19%	CMG	Chipotle Mexican Grill, Inc	5,608	0.32%
ARIA	Ariad Pharmaceuticals, Inc.	35,603	2.02%	GEVO	Gevo, Inc.	5,604	0.32%
KNDI	Kandi Technologies Group Inc	35,530	2.02%	Z	Zillow Group, Inc.	5,561	0.32%
INO	Inovio Pharmaceuticals Inc	33,746	1.92%	CLF	Cliffs Natural Resources Inc	5,418	0.31%
MNKD	MannKind Corporation	30,742	1.75%	FIO	Fusion-IO, Inc.	5,405	0.31%
JCP	JC Penney Company Inc	29,260	1.66%	HK	Halcon Resources Corp	5,354	0.3%
ZNGA	Zynga Inc	26,394	1.5%	RAD	Rite Aid Corporation	5,220	0.3%
GOOG	Alphabet Inc	26,291	1.49%	SWHC	Smith and Wesson Holding Corp	5,152	0.29%
AMD	Advanced Micro Devices	25,327	1.44%	CPRX	Catalyst Pharmaceuticals Inc	5,146	0.29%
GLUU	Glu Mobile Inc	23,692	1.35%	ACHN	Achillion Pharmaceuticals, Inc	5,098	0.29%
SCTY	SolarCity Corp	23,357	1.33%	KERX	Keryx Biopharmaceuticals	5,077	0.29%
AMZN	Amazon.com, Inc.	22,234	1.26%	RMTI	Rockwell Medical Inc	5,073	0.29%
BAC	Bank of America Corp	21,107	1.2%	APP	American Apparel Inc.	5,022	0.29%
UNXL	UniPixel Inc	20,672	1.17%	CYTR	CytRx Corporation	4,991	0.28%
PCLN	Priceline Group Inc	20,158	1.14%	IBM	International Business Machines Corp.	4,852	0.28%
YHOO	Yahoo! Inc.	19,804	1.12%	OPK	Opko Health Inc.	4,749	0.27%
DDD	3D Systems Corporation	19,448	1.1%	ACAD	ACADIA Pharmaceuticals Inc.	4,688	0.27%
RNN	Rexahn Pharmaceuticals, Inc	18,741	1.06%	MSTX	Mast Therapeutics Inc	4,665	0.26%
GALE	Galena Biopharma Inc	17,253	0.98%	VHC	VirnetX Holding Corporation	4,458	0.25%
GTAT	GT Advanced Technologies Inc	16,395	0.93%	NIHD	NII Holdings Inc.	4,436	0.25%
LNKD	LinkedIn Corp	15,085	0.86%	CRM	salesforce.com, inc.	4,402	0.25%
ARNA	Arena Pharmaceuticals, Inc	14,772	0.84%	IDRA	Idera Pharmaceuticals Inc	4,389	0.25%
GOGO	Gogo Inc	12,532	0.71%	CLSN	Celsion Corporation	4,383	0.25%
GPRO	GoPro Inc	12,312	0.7%	DGLY	Digital Ally, Inc.	4,372	0.25%
FSLR	First Solar, Inc.	12,184	0.69%	BBY	Best Buy Co Inc	4,352	0.25%
GILD	Gilead Sciences, Inc.	11,969	0.68%	SBUX	Starbucks Corporation	4,229	0.24%
GMCR	Keurig Green Mountain Inc	11,578	0.66%	SPWR	SunPower Corporation	4,214	0.24%
YELP	Yelp Inc	10,807	0.61%	USU	Centrus Energy Corp	4,214	0.24%
P	Pandora Media Inc	10,361	0.59%	MNGA	MagneGas Corporation	4,176	0.24%
FEYE	FireEye Inc	10,205	0.58%	NAVB	Navidea Biopharmaceuticals	4,151	0.24%
ONVO	Organovo Holdings Inc	10,004	0.57%	AA	Alcoa Inc	4,096	0.23%
MU	Micron Technology, Inc	9,818	0.56%	DRL	Diadem Resources Limited	3,979	0.23%
F	Ford Motor Company	9,342	0.53%	S	Sprint Corp	3,963	0.22%
LULU	Lululemon Athletica inc	9,249	0.53%	ISRG	Intuitive Surgical, Inc.	3,945	0.22%
WLT	Walter Energy Inc	9,222	0.52%	NEON	Neonode, Inc	3,884	0.22%
GRPN	Groupon Inc	8,681	0.49%	ZGNX	Zogenix, Inc.	3,843	0.22%
ISR	IsoRay, Inc.	8,394	0.48%	BA	Boeing Co	3,797	0.22%
MCP	McPherson's Ltd	8,109	0.46%	SHLD	Sears Holdings Corp	3,788	0.22%
RXII	RXi Pharmaceuticals Corp	8,084	0.46%	V	Visa Inc	3,697	0.21%
MSFT	Microsoft Corporation	7,500	0.43%	CAT	Caterpillar Inc.	3,669	0.21%
INVN	InvenSense Inc	7,253	0.41%	ZLCS	Zalicus Inc.	3,660	0.21%
SRPT	Sarepta Therapeutics Inc	6,315	0.36%	CPST	Capstone Turbine Corporation	3,631	0.21%
EBAY	Ebay Inc.	6,266	0.36%	SGYP	Synergy Pharmaceuticals Inc	3,631	0.21%
CYTK	Cytokinetics, Inc.	6,140	0.35%	PCYC	Pharmacyclics, Inc.	3,598	0.2%

Table 3: Summary Statistics

Note: In this panel we report summary statistics from the StockTwits data. In particular, Panel A present summary information on the coverage by stock and user, as well as user-level information. Panel B presents frequency distributions of users and messages posted by investment philosophy and experience, which are observed user profile characteristics.

Panel A: Characteristics of Messages and Users

	Mean	Stdev	Min	p25	p50	p75	Max
Number of messages per stock	14,487	32,577	616	1,576	5,296	14,864	275,969
Number of meesages per user	121	391	1	5	19	82	11,759
Number of messages per stock per day	44	135	1	3	10	31	4,728
Sentiment stock/day	0.441	0.516	-1	0.170	0.5	1	1
Number of followers user has	187	1,972	0	1	5	18	84,657
Number of people user follows	43	193.7	0	4	15	45	9,990
Total Days Active	462	412	1	137	349	685	1,909

Panel B: Frequencies of User Profile Characteristics

Approach	Num. Users	Percent Users	Num. Messages	Percent Messages
Fundamental	1,475	12.42%	206,075	14.11%
Technical	4,510	37.98%	540,003	36.98%
Momentum	2,388	20.11%	381,290	26.11%
Global Macro	271	2.28%	13,008	0.89%
Growth	2,145	18.06%	221,174	15.15%
Value	1,085	9.14%	98,799	6.77%
Total	11,874	100%	1,460,349	100%

Holding Period	Num. Users	Percent Users	Num. Messages	Percent Messages
Day Trader	1,840	15.50%	266,075	18.22%
Swing Trader	5,257	44.27%	673,558	46.12%
Position Trader	2,644	22.27%	291,237	19.94%
Long Term Investor	2,133	17.96%	229,479	15.71%
Total	11,874	100%	1,460,349	100%

Experience	Num. Users	Percent Users	Num. Messages	Percent Messages
Novice	3,406	28.68%	239,170	16.38%
Intermediate	6,147	51.77%	806,534	55.23%
Professional	2,321	19.55%	414,645	28.39%
Total	11,874	100%	1,460,349	100%

Table 4: Sentiment Measure

Note: This table presents summary information on the StockTwits measure of sentiment. Panel A shows the distribution of bearish, bullish, and unclassified messages. In Panel B, we report the distribution of messages into bullish and bearish after we classify the unclassified messages in the original sample. Panel C presents the sentiment (average bullishness) by investment philosophy, experience, and holding period that are reported in the StockTwits user characteristics.

Panel A: Original Sample

Sentiment	Num. Messages	Percent Messages
Bearish	87,193	5.97%
Bullish	388,110	26.58%
Unclassified	984,703	67.45%

Panel B: After Maximum Entropy Classifications

Sentiment	Num. Messages	Percent Messages
Bearish	458,218	31.38%
Bullish	1,001,788	68.62%

Panel C: Sentiment Summary Statistics

	Mean	Stdev
All users	0.372	0.928
Fundamental	0.277	0.960
Technical	0.345	0.444
Momentum	0.387	0.921
Global Macro	0.417	0.908
Growth	0.505	0.862
Value	0.351	0.936
Novice	0.390	0.920
Intermediate	0.396	0.917
Professional	0.314	0.949
Day Trader	0.294	0.955
Swing Trader	0.376	0.926
Position Trader	0.419	0.907
Long Term Investor	0.389	0.921

Table 5: Disagreement Measure

Note: This table presents summary information on the StockTwits measure of disagreement. The disagreement measures are calculated at the $firm \times day \times group$ level. Panel A shows the distributions of disagreement using the our main measure (following Antweiler and Frank), the linear disagreement measure (presented in the appendix). It further shows the distribution of disagreement by investment philosophy, experience, and holding period that are reported in the StockTwits user characteristics. In Panel B, we report how correlated disagreement measures are across different investment philosophies, experience levels, and holding period. Panel C presents the correlation between our main disagreement measure and other commonly used measures of disagreement (analyst dispersion, abnormal log volume, and return volatility)

Panel A: Disagreement Summary Statistics

	Mean	Stdev	Min	p25	p50	p75	Max
AF measure	0.469	0.447	0	0	0.637	0.932	1
Linear measure	0.322	0.347	0	0	0.229	0.639	1
Fundamental	0.214	0.385	0	0	0	0.631	1
Technical	0.360	0.439	0	0	0	0.866	1
Momentum	0.287	0.420	0	0	0	0.800	1
Global Macro	0.066	0.241	0	0	0	0.000	1
Growth	0.210	0.376	0	0	0	0.000	1
Value	0.173	0.361	0	0	0	0.000	1
Novice	0.254	0.407	0	0	0	0.745	1
Intermediate	0.398	0.445	0	0	0	0.904	1
Professional	0.323	0.437	0	0	0	0.866	1
Day Trader	0.265	0.415	0	0	0	0.800	1
Swing Trader	0.386	0.445	0	0	0	0.904	1
Position Trader	0.281	0.419	0	0	0	0.800	1
Long Term Investor	0.220	0.389	0	0	0	0.943	1

Panel B: Correlations Across Groups

	Fundamental	Technical	Momentum	Global Macro	Growth	Value
Technical	0.410	1.000				
Momentum	0.429	0.474	1.000			
Global Macro	0.200	0.205	0.214	1.000		
Growth	0.397	0.406	0.407	0.192	1.000	
Value	0.361	0.347	0.364	0.174	0.347	1.000

	Novice	Invermediate	Professional
Invermediate	0.482	1.000	
Professional	0.440	0.543	1.000

	Day Traders	Swing Traders	Position Traders	Long Term Investors
Swing Traders	0.488	1.000		
Position Traders	0.444	0.501	1.000	
Long Term Investors	0.409	0.441	0.442	1.000

Panel C: Other Disagreement Measures

Disagreement among	Analyst Dispersion	Abnormal Log Volume	Return Volatility
All Investors	0.042	0.117	0.036
Fundamentals	0.054	0.123	0.144
Technicals	0.028	0.121	0.025
Momentum	0.085	0.152	0.131
Global Macro	0.043	0.034	0.054
Growth	0.081	0.126	0.184
Value	0.072	0.128	0.234
Novices	0.064	0.130	0.198
Intermediate	0.055	0.125	0.086
Professionals	0.046	0.146	0.050
Day Traders	0.084	0.165	0.097
Swing Traders	0.006	0.134	0.046
Position Traders	-0.028	0.131	0.077
Long Term Investors	-0.003	0.105	0.082

Table 6: A Comparison of StockTwits Disagreement Measures

Note: This table presents correlations of our daily measure of disagreement with abnormal trading volume and the disagreement measure from Giannini et al. (2015). Column (1) shows correlations for all firm-day observations, while column (2) restricts the sample to the two weeks before and two weeks after earnings announcements.

	Abnormal Log Volume	
Disagreement	All time periods	Around EAs
Our measure	0.1183	0.1530
Giannini et al. measure	0.0641	0.0548

Table 7: Disagreement and Forecasting Trading Volume

Note: This table examines whether our measure of changes in investor disagreement forecasts future trading volume. We run the following regression:

$$AbLogVol_{i,t} = \alpha + \beta DisMeasure_{i,t} + \gamma AbLogVol_{i,t-1} + TimeFEs + FirmFEs + \varepsilon_{i,t}$$

Where in column (1) $DisMeasure_{it}$ is our disagreement measure for firm i on day $t-1$, in column (2) it's our disagreement measure on day t, and in column (3) it is the disagreement among messages posted before the market opens (BMO) (between 4pm on day $t-1$ and and 9am on day t). We standardize the measure by subtracting the mean and dividing by the standard deviation, over the entire sample period. $AbLogVol_{it}$ is the difference between log volume in timer period t and the average log volume from $t-140$ to $t-20$ trading days (6-month period, skipping a month) for firm i. Since trading volume tends to be autocorrelated, we also control for abnormal trading volume on day $t-1$. The regressions include year, moth, day-of-the-week, and firm fixed effects. Standard errors are clustered by company and date. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. Standard errors are in parenthesis.

	Abnormal Log Volume (t)		
Disagreement measure	(1)	(2)	(3)
Disagreement (t-1)	-0.006		
	(0.004)		
Disagreement (t)		0.110***	
		(0.008)	
Disagreement (BMO, t)			0.054***
			(0.005)
Abnormal Log Volume (t-1)	0.745***	0.726***	0.733***
	(0.013)	(0.014)	(0.014)
Observations	42,322	42,415	42,415
R-squared	0.600	0.608	0.602
Year, month, day of week FEs	X	X	X
Firm FEs	X	X	X

Table 8: Disagreement and Forecasting Abnormal Stock Returns

Note: In this table we examine whether changes in investor disagreement predict stock returns. We run the following regression:

$$Abret_{i,t+1} = \alpha + \beta DisMeasure_{i,t} + \nu AvgSentiment_{i,t} + \phi Abret_{i,t} + \gamma AbLogVol_{i,t} + \delta LogME_{i,t} + TimeFEs + \varepsilon_{i,t}$$

Where is the disagreement measure on day t for firm i. In column (1) $Abret_{i,t+1}$ is the abnormal return (minus the value-weighted market index) on day $t+1$ for firm i. In column (2) we put cumulative abnormal returns for days $t+1$ to $t+5$ ($CAR[1,5]$) on the left-hand side. We standardize the disagreement measure by subtracting the mean and dividing by the standard deviation, over the entire sample period. $AvgSentiment$ is the average sentiment measure for firm i on day t. $AbLogVol$ is the difference between log volume in time period t and the average log volume from $t-140$ to $t-20$ trading days (6-month period, skipping a month). $Log(ME)$ is the log of market capitalization of the firm. The regressions include year, moth, and day-of-the-week fixed effects. Standard errors are clustered by date. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. Standard errors are in parenthesis.

	(1)	(2)	(3)	(4)
	AbRet$_{t+1}$	AbRet$_{t+1}$	CAR[1,5]	CAR[1,5]
Disagreeement All Investors (t)	-0.0005**	-0.0006**	-0.0011*	-0.0012*
	(0.000)	(0.000)	(0.001)	(0.001)
Avg. Sentiment (t)		-0.0002		-0.0011
		(0.000)		(0.001)
AbRet (t)	0.0472**	0.0473**	0.0317	0.0326
	(0.020)	(0.020)	(0.030)	(0.030)
Abnormal Log Volume (t)	0.0011*	0.0011*	0.0032**	0.0032**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	42,432	42,432	42,432	42,432
R-squared	0.005	0.005	0.010	0.010
Year, month, day of week FEs	X	X	X	X

Table 9: Disagreement and Trading Volume around Earnings Announcements

Note: In this table, we examine disagreement among investors and trading volume around earnings announcements. We run the following regression:

$$
\begin{aligned}
AbLogVol_{it} &= \alpha + \beta_1 1WeekBeforeEA_{it} + \beta_2 EA_{it} + \beta_3 1WeekAfterEA_{it} \\
&+ \beta_4 2WeekAfterEA_{it} + \beta_5 3WeekAfterEA_{it} + \gamma Disagreement_{it} \\
&+ \delta_1 Disagreement_{it} \times 1WeekBeforeEA_{it} + \delta_2 Disagreement_{it} \times EA_{it} \\
&+ \delta_3 Disagreement_{it} \times 1WeekAfterEA_{it} + \delta_4 Disagreement_{it} \times 2WeeksAfterEA_{it} \\
&+ \delta_5 Disagreement_{it} \times 3WeeksAfterEA_{it} + SUE_{iq} + TimeFEs + FirmFEs + \varepsilon_{it}
\end{aligned}
$$

Where $AbLogVol_{it}$ is the abnormal log trading volume on day t for firm i, $1WeekBeforeEA$ is a dummy variable equal to 1 if day t for firm i is within a week before an earnings announcement for that firm, EA_{it} is a dummy variable equal one if firm i announces earnings on day t, $1WeekAfterEA_{it}$, $2WeekAfterEA_{it}$, $3WeekAfterEA_{it}$ are dummy variables for whether day t for firm i falls in week 1, week 2, or week 3 after an earnings announcement, respectively. $Disagreement_{it}$ is our measure of investor disagreement about stock i on day t. We standardize the disagreement measure by subtracting the mean and dividing by the standard deviation, over the entire sample period. SUE_{iq} is the earnings surprise in quarter q for firm i, defined as the earnings minus the median analyst forecast. Columns (1)-(3) include all observations that are around earnings announcements with a non-missing earnings surprise, while columns (4) and (5) have observations with a positive earnings surprise and columns (6) and (7) have observations with a negative earnings surprise. The regressions include year, moth, day-of-the-week, and firm fixed effects. Standard errors are clustered by company. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. Standard errors are in parenthesis.

	Abnormal Log Volume						
	Full Sample			Positive Earnings Surprise		Negative Earnings Surprise	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1 Week before EA	0.038	0.034	0.033	0.060**	0.065***	0.008	-0.024
	(0.024)	(0.022)	(0.024)	(0.023)	(0.022)	(0.037)	(0.035)
EA	0.670***	0.572***	0.499***	0.747***	0.595***	0.554***	0.335***
	(0.050)	(0.047)	(0.049)	(0.054)	(0.052)	(0.064)	(0.070)
1 Week after EA	0.399***	0.354***	0.314***	0.442***	0.355***	0.338***	0.241***
	(0.032)	(0.031)	(0.028)	(0.037)	(0.032)	(0.041)	(0.038)
2 Weeks after EA	0.117***	0.101***	0.073***	0.148***	0.114***	0.072*	0.013
	(0.022)	(0.022)	(0.022)	(0.025)	(0.024)	(0.036)	(0.035)
3 Weeks after EA	0.046**	0.038**	0.008	0.084***	0.056**	-0.008	-0.060*
	(0.020)	(0.019)	(0.019)	(0.024)	(0.023)	(0.037)	(0.035)
Disagreement		0.214***	0.199***		0.176***		0.262***
		(0.018)	(0.019)		(0.014)		(0.030)
Disagreement × 1 Week before EA			-0.024		-0.029*		-0.022
			(0.016)		(0.017)		(0.028)
Disagreement × EA			0.129***		0.112**		0.162**
			(0.043)		(0.048)		(0.061)
Disagreement × 1 Week after EA			0.104***		0.112***		0.090**
			(0.025)		(0.026)		(0.042)
Disagreement × 2 Week after EA			0.020		-0.002		0.039
			(0.019)		(0.022)		(0.035)
Disagreement × 3 Weeks after EA			0.007		-0.005		0.018
			(0.017)		(0.023)		(0.033)
SUE	-0.001	-0.020	-0.033	0.090	0.025	0.169	0.161
	(0.056)	(0.055)	(0.055)	(0.129)	(0.109)	(0.144)	(0.148)
Observations	33,111	33,111	33,111	20,129	20,129	12,908	12,908
R-squared	0.162	0.206	0.200	0.206	0.239	0.212	0.262
Year, month, dow FEs	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X

Table 10: Quantifying Disagreement Across Investment Models – Variation in Sentiment and Sentiment Trends Across Categories

Note: This table examines whether individuals with different investment philosophies have different changes in disagree over their assessment of stocks. To do this, we run the following regression in Panel A:

$$AvgSentiment_{itg} = FirmFEs + TimeFEs + GroupFEs + \varepsilon_{itg}$$

where $AvgSentiment_{itg}$ is the change in average sentiment for for group g (e.g., approach philosophy, experience level, holding period), firm i, on date t. In this regression Group fixed effects capture whether differences in groups that investors belong to explain changes average sentiment. As changes in average sentiment is what's driving disagreement among investors, Group fixed effects implicitly capture whether differences in groups that investors belong to explain changes in disagreement. In Panel B we examine whether individuals with difference investment philosophies have different accelerations in their disagreement. We run the following regression:

$$\Delta AvgSentiment_{itg} = FirmFEs + TimeFEs + GroupFEs + \varepsilon_{itg}$$

Where $\Delta AvgSentiment_{itg}$ is the difference between the average sentiment measure on day t and day $t-1$. The regressions include time (year, month and day-of-the-week) and firm fixed effects as noted in the columns. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. Standard errors are in parentheses.

Panel A: Analysis of Variance for Sentiment

					$Sentiment_{itg}$				
Sentiment Categories	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm FEs	X	X	X	X	X	X	X	X	X
Year, month, day of week FEs		X	X		X	X		X	X
Approach			X						
Experience						X			
Horizon									X
R-squared	0.099	0.101	0.111	0.153	0.155	0.156	0.005	0.132	0.133
F-stat across categories			6.64			3.85			4.47
Observations	107,090	107,090	107,090	75,278	75,278	75,278	90,941	90,941	90,941

Panel B: Analysis of Variance for Sentiment Trends

					$\Delta\ Sentiment_{itg}$				
Sentiment Categories	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm FEs	X	X	X	X	X	X	X	X	X
Year, month, day of week FEs		X	X		X	X		X	X
Approach			X						
Experience						X			
Horizon									X
R-squared	0.005	0.005	0.013	0.001	0.003	0.003	0.001	0.001	0.004
F-stat across categories			6.47			5.83			4.79
Observations	106,988	106,988	106,988	75,278	75,278	75,278	90,941	90,941	90,941

Table 11: Within-Group Disagreement, Cross-Group Disagreement, and Trading Volume

Note: In this table we examine whether changes in cross-group disagreement, on top of changes in within-group disagreement, help explain changes in trading volume. We run the following regression:

$$\begin{aligned} AbLogVol_{it} &= \alpha+\beta_1 Disagreement_{itg_1}+\beta_2 Disagreeemnt_{itg_2} \\ &+ \beta_3 Disagreement_{itg1g2}+AbLogVol_{it-1} \\ &+ TimeFEs+FirmFEs+\varepsilon_{it} \end{aligned}$$

Where $AbLogVol_{it}$ is the abnormal log trading volume on day t for firm i, $Disagreement_{itg_k}$ is our measure of investor disagreement about stock i, for group k (e.g., fundamental, technical, momentum, growth, or value investors.) on day t. $Disagreement_{itg_kg_s}$ is the disagreement measure across groups k and s, defined as the absolute value of the difference in average sentiment between groups k and s about firm i on day t. In column (11) we include a variable Cross-Group Disagreement, which is the standard deviation of the average sentiments for all groups (fundamental, technical, momentum, growth, and volume) for day t, for firm i. We standardize all disagreement measures by subtracting the mean and dividing by the standard deviation, over the entire sample period. The regressions include year, moth, day-of-the-week, and firm fixed effects. Standard errors are clustered by company and date. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. Standard errors are in parentheses.

	Abnormal Log Volume										
Disagreement Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Fundamental	0.055***	0.052***		0.057***			0.060***				0.035***
	(0.005)	(0.005)		(0.005)			(0.005)				(0.005)
Technical	0.091***		0.081***		0.089***			0.095***			0.065***
	(0.006)		(0.006)		(0.006)			(0.007)			(0.006)
Momentum		0.084***	0.078***			0.084***			0.088***		0.061***
		(0.005)	(0.005)			(0.005)			(0.005)		(0.005)
Growth				0.057***	0.052***	0.052***				0.058***	0.033***
				(0.004)	(0.004)	(0.004)				(0.004)	(0.004)
Value							0.054***	0.053***	0.051***	0.053***	0.036***
							(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Fundamental vs Technical	0.036***										
	(0.006)										
Fundamental vs Momentum		0.036***									
		(0.006)									
Technical vs Momentum			0.016***								
			(0.005)								
Fundamental vs Growth				0.039***							
				(0.005)							
Technical vs Growth					0.025***						
					(0.006)						
Momentum vs Growth						0.032***					
						(0.005)					
Fundamental vs Value							0.041***				
							(0.006)				
Technical vs Value								0.039***			
								(0.005)			
Momentum vs Value									0.042***		
									(0.006)		
Growth vs Value										0.034***	
										(0.005)	
Cross-Group Disagreement											0.048***
											(0.009)
Abnormal Log Volume (t-1)	0.719***	0.718***	0.717***	0.724***	0.721***	0.719***	0.722***	0.718***	0.716***	0.724***	0.703***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Observations	42,415	42,415	42,415	42,415	42,415	42,415	42,415	42,415	42,415	42,415	42,415
R-squared	0.611	0.611	0.612	0.608	0.610	0.610	0.608	0.611	0.611	0.607	0.618
Year, month, day of week FEs	X	X	X	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X	X	X	X

Appendix to:

Why Don’t We Agree? Evidence from a Social Network of Investors

Table 12: Robustness of Main Results to Different Sampling Restrictions and Measurement Choices

Panel A

Note: In this table we present the average changes in sentiment, average changes in disagreement, and the correlation between our disagreement measure and the abnormal log volume for different robustness specifications. Column (1) presents results for our main specifications. In column (2) when we construct the sentiment and disagreement measures we weigh each message by the number of followers the author of the message has. In column (3) we only include opinions by investors who joined StockTwits before 1 January, 2013. In column (4) we only use messages that were classified by users themselves as bullish or bearish. In column (5) we use a linear disagreement measure described in the appendix. In column (6) we only consider top 50 most talked-about firms. In column (7) we only consider top 51-100 most talked-about firms. In column (8) we consider the top 150 most talked-about firms.

	(1) Main dataset	(2) Weighted Disagreement	(3) Joined before 1 Jan 2013	(4) User-classified messages	(5) Linear Disagreement	(6) Top 50 firms	(7) Top 51-100 firms	(8) Top 150 firms
Avg. Sentiment	0.442	0.425	0.404	0.650	0.442	0.370	0.543	0.482
Avg Disagreement	0.469	0.368	0.382	0.199	0.219	0.722	0.227	0.336
Corr(Dis, Ablogvol)	0.117	0.127	0.143	0.137	0.103	0.114	0.169	0.099

Panel B

Note: In this table we examine how disagreement within different types of investors change around earnings announcements. We run the following regression:

$$
\begin{aligned}
AbLogVol_{it} &= \alpha + \beta_1 1WeekBeforeEA_{it} + \beta_2 EA_{it} + \beta_3 1WeekAfterEA_{it} \\
&+ \beta_4 2WeekAfterEA_{it} + \beta_5 3WeekAfterEA_{it} + \gamma Disagreement_{it} \\
&+ \delta_1 Disagreement_{it} \times 1WeekBeforeEA_{it} + \delta_2 Disagreement_{it} \times EA_{it} \\
&+ \delta_3 Disagreement_{it} \times 1WeekAfterEA_{it} + \delta_4 Disagreement_{it} \times 2WeeksAfterEA_{it} \\
&+ \delta_5 Disagreement_{it} \times 3WeeksAfterEA_{it} + SUE_{iq} + TimeFEs + FirmFEs + \varepsilon_{it}
\end{aligned}
$$

Where $AbLogVol_{it}$ is the abnormal log trading volume on day t for firm i, $1WeekBeforeEA$ is a dummy variable equal to 1 if day t for firm i happens to be a week before an earnings announcement for that firm, EA_{it} is a dummy variable equal one if firm i announces earnings on day t, $1WeekAfterEA_{it}$, $2WeekAfterEA_{it}$, $3WeekAfterEA_{it}$ are dummy variables for whether day t for firm i falls in week 1, week 2, or week 3 after an earnings announcement, respectively. $Disagreement_{it}$ is our measure of investor disagreement about stock i in the market on day t. We standardize the disagreement measure by subtracting the mean and dividing by the standard deviation, over the entire sample period. SUE_{iq} is the earnings surprise in quarter q for firm i, defined as the earnings minus the median analyst forecast In this table we present average sentiment, average disagreement measure, and the daily correlation between our disagreement measure and the abnormal log volume for different robustness specifications. Columns (1) and (2) presents results for our main specifications. In column (3) when we construct the sentiment and disagreement measures we weigh each message by the number of followers the author of the message has. In column (4) we only include opinions by investors who joined StockTwits before 1 January, 2013. In column (5) we only use messages that were classified by users themselves as bullish or bearish. In column (6) we use a linear disagreement measure described in the appendix. In columns (7) and (8) we only consider top 50 most talked-about firms. In columns (9) and (10) we only consider top 51-100 most talked-about firms. In columns (11) and (12) we consider the top 150 most talked-about firms. The regressions include year, moth, day-of-the-week, and firm fixed effects. Standard errors are clustered by company and date. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. Standard errors are in parentheses.

	Abnormal Log Volume											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
hline	Main dataset		Weighted Disagreement	Joined before 1 Jan 2013	User-classified Messages	Linear Disagreeement	Top 50 firms		Top 51-100 firms		Top 150 firms	
1 Week before EA	0.038	0.033	0.034	0.033	0.041*	0.039*	0.042	0.052*	0.038	0.017	0.041*	0.044*
	(0.024)	(0.024)	(0.024)	(0.023)	(0.024)	(0.023)	(0.030)	(0.030)	(0.032)	(0.032)	(0.024)	(0.024)
EA	0.670***	0.499***	0.524***	0.498***	0.492***	0.582***	0.716***	0.622***	0.623***	0.405***	0.677***	0.475***
	(0.050)	(0.049)	(0.051)	(0.049)	(0.049)	(0.048)	(0.062)	(0.060)	(0.074)	(0.073)	(0.049)	(0.056)
1 Week after EA	0.399***	0.314***	0.319***	0.315***	0.305***	0.356***	0.450***	0.395***	0.346***	0.243***	0.401***	0.288***
	(0.032)	(0.028)	(0.027)	(0.028)	(0.027)	(0.028)	(0.046)	(0.040)	(0.040)	(0.035)	(0.032)	(0.027)
2 Weeks after EA	0.117***	0.073***	0.079***	0.083***	0.080***	0.112***	0.113***	0.085***	0.120***	0.063**	0.118***	0.067***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.028)	(0.027)	(0.031)	(0.031)	(0.022)	(0.023)
3 Weeks after EA	0.046**	0.008	0.014	0.020	0.015	0.046**	0.037	0.004	0.051*	0.012	0.048**	0.008
	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)	(0.026)	(0.025)	(0.029)	(0.028)	(0.020)	(0.020)
Disagreement		0.199***	0.174***	0.215***	0.143***	0.118***		0.149***		0.189***		0.193***
		(0.019)	(0.017)	(0.020)	(0.015)	(0.013)		(0.019)		(0.026)		(0.018)
Disagreement × 1 Week before EA		-0.024	-0.014	-0.024	-0.035**	-0.008		-0.035*		-0.049*		-0.026*
		(0.016)	(0.016)	(0.015)	(0.014)	(0.014)		(0.018)		(0.029)		(0.015)
Disagreement × EA		0.129***	0.085**	0.121***	0.097***	0.058*		0.084		0.077*		0.118***
		(0.043)	(0.039)	(0.039)	(0.032)	(0.033)		(0.066)		(0.044)		(0.041)
Disagreement × 1 Week after EA		0.104***	0.105***	0.114***	0.096***	0.087***		0.075**		0.064*		0.097***
		(0.025)	(0.024)	(0.022)	(0.020)	(0.021)		(0.029)		(0.034)		(0.024)
Disagreement × 2 Week after EA		0.020	-0.002	0.013	0.012	-0.018		-0.020		0.031		0.020
		(0.019)	(0.018)	(0.016)	(0.017)	(0.016)		(0.016)		(0.031)		(0.018)
Disagreement × 3 Weeks after EA		0.007	0.009	0.012	-0.019	0.010		0.005		0.004		0.005
		(0.017)	(0.017)	(0.014)	(0.015)	(0.015)		(0.019)		(0.034)		(0.017)
SUE	-0.001	-0.033	-0.032	-0.034	-0.029	-0.012	0.048	0.019	-0.040	-0.081	-0.132*	-0.151**
	(0.056)	(0.055)	(0.055)	(0.055)	(0.054)	(0.055)	(0.089)	(0.090)	(0.068)	(0.064)	(0.074)	(0.068)
Observations	33,111	33,111	33,111	33,111	33,111	33,111	16,811	16,811	16,300	16,300	33,489	33,489
R-squared	0.162	0.200	0.195	0.212	0.192	0.185	0.194	0.222	0.141	0.186	0.164	0.202
Year, month, dow FEs	X	X	X	X	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X	X	X	X	X