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 document that much of the market-wide disagreement arises from differing investment philosophies rather than differences in information. This finding suggests that – even with perfectly informationally efficient markets – investor disagreement 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 in financial markets (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 the extant work on the consequences of investor disagreement, much less is known about the *sources* of disagreement. That is, why do investors disagree in the first place?

In this paper, we address this question by empirically distinguishing disagreement due to differing investment approaches from disagreement due to different information sets. Leading theories have identified these two channels as the most important sources of disagreement (Hong and Stein, 2007), but in most available data sets on trading, it is impossible to distinguish different investment approaches from different information. Indeed, trading approaches are often inferred from actual trading behavior (e.g., see Rothschild and Sethi (2014) and Baldauf and Mollner (2015)), and thus, it is challenging to distinguish approaches from information, which may also influence behavior. We overcome this challenge by studying disagreement among investors on a social investing platform (called StockTwits) in which investor profile information *explicitly* gives a user's investment approach. Knowing each investor's approach *ex ante*, enables us to directly measure disagreement, and use this measure to evaluate how much of investor disagreement is because investors adopt different approaches rather than having different information sets.

Our empirical work documents substantial disagreement arising from differing investment approaches, and this disagreement – both within and across approaches – rises around the time of earnings announcements. We focus on earnings announcement periods because these are times when individual investors pay more attention to stocks, and thus, any set of individual investors will have similar information sets. On this basis, our findings suggest that much of market-wide disagreement is driven by differences in market approach, and that much of the disagreement and trading volume we observe in markets would persist even as markets became more informationally efficient.

Hong and Stein (2007) and Kondor (2012) develop a theoretical foundation that motivates our empirical analysis. According to Hong and Stein (2007), disagreement among investors can arise for two main reasons. First, gradual information flow and limited investor attention can cause investors to disagree, as different investors have different information sets. We call this "information asymmetry hypothesis." Second, even if all investors obtain the same information at the same time, investors can still disagree about what that piece of information implies for the company's future cash flows, because they have different economic models, or priors, which they use to interpret the information. We call this the "heterogeneous models hypothesis." Our evidence that disagreement arises within and across approaches suggests that both "information asymmetry" and "heterogeneous models" rationales for disagreement are important.

Before analyzing disagreement within and across investment approaches, we need to reliably measure disagreement. For this purpose, we adopt the disagreement measure of Antweiler and Frank (2004) to convert investor sentiment about the same stock and on the same day into a measure of disagreement. It is useful that users frequently self-classify their sentiment into positive (bullish) and negative (bearish) sentiment about a particular stock. Because users self-classify their sentiment for a large subset of messages, we are able to inform the textual analysis of sentiment with reliable classifications, and thus, our measures of sentiment and disagreement are more precise than in other settings where sentiment must be inferred for the entire sample.

We contrast our measure of disagreement with other notable alternatives, and find that our measure has a number of notable advantages. First, our measure can be computed at a reasonably high frequency, whereas other leading measures (e.g., analyst dispersion, stock volatility) are most reliable for a monthly frequency. Second, our measure of disagreement can be computed separately for observable sub-groups of investors. In our analysis, we compute disagreement separately by stock-day-approach as well as by stock-day-experience level. Third, our measure of disagreement is strongly correlated with abnormal volume, which suggests that it is a reliable predictor of trading behavior. By contrast, other measures bear a weaker correlation with volume. Finally, even for measures that have been shown to be related to volume, our measure provides independent information on disagreement. In particular, our measure of disagreement is broadly uncorrelated with the dispersion of analyst forecasts, and is conceptually distinct from the measure of Giannini et al. (2015), which studies the contrast of the opinions on an investor social network (incidentally, StockTwits) with those in the media.

Our results, measure of disagreement, and approach should be of broad interest to scholars in individual investing behavior, 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. We fill this gap by combining our setting – which yields daily measures of sentiment at the individual $\times$ stock $\times$ 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.

Our results on abnormal trading and disagreement also relate to the literature in individual investor behavior on the abnormal trading of individual investors (Barber and Odean, 2000). In particular, this literature has identified numerous behavioral rationales for overtrading, including entertainment, sensation seeking, gambling, and learning by doing (Dorn and Sengmueller, 2009; Grinblatt and Keloharju, 2009; Kumar, 2009; 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 other research 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 in the context of sentiment and disagreement, but their paper is substantially different from ours in both the aims of the research, and the measurement of disagreement. First, our aim is to study the sources of disagreement, whereas theirs is to study disagreement's consequences for trading and volume. To this end, our paper utilizes the investor approach information in the StockTwits user profiles to directly study how differing approaches contribute to disagreement. Second, our measure of disagreement based on Antweiler and Frank (2004) 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. These are distinct notions of disagreement.

Ultimately understanding the cause of investor disagreement has important policy implications. Regulators put a lot of 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 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, as two people reading the same piece of information might draw different conclusion about what the report says[1]. 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 can be empirically challenging, in part due to data limitations. First, disagreement refers to differences in investors' opinions, which can be hard to observe. Even if a researcher had individual-level trading data (which itself is hard to come by), it would be difficult to impute investors' opinions from the trading data, as investors can trade for reasons unrelated to their opinion - like liquidity. Second, as 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

[1]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)

– 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 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 . While the website doesn't by default 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 each user, 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) 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.

As StockTwits has grown substantially over time, the best quality data comes from more recent years, we restrict our data to January, 2013 to September, 2014. As can be seen in Table 1, this 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. Further, we restrict attention to messages by users who have indicated their approach , holding period, and experience. We focus on stocks that are headquartered in the US and thus have regular filings with the SEC. In order to construct a reliable time series of the disagreement measure, we would ideally observe investors' opinions about individual stocks every day. In order to get as close to that ideal as possible, we concentrate on stocks for which there is a high amount of StockTwits coverage. The top 100 stocks 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.

Table 2 presents summary statistics of the sample coverage. The median number of messages per stock per day is 10, with some stocks reaching as many as 5,000 messages on some days.

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 have joined before January 1, 2013.

2.3 StockTwits Users

When users register with StockTwits they fill out an online form with 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, or Professional). In Table 2 Panel B, we show the breakdown of users by their approach, holding period and experience. Interestingly, the largest group of investors by approach is Technical, representing 38% of users and also posting about 38% of messages. Momentum and Growth investors represent the next two larges groups

(20% and 18% of investors, respectively), followed by Fundamental and Value investors. While some groups post more than their fair share (Momentum investors) and some less (Value investors) overall investor groups seem to post a similar amount. To the best of our knowledge this is the first paper to use a measure of investors' approach, and therefore we can't compare whether this breakdown representative of other samples in the market.

Next we examine the holding horizons of investors. The majority 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.

One potential concern about our dataset is that it is mostly opinions of retail investors who are not representative of investors in the market. To evaluate this concern, we examine the self-reported experience measure, and find that about half of the investors report to be intermediate. 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 have hand-checked a number of user profiles using identifying information when available. In the cases we have been able to check, self-reported experience appears to be a reliable indicator of the user's experience. Figure 1 presents three representative examples of user profiles, giving 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.

2.4 Why do users post messages?

For constructing a measure of disagreement, it is essential that most of the opinions observed on StockTwits are the true opinions of the investors. One potential concern with using our data to measure investor disagreement is if users are trying to manipulate the stock market, and thus post fake opinions. For example, if a user thinks the stock 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. We have several reasons to believe that this is not a big concern in our data. First, there is anecdotal evidence that investors post on the social networks to attract followers, and gain internet fame or a job.[2] 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 stocks have large market caps, and therefore it is very unlikely that an individual investor think they can move prices.

3 Sentiment

3.1 Sentiment measure

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

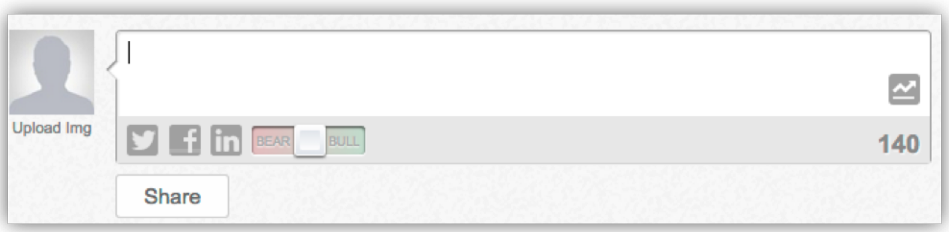

Table 3 Panel A shows the distribution of sentiment across messages. According to these summary statistics, 6.14 percent of messages are bearish, 27.36 percent are bullish, and 66.5 percent are unclassified. Even though the setting and timeframe are different, our

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

classifications give similar relative frequencies to the distribution reported in Antweiler and Frank (2004).

When reading the unclassified messages, it becomes clear that most of them are quite bullish or quite bearish. We follow prior literature and we 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)) have to hand-classify a training dataset (usually ~1,000 messages), and then use the calibrated (usually an entropy-based) model to classify the rest of the data. Hand-classification introduces subjectivity into the process. Our data is unique in that we have 475,642 messages that were pre-classified by the users. We use a maximum entropy-based method (described in the appendix) to classify the rest of the messages. Table 3 Panel B shows the distribution of the final dataset. We have 613,729 bearish and 846,620 bullish messages.

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

$$AvgSentiment_{gst} = \frac{N_{gst}^{bullish} - N_{gst}^{bearish}}{N_{gst}^{bullish} + N_{gst}^{bearish}}.$$

The $AvgSentiment_{gst}$ measure ranges from -1 (all bearish) to $+1$ (all bullish). Table 3, Panel C displays the summary statistics of $AvgSentiment_{gst}$ for all users, and then broken down by investment philosophy, experience, and holding period. As with the distribution of bullish and bearish messages, that 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 bullish, whereas fundamental investors are the most bearish. Novice investors are more bullish than professional investors, and longer-term investors are more bullish than day traders.

3.2 Validating the Sentiment Measure

We validate the sentiment measure in two 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 in a sensible way with actual trading sentiment given the short sale constraints that investors face.

3.2.1 Cross Validating Sentiment

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 enhances our confidence in using the classification scheme on the unclassified message. 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

A potential concern with an expressed sentiment measure like ours or Antweiler and Frank (2004)'s is that expressed opinions are not representative of true beliefs about investing behavior, 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, (2) we relate the propensity to report positive news to the technological likelihood that an investor cannot express extreme negative sentiment because of short selling constraints. This pattern would be consistent with how a measure of sentiment should behave, and thus, enhance confidence that our measure of sentiment is representative of investor beliefs.

Given short selling constraints facing retail investors (as in Hong and Stein (2003), Engelberg et al. (2014)) and the fact that most investors in the data are not professionals, it is natural that sentiment tends to be bullish rather than bearish. 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.

If this underlying mechanism behind the bullish-bearish imbalance is important, expressed sentiment should vary systematically with proxies for the ability to short sell a stock. We evaluate this prediction 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. Consistent with this mechanism, we find that the the fraction of bullish of messages for companies in the top quartile of institutional holdings is 0.28, compared with 0.13 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

One question that arrises naturally from the sentiment measure is whether investors are able to predict stock returns. We explore this by looking at the abnormal cumulative returns of stocks after investors issue a bearish or a bullish opinion. Every day, we form two portfolios: a portfolio of stocks that investors wrote bullish messages about, and a portfolio that investors wrote bearish messages about. The portfolio weights are proportional to the number of messages that about a given stock on that day. For example if stock A had 15 bullish messages and stock B had 5 bullish messages then stock A will get a weight of 0.75 and stock 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 5 presents the graphs of the portfolios based on sentiment from all investors. We can see that the returns are flat for a long time, and then increase over the coming months. Note that the stocks that investors are bullish on don't perform any better than the stocks that investors are bearish on. This is in line with prior findings that investors, especially retail investors, can't predict returns, on average. However, it could be the case that some groups of investors are better at predicting returns than other. Then in Figure 5, we examine the predictability separately for novices, intermediate investors, and professionals. We find that, indeed, stocks that novice investors are bullish on tend to underperform the stocks that investors are bearish on. This is in line with prior research that retail investors lose money in the market. Intermediate investors do a little less worse. Interestingly, investors that claim to be professionals, actually have some predictive power. The stocks that they are bullish on, outperform the stocks that they are bearish on by almost 2% over a 60 trading-day period.

4 Disagreement

4.1 Disagreement Measure

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 could be $stock \times day$ or $stock \times day \times approach \times group$). First, we calculate the average sentiment measure at the group/day/stock level

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

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

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

Note, the disagreement measure is scaled between 0 and 1, with 0 being no disagreement and 1 being maximum 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 6, we show how disagreement changes as the number of bearish investors goes from 0 (all bullish investors) to 10 (all bearish investors). There is no disagreement if all investors are bearish or bullish, and the disagreement is maximized at 1, when there are 5 bullish and 5 bearish investors. Since the measure is a square root function, the disagreement changes the most when there are few bullish or few bearish investors (the measure has the largest slope). In the Appendix, we also discuss a measure that is a linear function of the number of bullish/bearish investors. 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 say that no information came out during that time period, and thus there is latent disagreement. We set the disagreement measure for the given group and time period to the last observed disagreement measure. 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 for fundamental investors about Apple on Tuesday to be the last observed measure (0.6). Intuitively, if no information came out that fundamental investors viewed as informative, we assume that their opinions about the stock (and thus the disagreement level) has not changed.

4.2 Disagreement and Investor Groups

In Table 4, we summarize the disagreement measure. The average for our main disagreement measure is 0.47, and the median is 0.644. The linear measure described in the appendix portrays a similar picture, with the correlation between the levels of the two measures is 0.93 and between the changes in the two measures is 0.9.

Using the direct observation of user approaches from investor profiles, we break down our main disagreement measure by the approach of investors. Specifically, we construct the disagreement measure separately for messages about the same stock on the same day by investors of the same approach type. In so doing, we are able to measure how much investors disagree about the prospects of a stock with investors of the same investment philosophy. We also perform the same exercise for different experience levels and holding periods. The results are presented in Table 4. Interestingly, technical investors disagree the most, whereas value and fundamental investors disagree much less. Also intermediate and professional investors disagree more than novices. That could be driven by the fact that professional investors might be writing more "novel" comments, while novices might be copying opinions from the media. Finally, disagreement within groups does not appear to vary systematically with investment horizon.

4.3 StockTwits vs. Other Disagreement Measures

We examine how our measure relates to measures of disagreement used in the prior literature. One of the most commonly used proxies for disagreement has been analyst dispersion (Diether et al., 2002). We follow prior literature and calculate monthly analyst dispersion as the standard deviation of analyst forecasts made in a given month. We then aggregate our measure to the monthly level and calculate the correlation between the two measures. As can be seen in Table 4, Panel C, column (1) the two measures are uncorrelated .

When evaluating disagreement measures, it is important to consider how the measure correlates with abnormal trading volume. What exactly drives trading volume and why it varies so much over time is still subject to much debate in the finance literature. One theory is that trading volume reflects differences in investors' opinions. Despite the compelling logic, there is not much empirical for a correlation between existing measures of disagreement and abnormal trading volume. In fact, when we correlate analyst dispersion at the monthly level with abnormal trading volume, the correlation is quite small (0.0388). In contrast, our measure of disagreement correlates much better with volume. Specifically, in Table 4, 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 disagreement among all investors and the abnormal log trading volume is 0.18. This represents a substantial improvement in the ability to explain abnormal trading volume. The abnormal trading volume is slightly more correlated with disagreement among professional and among momentum investors than with disagreement among other investor groups.

4.4 Disagreement, Volume, and Returns

In the last section, we showed that the disagreement measure has a relatively strong correlation with trading volume in comparison to alternatives. Nevertheless, because the two measures are measured contemporaneously, it remains unclear whether trading volume drives disagreement among investors (as investors observe a higher trading volume, they disagree about what that means), whether increased disagreement causes higher trading volume, or whether a third variable is driving both (like an earnings announcement). One concern that we have, is that the investors that write on StockTwits are not representative of the investors who typically trade in the stock market, and therefore, their disagreement is not related to the disagreement in the stock market. We alleviate that concern by examining whether disagreement predicts future changes in trading volume.

Before examining whether disagreement predicts trading volume, we need to determine which measure of disagreement to use. Trading volume increases because the stock changes hands more. If disagreement is high (half of the investors are bullish and half are bearish), and investors don't change their opinion, expressed disagreement today will lead to no additional trading tomorrow. However, if investors change their opinion, and thus disagreement changes, we expect more trading to occur. On this logic, it is more appropriate to examine how changes in disagreement (rather than levels of disagreement) forecast trading volume . Table ?? shows how differences in disagreement correlation across the various within-group measures we construct.

First, we examine whether levels in disagreement forecast future trading volume. We run the following regression:

$$AbLogVol_{t+1} = \alpha + \beta Dis_t + \gamma_1 AbLogVol_t + \gamma_2 AbLogVol_{t-1} + \delta LogME + \varepsilon \quad (1)$$

Where Dis_t is our disagreement measure in time period t. 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 in time periods t and $t-1$. The results are presented in Table ??, column (1). The coefficient on disagreement is close to zero and statistically insignificant, suggesting, as expected, that the level of disagreement does not forecast future trading volume.

Next we look at the changes in our disagreement measure. We run the same regression as in Eq (1), however, we replace Dis_t with ΔDis_t, which is the change in disagreement between $t-1$ and t. Again, we standardize the change in disagreement by subtracting the mean and dividing by the standard deviation over the sample period. The results of the regression are presented in Table ??, column (2). The coefficient on the change in disagreement is positive and statistically significant. Since the change in disagreement is standardized, we can interpret the coefficient as change in standard deviation. In other words, if the change in disagreement increases by one standard deviation, abnormal trading volume next period is higher by 0.8%. Given that many of the traders that post on StockTwits are not large institutional investors, this is an economically large effect.

Next, we examine how disagreement among individual investor groups affects abnormal trading volume. In order to do so we calculate the disagreement measure only for individuals who self-report being in a given group (for example for all investors who self-report being fundamental). We split individuals into groups by their investment philosophy, their experience level, and their holding period. We then regress abnormal log trading volume on changes in the disagreement measure within the individual groups. The results are presented in Table ??, columns (3), (4), and (5). We find that changes in disagreement among momentum investors have the most predictive power for future trading volume. One change deviation increase in changes in disagreement on day t is associated with a 1.6% increase in abnormal trading volume on day $t+1$. For the rest of investment philosophies the effect is around 1%. Interestingly disagreement within different self-reported experience groups has a similar effect on abnormal trading volume. Finally, disagreement within various holding-period groups has very little effect on future trading volume. The coefficients on changes in disagreement are mostly insignificant.

Finally we examine whether either levels or changes in investor disagreement predict stock returns. In Table ?? we look at abnormal stock returns on day $t+1$ and cumulative abnormal returns over days $t+1$ to $t+5$. We run the following regression:

$$Abret_{t+1} = \alpha + \beta DisMeasure_t + \phi Abret_t + \gamma AbLogVol_t + \delta LogME + \varepsilon$$

where $Abret_{t+1}$ is the abnormal return (minus the value-weighted market index) on day $t+1$, $DisMeasure$ is either the level our disagreement measure on day t or the change in the disagreement measure between days t and $t-1$. In columns (3) and (4) we put cumulative abnormal returns for days $t+1$ to $t+5$ ($CAR[1,5]$) on the left-hand side. Although we find that investors' sentiment predicts future stock returns, we don't find that disagreement among investors predicts stock returns as the coefficients on the disagreement measure among all investors and the changes in disagreement among all investors are zero and statistically insignificant.

5 Disagreement: Different Models or Different Information?

Now, we turn to a central question – does disagreement arise because of difference in models or differences in information? We will try to address this question by looking at a situation where we can assume that most market participants, that are interested in the stock, observe the piece of information, and we examine how disagreement changes across different groups around the event. As the setting, we will examine the behavior of disagreement around earnings announcements. Earnings announcements are the most important financial events for companies, as crucial information about the cashflows of the company, as well as the company's potential prospects are revealed. Prior literature has shown that earnings announcements are carefully watched by professional and amateurs investors. One puzzling fact about earnings announcements is that trading volume goes up after earnings announcements, relative to the time before earnings announcements, even though important financial information is released to the market, which should resolve a lot of uncertainty. One potential explanation for this phenomenon is that disagreement among investors goes up, as different types of investors could be interpreting that information differently.

To examine whether differences in models across investors play a role in increased trading volume around earnings announcements, we look at how disagreement within different types of investors change around earnings announcements. First we replicate the fact that trading volume is high after earnings announcements. We run the following regression:

$$
\begin{aligned}
AbLogVol_{ti} = \alpha + \beta_1 1WeekBeforeEA_{ti} + \beta_2 EA_{ti} + \beta_3 1WeekAfterEA_{ti} \\
+\beta_4 2WeekAfterEA_{ti} + \beta_5 3WeekAfterEA_{ti} + TimeFEs + \varepsilon_{ti}
\end{aligned}
\tag{2}
$$

Where $AbLogVol_{ti}$ 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_{ti} is a dummy variable equal one if firm i announces earnings on day t, $1WeekAfterEA_{ti}$, $2WeekAfterEA_{ti}$, $3WeekAfterEA_{ti}$ are dummy variables for weather day t for firm i falls in week 1, week 2, or week 3 after an earnings announcement, respectively.

The results are presented in Table **??**, column (1). 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. We can see that the trading volume before an EA is about the same level as it is during the time outside of the earnings announcement period. It's slightly higher, but not statistically significant. Then it increases by 64% on the day of the earnings announcement, and stays high (36% higher) for one week and then slowly decreases over time. Note it's still 5% higher three weeks after the earnings announcement.

The remaining columns of Table **??** present a test of the role of disagreement as measured by our measure of disagreement. In particular, one may suspect that rising disagreement among investors can explain some of the spike in volume. 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 disagreement. Table **??** shows that controlling for disagreement can explain approximately one eighth of the spike in abnormal volume around the earnings announcement. This is meaningful because there are very few predictors that well explain changes in abnormal volume. We also examine how the lag in disagreement affects abnormal volume. We find that controlling for todays' disagreement, lagged disagreement is positively asociated with trading volume, but less so than contemporaneous disagreeemnt.

Next we examine how the disagreement among investors changes around that time period. We run the same regression as in equation (2), except we put disagreement among investors (all investors, or within different groups of investors) on the left hand side. The results are presented in Table ??. First, we look at disagreement among all investors. We find that the disagreement is slightly higher in the week prior to the earnings announcement, then it increases by almost one half of a standard deviation on the day of the earnings announcement, and then decreases slowly over time. The rate at which disagreement changes around earnings annoucenments is very similar to the rate at which abnormal trading volume changes during that time.

Next we examine how disagreement within different groups of investors changes during that time period. We consider groups with different investment philosophies. Interestingly disagreement goes up the most for fundamental investors, and stays high the longest. Disagreement is also high among momentum, growth, and value investors. It's lowest for technical and global macro investors. These findings suggest that the models investors use to interpret information matter for the level of disagreement among investors. Therefore, the types of information that are disclosed at various time, interacted with different models investors use to interpret that information, could be explaining the varying levels of disagreement through time.

6 Conclusion

In this paper, we utilize the unique features of sentiment of retail investors on a social network to constructe a novel and theoretically-grounded measure of disagreement. We show that our measure of disagreement correlates more strongly than relevant alternatives with abnormal trading volume, which is what is to be expected given seminal underlying theories of disagreement and trading. Despite driving volume, we find that disagreement is unrelated to stock returns. We plan to relate our measure of disagreement with other, newer measures of disagreement, such as open short interest, and the sentiment-based measure of Giannini et al. (2015) who measure disagreement between media articles and retail investors.

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7 Appendix

7.1 Alternative Disagreement Measure

As mentioned in section ..., 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 investors. We follow that method in our main analysis. However, as a robustness test, we also try a function that is liner in sentiment.

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

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 investors increases in the market. We rerun our analysis using this measure of disagreement and get similar results as our main disagreement measure.

7.2 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 Tables and Figures

8.1 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).

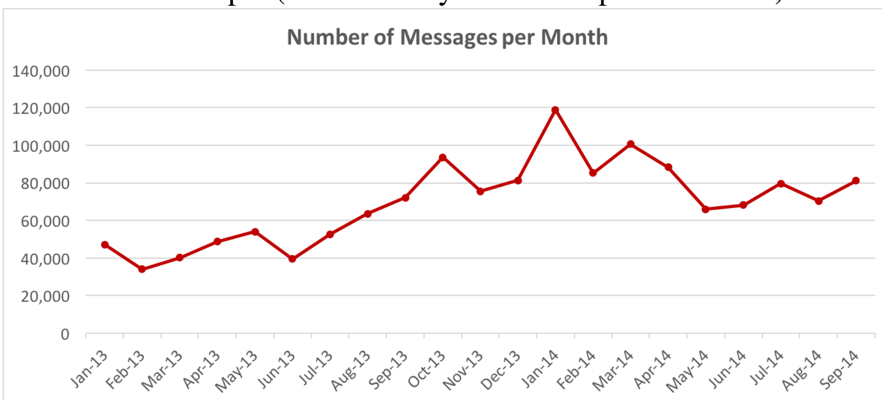


Figure 3: Day-of-Week Frequency Distribution of Messages Posted

Note: This figure presents a frequency distribution of the weekday messages posted to StockTwits.

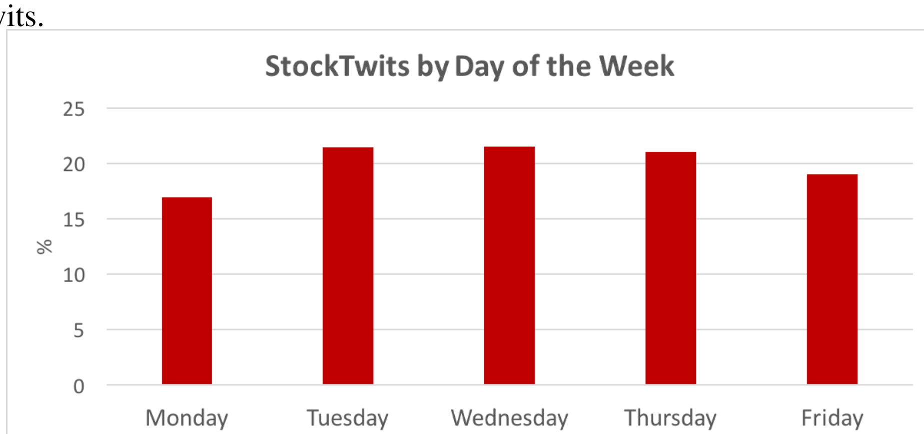


Figure 4: Hour-of-Day Frequency Distribution of Messages Posted

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.

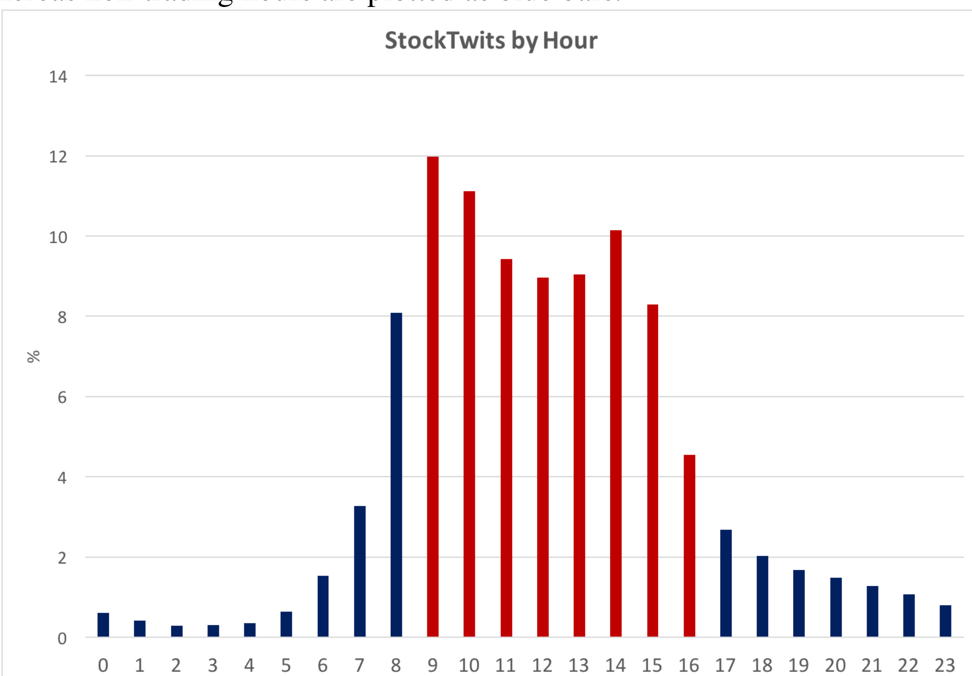
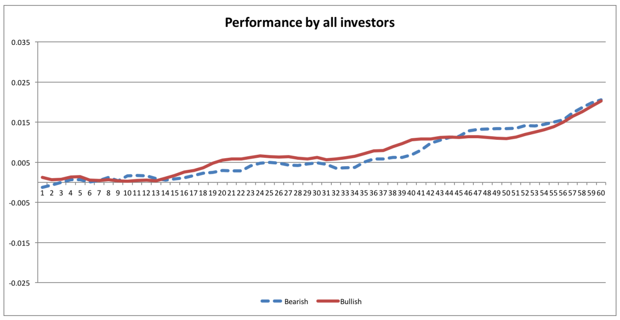


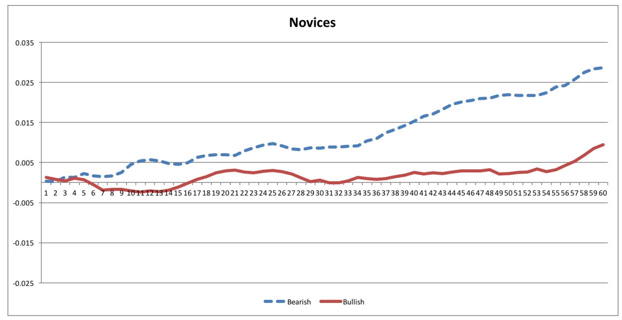
Figure 5: Performance of StockTwits Sentiment Strategies

Note: This figure presents the cumulative abnormal returns of strategies that buy when sentiment is bullish and short-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.

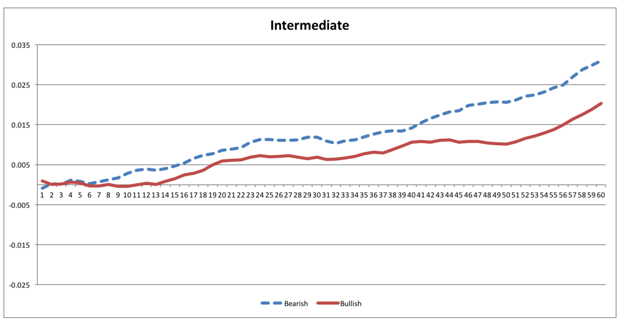
(a) All Investors



(b) Novices



(c) Intermediate



(d) Professionals

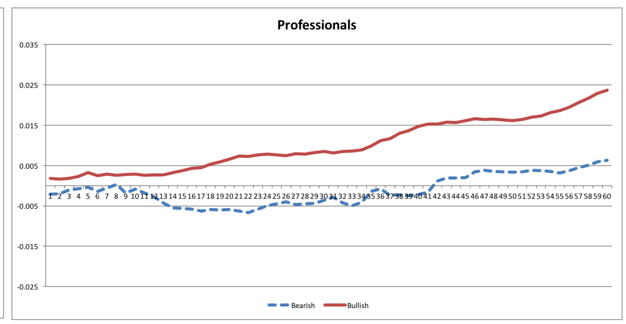


Figure 6: An Example of the Disagreement Measure

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

9 Tables

Table 1: How Sampling Choices Influence 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: 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, Users, and Stock Tickers

	Mean	Stdev	Min	p25	p50	p75	Max
Number of messages per stock	14,604	32,831	751	1,588	5,366	14,978	278,189
Number of meesages per user	123	395	1	5	20	83	11,770
Number of messages per stock per day	44	135	1	3	10	31	5,056
Sentiment stock/day	0.439	0.518	-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	1,908

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%
Long Term Investor	2,133	17.96%	229,479	15.71%
Position Trader	2,644	22.27%	291,237	19.94%
Swing Trader	5,257	44.27%	673,558	46.12%
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 3: 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	87,157	6.14%
Bullish	388,48	27.36%
Unclassified	944,426	66.50%

Panel B: After Maximum Entropy Classifications

Sentiment	Num. Messages	Percent Messages
Bearish	613,729	42.03%
Bullish	846,620	57.97%

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 4: Disagreement measure

Note: This table presents summary information on the StockTwits measure of disagreement. The disagreement measures are calculated at the $stock \times day \times group$ 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 philosphies, 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	0.470	0.446	0	0	0.644	0.933	1
Linear measure	0.347	0.349	0	0	0.308	0.667	1
Fundamental	0.241	0.401	0	0	0	0.661	1
Technical	0.387	0.444	0	0	0	0.899	1
Momentum	0.317	0.431	0	0	0	0.866	1
Global Macro	0.095	0.284	0	0	0	0	1
Growth	0.239	0.394	0	0	0	0.628	1
Value	0.208	0.387	0	0	0	0	1
Novice	0.279	0.418	0	0	0	0.800	1
Intermediate	0.436	0.448	0	0	0	0.930	1
Professional	0.357	0.457	0	0	0	0.904	1
Day Trader	0.514	0.459	0	0	0.745	0.979	1
Swing Trader	0.490	0.461	0	0	0.679	0.968	1
Position Trader	0.532	0.453	0	0	0.781	0.968	1
Long Term Investor	0.541	0.447	0	0	0.796	0.985	1

Panel B: Correlations Among Groups

	Fundamental	Technical	Momentum	Global Macro	Growth	Value
Technical	0.326	1.000				
Momentum	0.360	0.400	1.000			
Global Macro	0.158	0.153	0.174	1.000		
Growth	0.328	0.316	0.335	0.138	1.000	
Value	0.296	0.285	0.315	0.137	0.2746	1.000

	Novice	Invermediate	Professional
Invermediate	0.426	1.000	
Professional	0.383	0.463	1.000

	Day Traders	Swing Traders	Position Traders	Long Term Investors
Swing Traders	0.337	1.000		
Position Traders	0.265	0.360	1.000	
Long Term Investors	0.237	0.305	0.249	1.000

Panel B: Other Disagreement Measures

Disagreement among	Analyst Dispersion	Abnormal Log Volume	Return Volatility
All Investors	0.045	0.179	0.045
Novices	0.064	0.205	0.198
Intermediate	0.059	0.188	0.095
Professionals	0.049	0.211	0.064
Fundamentals	0.058	0.189	0.156
Technicals	0.031	0.185	0.030
Momentum	0.087	0.215	0.144
Global Macro	0.069	0.061	0.042
Growth	0.0776	0.173	0.176
Value	0.0726	0.191	0.234
Day Traders	0.0920	0.156	0.085
Swing Traders	0.0070	0.183	0.050
Position Traders	-0.0461	0.137	0.098
Long Term Investors	-0.0154	0.087	0.068

Table 5: Differences in Disagreement

Note: This table presents correlations of daily changes in our main disagreement measure across different investment philosophies, experience levels, and holding period.

	ΔFundamental	ΔTechnical	ΔMomentum	ΔGlobal Macro	ΔGrowth	ΔValue
ΔTechnical	0.061	1.000				
ΔMomentum	0.052	0.068	1.000			
ΔGlobal Macro	0.032	0.000	0.012	1.000		
ΔGrowth	0.057	0.039	0.066	0.017	1.000	
ΔValue	0.048	0.031	0.051	0.028	0.040	1.000

	ΔNovice	ΔInvermediate	ΔProfessional
ΔInvermediate	0.044	1.000	
ΔProfessional	0.050	0.063	1.000

	ΔDay Traders	ΔSwing Traders	ΔPosition Traders	ΔLong Term Investors
ΔSwing Traders	0.051	1.000		
ΔPosition Traders	0.029	0.077	1.000	
ΔLong Term Investors	0.018	0.066	0.041	1.000

Table 6: Disagreement Forecasting Trading Volume

Note: This regressions examines whether our measure of disagreement forecasts further trading volume. We run the following regression:

$$AbLogVol_{t+1} = \alpha + \beta DisMeasure_t + \gamma_1 AbLogVol_t + \gamma_2 AbLogVol_{t-1} + \delta LogME + TimeFEs + \varepsilon$$

Where in column (1) $DisMeasure_t$ is our disagreement measure in time period t, and in columns (2)-(5) it is the change in disagreement between $t-1$ and t. 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 in time periods t and $t-1$. *LogME* 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 company. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. Standard errors are in parenthesis.

	Abnormal Log Volume (t+1)				
Disagreement measure	(1)	(2)	(3)	(4)	(5)
All Investors	-0.001				
	(0.005)				
ΔAll Investors		0.008***			
		(0.003)			
ΔFundamental			0.009***		
			(0.002)		
ΔTechnical			0.011***		
			(0.003)		
ΔMomentum			0.016***		
			(0.003)		
ΔGlobal Macro			0.010***		
			(0.002)		
ΔGrowth			0.011***		
			(0.003)		
ΔValue			0.007***		
			(0.003)		
ΔNovice				0.010***	
				(0.003)	
ΔInvermediate				0.008***	
				(0.003)	
ΔProfessional				0.010***	
				(0.003)	
ΔDay Traders					0.004
					(0.003)
ΔSwing Traders					0.005
					(0.003)
ΔPosition Traders					0.005*
					(0.003)
ΔLong Term Investors					0.003
					(0.003)
Abnormal Log Volume	0.616***	0.614***	0.599***	0.607***	0.613***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Abnormal Log Volume (t-1)	0.189***	0.191***	0.207***	0.198***	0.192***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Log(ME)	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.151***	0.151***	0.153***	0.151***	0.153***
	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)
Observations	30,173	30,172	30,099	30,170	30,153
R-squared	0.619	0.619	0.620	0.619	0.618
Year, month, day of week FEs	X	X	X	X	X

Table 7: Disagreement Forecasting Returns

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

$$Abret_{t+1} = \alpha + \beta DisMeasure_t + \phi Abret_t + \gamma AbLogVol_t + \delta LogME + TimeFEs + \varepsilon$$

Where $Abret_{t+1}$ is the abnormal return (minus the value-weighted market index) on day $t+1$, *DisMeasure* is the level our disagreement measure on day t in columns (1) and (3) or the change in the disagreement measure between days t and $t-1$ in columns (2) and (4). In columns (3) and (4) we put cumulative abnormal returns for days $t+1$ to $t+5$ ($CAR[1,5]$) on the left-hand side. 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 in time periods t and $t-1$. *LogME* 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 company. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. Standard errors are in parenthesis.

	AbRet$_{t+1}$	AbRet$_{t+1}$	CAR[1,5]	CAR[1,5]
All Investor	-0.000	-0.000		
	(0.000)	(0.001)		
ΔAll Investors			-0.000	-0.000
			(0.000)	(0.001)
AbRet	0.054*	0.054*	-0.003	-0.003
	(0.028)	(0.028)	(0.029)	(0.029)
Abnormal Log Volume	0.001	0.001	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
Log(ME)	-0.000	-0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.004	0.004	0.024***	0.025***
	(0.003)	(0.003)	(0.007)	(0.007)
Observations	30,184	30,183	30,184	30,183
R-squared	0.007	0.007	0.014	0.014
Year, month, day of week FEs	X	X	X	X

Table 8: Trading Volume around Earnings Announcements

Note:In this table we examine how disagreement within different types of investors change around earnings announcements.

$$AbLogVol_{ti} = \alpha + \beta_1 1WeekBeforeEA_{ti} + \beta_2 EA_{ti} + \beta_3 1WeekAfterEA_{ti}$$
$$+\beta_4 2WeekAfterEA_{ti} + \beta_5 3WeekAfterEA_{ti} + TimeFEs + FirmFEs + \varepsilon_{ti}$$

Where $AbLogVol_{ti}$ 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_{ti} is a dummy variable equal one if firm i announces earnings on day t, $1WeekAfterEA_{ti}$, $2WeekAfterEA_{ti}$, $3WeekAfterEA_{ti}$ are dummy variables for weather day t for firm i falls in week 1, week 2, or week 3 after an earnings announcement, respectively. 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.

	Abnormal Log Volume		
1 Week Before EA	0.011	0.003	0.002
	(0.026)	(0.025)	(0.025)
EA day	0.641***	0.560***	0.563***
	(0.052)	(0.051)	(0.050)
1 Week After EA	0.368***	0.333***	0.318***
	(0.036)	(0.035)	(0.035)
2 Weeks After EA	0.104***	0.096***	0.093***
	(0.025)	(0.024)	(0.024)
3 Weeks After EA	0.047**	0.044*	0.043*
	(0.024)	(0.023)	(0.023)
Disagreement (t)		0.180***	0.156***
		(0.014)	(0.012)
Disagreeement (t-1)			0.071***
			(0.010)
Observations	30,184	30,184	30,183
R-squared	0.212	0.238	0.242
Year, month, dow FEs	X	X	X
Firm FE	X	X	X

Table 9: Disagreement around Earnings Announcements

Note:In this table we examine how disagreement within different types of investors change around earnings announcements.

$$Disagreement_{ti} = \alpha + \beta_1 1WeekBeforeEA_{ti} + \beta_2 EA_{ti} + \beta_3 1WeekAfterEA_{ti}$$
$$+ \beta_4 2WeekAfterEA_{ti} + \beta_5 3WeekAfterEA_{ti} + TimeFEs + FirmFEs + \varepsilon_{ti}$$

Where $Disagreement_{ti}$ is our disagreement measure 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_{ti} is a dummy variable equal one if firm i announces earnings on day t, $1WeekAfterEA_{ti}$, $2WeekAfterEA_{ti}$, $3WeekAfterEA_{ti}$ are dummy variables for weather day t for firm i falls in week 1, week 2, or week 3 after an earnings announcement, respectively. 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.

	Disagreement						
	All Investors	Fundamental	Technical	Momentum	Global Macro	Growth	Value
1 Week Before EA	0.043**	0.016	0.013	0.023	-0.050	-0.006	0.031
	(0.020)	(0.032)	(0.021)	(0.029)	(0.033)	(0.028)	(0.032)
EA day	0.44***	0.68***	0.500***	0.634***	0.323***	0.632***	0.664***
	(0.048)	(0.070)	(0.047)	(0.059)	(0.067)	(0.061)	(0.070)
1 Week After EA	0.197***	0.267***	0.197***	0.197***	0.175***	0.232***	0.303***
	(0.026)	(0.032)	(0.029)	(0.034)	(0.047)	(0.041)	(0.043)
2 Weeks After EA	0.045**	0.059**	0.053**	0.028	0.071**	0.051	0.074*
	(0.017)	(0.029)	(0.022)	(0.030)	(0.034)	(0.033)	(0.042)
3 Weeks After EA	0.018	0.002	0.004	-0.002	0.052*	0.032	-0.010
	(0.021)	(0.031)	(0.023)	(0.029)	(0.029)	(0.031)	(0.033)
Observations	30,248	30,248	30,248	30,248	30,248	30,248	30,248
R-squared	0.445	0.281	0.370	0.324	0.191	0.248	0.245
Year, month, dow FEs	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X