Investor Disagreement: Daily Measures from Social Media *

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Abstract

Disagreement is pervasive in financial markets. This paper highlights the properties of daily disagreement and daily attention measures derived from the investor social network StockTwits. Daily disagreement and trading volume are strongly related to one another, both in the sample used in Cookson and Niessner (2020) and out of sample through 2021. Disagreement among investors using different investment strategies as well as within them each relate to trading volume, but within-strategy disagreement exhibits a stronger relationship. These findings all hold after controlling for attention, which is also positively related to daily trading volume.

Keywords: Disagreement, Social Media, Social Finance, FinTech

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1. Introduction

Academic research in financial economics has devoted substantial attention toward understanding investor disagreement and its consequences. This inquiry has resulted in a rich theoretical literature with many testable implications (Aumann, 1976; Miller, 1977; Varian, 1985; Karpoff, 1987; Scheinkman and Xiong, 2003; Banerjee and Kremer, 2010; Banerjee et al., 2018, 2023). The empirical side of this literature has, out of necessity, employed proxies for investor disagreement that are either indirect or at low frequency (Kandel and Pearson, 1995; Daniel et al., 1998; Diether et al., 2002; Garfinkel and Sokobin, 2006). Many open questions remain. For example, disagreement is thought to be related to the very high average level of *daily* trading volume (Hong and Stein, 2007), whereas traditional disagreement proxies are measured monthly or quarterly. Similar measurement challenges confront researchers interested in the weak relationship between beliefs and trading (Charles et al., 2022; Giglio et al., 2021a) because proxies for disagreement are often based on investors' trading (e.g., Garfinkel, 2009).

A recent stream of papers has made progress on measurement of daily disagreement, drawing upon bullish and bearish posts of users of investor social media platforms (Giannini et al., 2018, 2019; Cookson and Niessner, 2020). This research has extended seminal work that analyzed the content of internet message boards (Antweiler and Frank, 2004) to provide daily measurement of disagreement. However, beyond the substantive contributions, these initial papers and the work on internet message boards that preceded them provided more of a proof of concept than a broad market measure of disagreement. For example, Cookson and Niessner (2020) focused on the 100 most actively discussed stocks on StockTwits using 1.5 years of data from 2013 to 2014. For questions that require a broad cross-section of firms, this sample frame is limiting, and the generalizability of the results to other firms and more recent time periods is unclear. This is a particularly salient concern as investor social media platforms − in particular, StockTwits − have become more popular over time. Figure 1 shows activity on the StockTwits platform, which saw consistent growth over the entire sample period, especially during the pandemic and throughout 2021.

In this paper, we extend the Cookson and Niessner (2020) disagreement measure from the original 2013-2014 sample to the full sample for which data are now available (2010-2021). We also extend the sample beyond the original 100 firms studied in Cookson and Niessner (2020), which now includes 10,390 firms with enough social media activity to define daily disagreement measures. Concurrent with posting this paper publicly, we are disclosing disagreement *and attention* data at the stock-day level.[1]

In this paper, we produce three sets of results that show that these updated measures behave

[1] Although disagreement and attention are theoretically distinct concepts, and recognized as such in the literature, they might still be related empirically. For this reason, we disclose the attention measure alongside the disagreement measures: it is natural to control for attention in tests that related disagreement to market outcomes. The disagreement and attention measures are available at `www.tonycookson.com/data-and-programs` and at `https://www.marinaniessner.com/data`. This initial data disclosure runs from 2010-2021. However, as part of this project, we plan to post updates to the data as new time periods become available.

very similarly to the original analysis on the broad sample of firms. That is, consistent with our original work, disagreement exhibits a tight connection with abnormal trading volume, within-group disagreement bears a closer relationship to abnormal trading activity than cross-group disagreement, and attention (i.e., number of messages at the stock-day level) also exhibits its own positive relation to abnormal trading volume. As in the original work, these findings are robust to the inclusion of controls for media coverage, recent returns, lagged trading activity, and recent volatility. Reassuringly, the magnitude of the disagreement-trading relationship does not change much upon expanding the sample to a broader cross-section and a longer time series.

In extending the sample to 2021, we consider three alternative ways to classify message sentiment, which underpins our disagreement measures. First, we extend the Maximum Entropy (MaxEnt) classifier developed in Cookson and Niessner (2020), second, we employ Stocktwits' own sentiment measure (which relies on a model called MarketLex), and finally we classify StockTwits messages based on VADER sentiment analysis (Hutto and Gilbert, 2014).[2] Irrespective of the underlying sentiment classification (MaxEnt, MarketLex or VADER), the resulting disagreement measures produce similar coefficient estimates in a regression of abnormal daily log volume on disagreement and controls.[3] Thus, given the similarity to other approaches and the transparency of applying the VADER model to our corpus, we have chosen to disclose measures of disagreement based on VADER sentiment classification, which produces an easily extendable measure with all classification choices in the public domain.

In addition to showing robustness to other measures, we obtain a similar estimates if we extend the sample beyond the 100 most actively-discussed firms (estimates range from 0.082 to 0.150). We also show that the estimates produce similar insights if we extend the sample through 2018 (for the MaxEnt classification measure) or until 2021 (for MarketLex and VADER). The resulting estimates from extending the sample in time range from 0.068 to 0.099 on the full sample. We similarly update the tests using within-group and cross-group disagreement measures as in Cookson and Niessner (2020). The finding that within-group disagreement is more tightly related to trading than cross-group disagreement is also robust to these extensions of the sample.

We expect our results and accompanying data disclosure to be of interest to the disagreement literature. In contrast to our firm-daily measures, most prior work on disagreement has employed disagreement measures that are low-frequency and indirect. For example, one popular proxy for investor disagreement is the dispersion of analyst forecasts (Diether et al., 2002; Nagel, 2005; Fischer et al., 2022), yet questions remain about whether investors' beliefs match those in analyst forecasts (McLean et al., 2020) and also whether investors update their beliefs with the same frequency. Hong and Stein (2007) note that much of the puzzle about the sheer volume of daily trade could be explained if we could properly measure disagreement. Indeed, this

[2]To match our entropy classification technique, we classified the messages that were scored by MarketLex's and VADER's continuous scale into bullish (Sentiment >0) and bearish (Sentiment <0) messages.

[3]Prior to this project to update the data to 2021, we updated the disagreement measures through 2018. This update to the disagreement measure held constant the entropy classification model, which was trained on 2013-2014 data, while extending the sample to 2018.

observation has led some scholars to use abnormal daily trading volume to proxy for investor disagreement (Garfinkel and Sokobin, 2006; Garfinkel, 2009; Hirshleifer et al., 2021)

Relying on these indirect proxies makes it difficult for academic research speak to questions about how belief differences (and their changes) lead to trading, and the conditions under which investors trade on belief differences. Hearkening back to the no trade theorem (Milgrom and Stokey, 1982), recent work that has matched survey responses to portfolio changes has shown that there is a surprising disconnect between belief changes and actions (Ben-David et al., 2018; Giglio et al., 2021b,a; Charles et al., 2022). Since our measure is based on investor *beliefs*, distinct from market outcomes like trading, our measure is potentially useful to consider the relation between beliefs and market actions.

There are many possible applications to the data we are disclosing as a companion to this paper. These applications have the potential to enrich the literature on disagreement, the literature on firm-daily measures of sentiment, and the literature on attention. Additionally, since these measures are explicitly drawn from social media, this setting permits further interesting applications within social finance (Bailey et al., 2018; Hirshleifer, 2020; Kuchler and Stroebel, 2021). For example, Cookson and Niessner (2020) and Giannini et al. (2019) shed new light into disagreement's evolution around earnings announcements. In a similar vein, Ben-Rephael et al. (2022) employ the daily disagreement measure through 2018 to show that equity market ambiguity creates a wedge between disagreement and trading. Hirshleifer et al. (2023) also employ StockTwits data on disagreement to speak to aspects of gradual information diffusion through social networks.

We also expect fruitful applications of the measures to speak to how retail traders interact with others in the market. For example, Cookson et al. (2021) show a relationship between disagreement on StockTwits and informed trading by short sellers and activists. Unlike measures that explicitly use short selling as a type of disagreement between short sellers and other market participants (e.g., Daniel et al., 2023), the StockTwits measure is a measure of disagreement among investors who post on the platform. As these investors are less sophisticated on average, it enables research to think about interactions between sophisticated and unsophisticated traders. Spurred partly by the GameStop short squeeze (Pedersen, 2022), there has been recent interest in the interaction between sophisticated market participants and retail investors (Welch, 2022; Ozik et al., 2021; Eaton et al., 2022). Our data disclosure provides a tool to understand these interactions.

Furthermore, the disagreement measure can be inverted to study questions about firm-day sentiment drawn from StockTwits. Renault (2017) showed that there are intraday predictability patterns using StockTwits sentiment. Cookson and Niessner (2020) showed longer term predictability that is different for novices versus professionals. Cookson et al. (2020) showed a differential evolution of sentiment by Republican investors relative to others, the pricing implications of which were also studied in Sheng et al. (2023).[4] While some of these existing

[4]Cookson et al. (2022) examine the differences in sentiment across different social media platforms. They find that there is a common component between StockTwits, Twitter and SeekingAlpha, but that common

applications require the use of message-level data, not all of them do. For example, Cookson et al. (2023) construct an abnormal sentiment measure around the timing of M&A announcements using stock-day level sentiment data. We expect other firm-specific market events could be studied in a similar fashion using the sentiment data that we are disclosing at the stock-day level.

Social media activity at the stock-day level can be used as a proxy for investor attention, which has generated significant academic interest in recent years (Da et al., 2011; Kwan et al., 2022; Levy et al., 2023; Da et al., 2022). The StockTwits-derived attention measure has been used as a control in Cookson and Niessner (2020) and in Cookson et al. (2022), and has also been the explicit subject of study in Irvine et al. (2021). Notably, the papers find that sentiment and attention capture qualitatively different economic phenomena (Cookson et al., 2022). Generally, there has been significant interest in financial research on social media more broadly as social media usage by investors has become more widespread (Dim, 2020; Chen et al., 2014; Chen and Hwang, 2022). In disclosing both sentiment and attention from social media to the academic community, we anticipate there being many potential applications.

2. Data and Measurement

In this section, we describe the StockTwits data, how the data update relates to the original published work (Cookson and Niessner (2020)), the different sentiment classifications (MaxEnt, MarketLex, VADER), and how these classifications are used to construct measures of disagreement.

2.1 Background or Overview of StockTwits

StockTwits is one of the largest investor social media platforms. It was founded in 2008 as a social network platform that enables investors to share their opinions about stocks. The website has a Twitter-like format, where participants post short messages and use "cashtags" with the stock ticker symbol (e.g., *"$AAPL"*) to link a user's message to a particular company. According to a website analytics tool, Alexa, StockTwits was ranked as the 505th most popular website in the US as of June 2021. Its users are predominantly male, and the number of users on StockTwits with a graduate school degree is over-represented relative to the educational attainment of users of other websites.

StockTwits provided us with the universe of messages posted between January 1, 2010 and December 31, 2021. In total, the dataset consists of 417,002,390 messages posted by 1,606,826 unique users. For each message, we observe a user identifier and the message content. We also observe indicators for self-classified sentiment (bullish, bearish, or unclassified), and "cashtags" that link the message to particular assets. We furthermore obtain the sentiment classification provided to us by StockTwits, which we describe in detail below. For more information about the

component is weaker. Still, StockTwits sentiment exhibits a stronger relation to retail trading and returns than the other platforms, which makes StockTwits a testing ground for theories about retail traders, which have gained popularity in the wake of the GameStop episode (Pedersen, 2022).

data, please refer to Cookson and Niessner (2020), who perform a series of validation exercises for using StockTwits data.

Following prior work, we restrict attention to messages that mention only one ticker to focus on sentiment that can be directly linked to a particular stock. This decreases the sample from 417,002,390 messages to 161,326,695 messages, which are authored by 1,033,417 users and cover about 10,390 firms. The summary statistics for this sample are presented in the first row of Table 1 Panel A.

StockTwits has grown significantly over time. Figure 1 shows that the monthly number of messages has gone up from several hundreds in 2010 to over 5 million by 2021. The figure also highlights the almost two-fold jump in the monthly number of messages between December 2020 and January/February 2021, during the Gamestop episode. Similarly, Figure 2 displays the number of unique users that have posted in a given month. We can see a similar pattern as in Figure 1, as well as a drastic jump around the Gamestop event. Figure 3 shows that the number of firms covered in a given month has grown in 2010, and has stayed pretty constant since then, experiencing a small jump around Gamestop. Finally, Figure 4 shows that the average number of messages per firm-day, has followed a similar growth pattern, as the total number of messsages and the number of unique users in Figures 1 and 2.

2.2 Sentiment and Disagreement from StockTwits

2.2.1 Sentiment Classification

We employ several sentiment-classification techniques.

First, we use the sentiment selected by the author of the post. When posting on StockTwits a user has the option of selecting a "Bullish" or a "Bearish" sentiment, or leaving the sentiment blank. We call this self-classified sentiment, and code it as +1 for "Bullish" and -1 for "Bearish."

Second, we use the Maximum Entropy classification used in Cookson and Niessner (2020). The underlying 'Principle of Maximum Entropy' states that when nothing is known about the distribution, it should be as uniform as possible, i.e., have maximum entropy. Due to the minimal assumptions made by the Maximum Entropy classification approach, it is commonly used for language detection, topic classification, and sentiment analysis. We use the set of messages with self-classified sentiment as the training dataset, and classify all messages with missing self-classified sentiment on a continuous scale that is normalized to be between -1 (extremely bearish) to +1 (extremely bullish). We train/classify messages within the same investment approach, as language used by Technical and Fundamental investors, for example, can be quite different.

Third, we use the sentiment calculated and provided by StockTwits based on a proprietary text-classification algorithm called MarketLex. According to StockTwits, this methodology uses lexical and semantic rules based on a custom-built lexicon for social finance, constructed from a combination of words and phrases from 4 million messages with user-provided bullish or bearish tags and manual human supervision. The final sentiment score for each tweet is a continuous measure that is normalized to be between -1 (extremely bearish) to +1 (extremely bullish).

Finally, we use VADER (Valence Aware Dictionary and Sentiment Reasoner) to classify the sentiment of the message's text. VADER is a sentiment package that was explicitly designed to measure sentiment from social media. VADER relies on a lexicon and five general rules to map lexical features to sentiment scores (Hutto and Gilbert (2014)). VADER does not require any training data, as it uses a human-validated sentiment lexicon and general rules that are related to grammar and syntax.

2.2.2 Disagreement measures

To construct disagreement measures, we follow Cookson and Niessner (2020) and discretize continuous sentiment measures from Maximum Entropy, MarketLex, and VADER to be +1 (Bullish) if sentiment is greater than 0, and -1 (Bearish) if sentiment is less than zero. We exclude observations with sentiment equal 0 (neutral). As seen in Table 1, Panel A, for MarketLex that reduced the number of messages to 78,605,805 and for VADER to 86,375,771. The decrease in firm-day observations and the average number of messages per firm-day is less as a percentage of the overall sample sizes.

In later tests, we decompose the disagreement measure into disagreement within and across groups of investors with different investment philosophies. Therefore, we follow Cookson and Niessner (2020) and drop StockTwits messages posted by users who don't select an investment approach in their profile, as well users with a "Global macro" approach, since there are very few of those users. The summary statistics of the samples with these restrictions for StockTwits-classified and VADER-classified sentiment measures are presented in Table 1, Panel A.

We construct the main disagreement measure by computing the standard deviation of expressed sentiment across messages for a given $firm \times day$. To aggregate sentiment at the firm-day level ($AvgSentiment_{it}$), we compute average sentiment across all tweets about a firm i from 4:00 pm (close) on date $t-1$ to 4:00 pm on date t. Because the underlying sentiment variable is binary (-1 for a bearish sentiment and 1 for a bullish sentiment), the variance in the sentiment measure for a firm i during a time period t equals $1 - AvgSentiment_{it}^2$. Our disagreement measure is the standard deviation of sentiment, which equals:

$$Disagreement_{it} = \sqrt{1 - AvgSentiment_{it}^2}. \tag{1}$$

The $AvgSentiment_{it}$ measure ranges from -1 (all bearish) to $+1$ (all bullish), while the disagreement measure ranges from 0 to 1, with 1 signifying maximal disagreement. We apply the formula to firm-day observations that have non-zero messages. When there are no messages for a firm-day-group, it is not possible to compute the standard deviation of sentiment across messages. For this corner case, we maintain the assumption that non-posting means that traders do not wish to buy or sell in the near term. Accordingly, we normalize disagreement in the no-message case to 0, consistent with latent agreement, following the definition in Cookson and Niessner (2020). This choice regarding how to normalize the no-message case is consistent with the idea that minimal disagreement should correspond to minimal trading.

As in Cookson and Niessner (2020), we also construct within-group disagreement and cross-group disagreement to proxy for information-based and model-based disagreement among investors. For within-group disagreement, we first apply the formula in equation (1), to messages of individuals with the same investment philosophy: Technical, Fundamental, Value, Growth, Momentum. Then we take the weighted-average of the within-group disagreement measures. The weights are proportional to the number of investors adhering to each approach. Separately, we construct a measure of cross-group disagreement by computing the standard deviation of average sentiment ($AvgSentiment_{itg}$) across investment approaches, weighted by the number of individuals in that approach group. We implement the weighted approach to give our measure internal consistency, as dispersion of beliefs between two groups with many investors will contribute more to trading volume than dispersion of beliefs between two groups with few investors. The formula for cross-group disagreement is

$$CrossDisagremeent_{it} = \sqrt{\frac{\sum_{a \in A} n_a (AvgSentiment_{at} - AvgSentiment_t)^2}{\frac{G-1}{G}(n_F + n_T + n_M + n_V + n_G)}} \ , \tag{2}$$

where A ={Fundamental, Technical, Momentum, Value, or Growth}, n_a is the number of individuals in group a in January 2013, $AvgSentiment_{at}$ is the average sentiment of group a from 4:00 pm (close) on date $t-1$ to 4:00 pm on date t, $AvgSentiment_t$ is the average sentiment of all groups from 4:00 pm (close) on date $t-1$ to 4:00 pm on date t, and G is the number of investment philosophies.

2.3 Attention from StockTwits messages

We construct two versions of the attention measure from StockTwits messages. First, we count the number of messages on StockTwits about a firm i from 4:00 pm (close) on date $t-1$ to 4:00 pm on date t. This count is an absolute measure of firm-day attention derived from StockTwits activity. To control for investor attention in a non-linear fashion, we split the absolute attention measure into quartiles. In particular, *Num. Messages Q1* through *Q4*, is the number of non-zero and non-missing-sentiment messages in a given quartile. To account for growth in messages on StockTwits over time, the quartiles are generated within a year. When we control for attention non-linearly, *Num Messages Q1* is the omitted category. Both Cookson et al. (2022) and Irvine et al. (2021) employ versions of this relative attention measure.

2.4 Discussion of Validation and Uses of the Measures

Previous work on StockTwits has validated the use of these measures across a variety of sample choices.

The first and most basic validation of the disagreement measure is that disagreement bears a tight relation to trading volume at the stock-day level. Cookson and Niessner (2020) show this basic finding on an early StockTwits sample (2013-2014), and Cookson et al. (2022) replicate and extend the result in the 2013-2020 sample of stock-day observations. Giannini et al. (2018) and Giannini et al. (2019) assemble independently-constructed disagreement measures from StockTwits, also finding a tight connection to trading. In all these examples, StockTwits disagreement has a strong relationship contemporaneously and for next-day trading. However, the connection to trading is short lived, lasting one or two days. Consistent with these short-lived effects, these measures exhibit relatively low autocorrelation. An important implication of this is that monthly disagreement measures, like those drawn from dispersion in analyst forecasts, have a weak correlation with the daily measures we emphasize in this article. The two kinds of measures serve different purposes, depending on whether the appropriate frequency of a study is daily versus monthly or quarterly.

Other research has validated the measurement of sentiment from StockTwits in complementary ways. Renault (2017) shows that there is intra-day stock return predictability, whereas Cookson and Niessner (2020) show that this predictability is longer-lived if you focus on the sentiment of professionals whose recommendations consistently outperform the recommendations of novices. Cookson and Niessner (2020) also show that sentiment on StockTwits updates positively around positive news earnings announcements, and vice versus around negative earnings announcements, especially for self-proclaimed fundamental investors. Moreover, Cookson et al. (2020) show that the aggregate sentiment on StockTwits tracks well the fall of the S&P500 through the onset of the Covid-19 pandemic and that the index constructed from StockTwits bears a strong similarity to sentiment indexes based on aggregate news.

Lastly, there are at least two other ways that the daily disagreement measures from StockTwits interact with other market phenomena that show the potential for using the measures in new applications. First, Cookson et al. (2021) shows that high levels of daily StockTwits translate into higher stock prices, followed by a reversal, especially in the presence of short sale constraints. This is evidence of a Miller (1977)-style disagreement effect that occurs at the daily frequency. Second, Ben-Rephael et al. (2022) show that disagreement's relation to trading weakens in the presence of higher stock-day ambiguity, consistent with a weaker transmission of beliefs into actions. All these results are consistent with what should be theoretically expected of a disagreement measure, and they also show the viability of using the measure beyond the initial sample in which it was proposed.

Other research has used the StockTwits sentiment indexes that form the basis of our disagreement measures. For example, Hirshleifer et al. (2023) employ StockTwits data in tests of gradual information diffusion, Cookson et al. (2023) show that abnormal StockTwits sentiment around merger announcements is predictive of merger completion, Dessaint et al. (2021) show that the introduction of social media information on StockTwits makes short horizon forecasts more accurate, but not long-term forecasts, and Sheng et al. (2023) show that political disagreements are priced during Covid-19, employing StockTwits data in several important tests. These and other concurrent findings using StockTwits data highlight the promise of the measures presented here.

In the following section, we replicate and extend the findings from Cookson and Niessner (2020), showing the stability of the measure's relation to trading activity, which remains as we expand the sample in time and in the number of firms covered.

3. Results

In this section, we show how the disagreement measures described in the previous section replicate the focal specifications in Cookson and Niessner (2020). We next proceed to show how these results generalize out of sample in two ways: (i) applying to a broader cross-section of firms, and (ii) updating through present day. We also describe the properties of the attention measures that can be derived from social media activity.

3.1 Overall Disagreement

We first replicate our main result in Cookson and Niessner (2020) that disagreement among investors on StockTwits is positively correlated with contemporaneous abnormal trading volume. As seen in Table 2, Panel A, column (1), a standard deviation increase in investor disagreement is associated with a 9.6% higher contemporaneous abnormal trading volume. As in the original paper, we restrict our analysis to January 2013 trough September 2014, as well as to the top 100 most talked-about firms on StockTwits during that time period. We next examine different vintages of our disagreement measure, as well as different sentiment classification schemes. In columns (2) and (3), we use the Maximum Entropy classification method, but using the same 2010-2014 time period as the training dataset. In column (2) we keep the original time period, but expand the cross-sectional number of firms to all firms mentioned on StockTwits during that time period. In column (3) we expand the time period to cover 2010 to 2018. While the effect decreases slightly when we expand the cross-section of firms covered, the effect drops by about 1/3 when we expand the time period to 2010-2018. This is in part due to the fact that we use the 2010-2014 training sample to classify data through 2018. As the language changes over time, classification precision can decline. In columns (4)-(6) and (7)-(9) we replicate the original analysis, as well as the expanded cross section and time series, using the two new sentiment classification methods: the one provided to us by StockTwits that uses MarketLex, and using VADER. As the results suggest, both sentiment classification methods, produce very similar results. The effect for the full sample and all of the specifications that employ VADER – columns (7) and (9) – is also strikingly similar to the original effect in Cookson and Niessner (2020).

Since in the next section we focus on within- and across-group disagreement, in Panel B, we restrict the analysis to messages that are written by authors with non-missing self-reported approach. Similar to the original paper, we also exclude authors with self-reported "Global-Macro" approach, as there are very few individuals who follow that investment philosophy. Which excluding these messages changes the coefficients, increasing some and decreasing others, the overall results are pretty similar to using all messages in Panel A. Furthermore, given that VADER and ST sentiment, yield very similar results, for the rest of the note we use the VADER classification, as it's more generalizable to future data versions and other social media datasets. Therefore, going forward, Disagreement 2021 refers to the VADER-implied disagreement measures.

3.2 Within- and Across-group Disagreement

In Cookson and Niessner (2020), we use disagreement among individuals with different investment philosophies (cross-group) to proxy for model-based investor disagreement, and disagreement among individuals with the same investment philosophy (within-group) to proxy for information-based investor disagreement. In Table 3, we replicate our original results, and then examine how increases in cross-section and time series impact the results. In column (1), we find that, as in the original paper, information-based disagreement has a stronger association with same-day abnormal trading volume than model-based disagreement (17.6% increase vs. 4.5%). In columns (2) - (6), we show that this difference in the two sources of disagreement is consistent across different cross-sections of stocks as well as different time periods. In particular, the effects in column (6) using all firms mentioned at least once on StockTwits, 2010-2021 time period, as well as the VADER sentiment classifier, yields very similar relationship between within- and across-group disagreement measures and abnormal trading volume to the original results in column (1).

3.3 Attention Controls

One problem with just using the disagreement measure is that its precision varies with the number of messages posted. For this reason, it is useful to control for number of messages, or attention, when relating disagreement to market outcomes.

In this section, we replicate the analysis in Tables 2 and 3 while controlling for attention. We present the results in Tables 4 and 5. In Table 4 we control for attention linearly by including a the number of messages at the firm-day level. As expected, attention to a stock is positively associated with contemporaneous abnormal trading volume. While the coefficients on disagreement are slightly smaller after controlling for attention, the overall relationship between disagreement and trading volume does not change much.

Because the relationship between investor attention and abnormal trading volume could be non-linear, in Table 5, we control for investor attention flexibly using indicator variable for quartiles of message volume. In particular, *Num. Messages Q1* through *Q4* indicate whether the firm-day observation belongs to quartiles Q1, Q2, Q3 or Q4 in terms of its number of non-missing-sentiment messages in a given quartile (in comparison to firm-day observations within the same year). The quartiles are generated within a year, to account for the growth of messages over time. Num. Messages Q1 is the omitted category. The coefficients on disagreement in Panel A, decrease by about half, relative to controlling for attention linearly. In column B, the importance of cross-group disagreement decreases even further, while the within-group disagreement coefficients barely change. This is even stronger evidence, that disagreement driven by information differences has an important effect on trading volume.

4. Conclusion

Disagreement is a fundamental aspect of financial market equilibrium. Until recent data from investor social media, a beliefs-based measure of disagreement in a broad market setting has remained elusive. With the spike in popularity of investor social media platforms concurrent with the democratization of finance, the coverage of firms at the daily frequency and depth of the information contained in social media has increased dramatically over time. In this paper, we show that this spike in investor social media activity creates an opportunity for academic research to provide insight into questions around higher-frequency investor disagreement and attention. Not only do the original findings in this literature generalize, but the data have increased in their depth of information and coverage to a broad cross-section of stocks. We anticipate many future applications to the disagreement and attention measures we disclose here, and we look forward to the insights derived from this future work.

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Figure 1. **Number of Messages over Time**

In this figure, we plot the number of messages on StockTwits over time, at the monthly frequency. The data spans from January 2010 until December 2021.

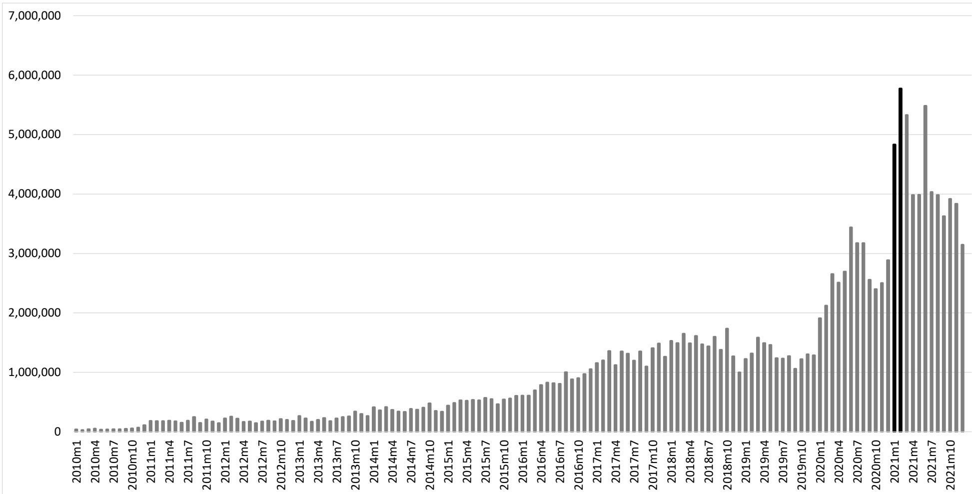

Figure 2. **Number of Unique Users over Time**

In this figure, we plot over time the number of unique users who posted on StockTwits in a given month. The data spans from January 2010 until December 2021.

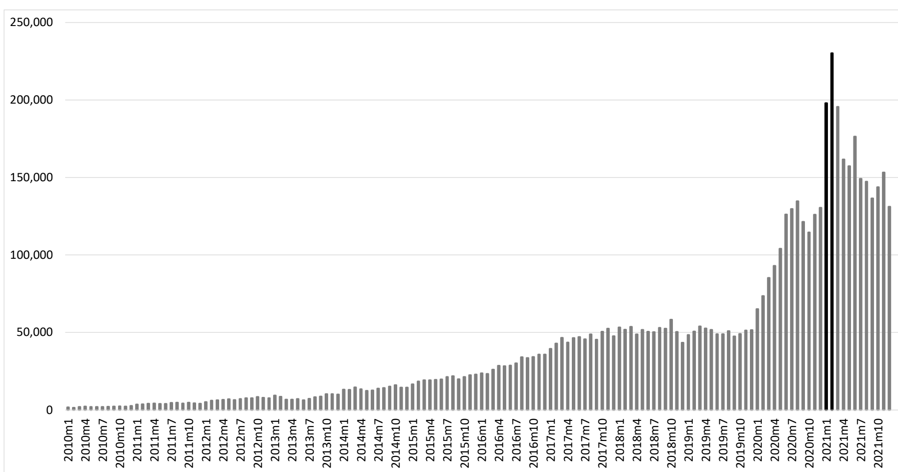

Figure 3. **Number of Unique Firms Covered over Time**

In this figure, we plot over time the number of unique firms that were covered on StockTwits in a given month. The data spans from January 2010 until December 2021.

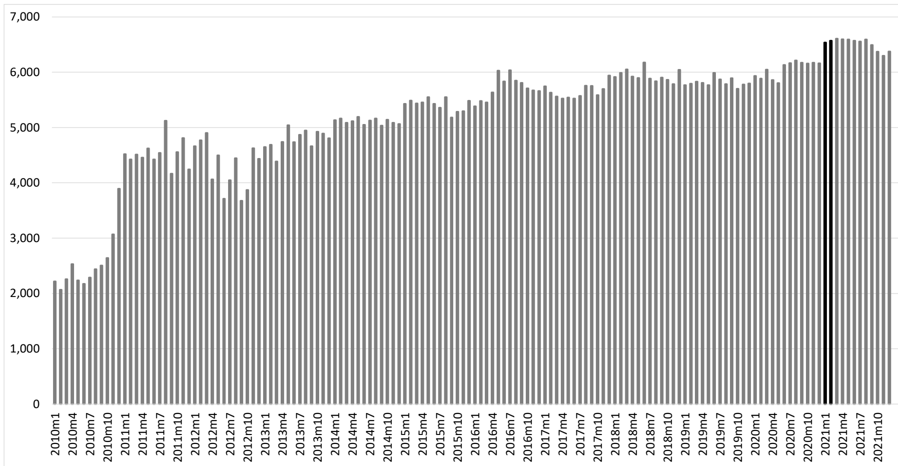

Figure 4. **Average Number of Messages per Firm-Day**

In this figure, we plot the number of messages on StockTwits on a given firm-day averaged at the monthly level. The data spans from January 2010 until December 2021.

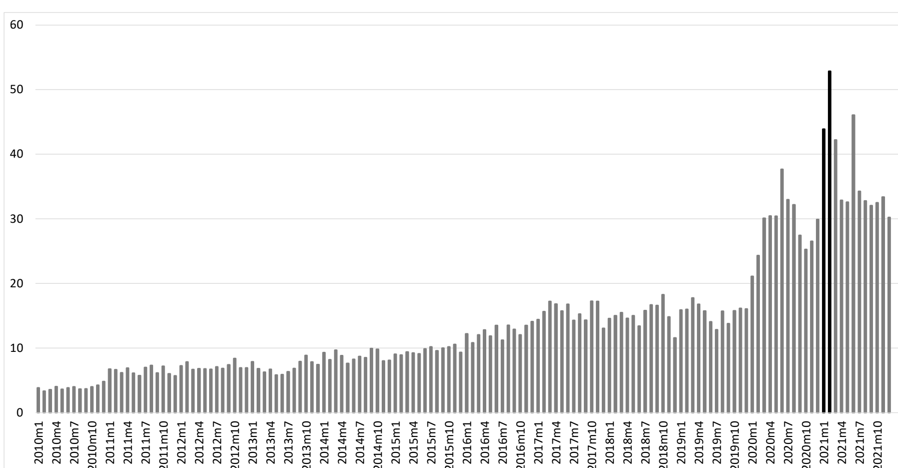

Table 1. **Summary Statistics**

This tabled displays summary statistics for the StockTwits dataset from 1 January, 2010 to 31 December, 2021. Panel A shows how sample restrictions reduce the of observations to arrive at our analysis sample. The 1st row is the full sample. The 2nd and 4th rows show the restriction of keeping non-missing and non-zero sentiment provided by StockTwits (using MarketLex) or obtained applying the VADER method, respectively. The 3rd and 5th rows, show how the sample changes when we add the restriction that the self-reported approach has to be non-missing and non-global-macro. Panel B shows the correlation between disagreement measures constructed from the StockTwits-generated sentiment, VADER-based sentiment, and self-reported sentiment.

Panel A: Observations satisfying sample restriction

Sample Restriction	Number of messages	Firm-day obs.	Avg. Num. Messages per firm-day	Firms covered per month
Full sample	161,326,695	8,851,529	18.22	4,832.6
Non-missing & non-zero ST sentiment	78,605,805	6,074,032	12.94	4,468.54
Non-missing & non-"Global macro" approach	18,068,140	3,482,891	5.18	3,895.68
Non-missing & non-zero VADER sentiment	86,375,771	6,267,196	13.78	4,347.77
Non-missing & non-"Global macro" approach	19,319,089	3,818,621	5.05	3,838.15

Panel B: Correlation of Disagreement Measures

	ST	VADER	Self-reported
ST	1	0.5684	0.4436
VADER	0.5684	1	0.4305
Self-reported	0.4436	0.4305	1

Table 2. **Disagreement**

$AbLogVol(t)$ is the difference between log volume in period t and the average log volume from trading days t-140 to t-20 (six-month period, skipping a month) for firm i. *Disagreement 2015 (z)* is the disagreement among all investors from January 2013 to September 2014, used in Cookson and Niessner (2020), with sentiment classified using MaxEnt method. *Disagreement 2018 (z)* is the disagreement among all investors from January 2010 to December 2018, using StockTwits' sentiment classification. *Disagreement ST 2021 (z)* and *Disagreement VADER 2021 (z)* are the disagreement among all investors from January 2010 to December 2021 using sentiment from StockTwits (MarketLex) and VADER, respectively. We standardize the disagreement measure and the number of messages by subtracting the mean and dividing by the standard deviation, calculated over the entire sample period. Columns (1), (4), and (7) restrict the sample to the top 100 firms talked about on StockTwits between 2010-2014, used in Cookson and Niessner (2020). The rest of the columns use all firms available during the sample period. Since trading volume tends to be autocorrelated, we also control for abnormal trading volume on day t-1. Controls include $Media(t)$, a dummy variable equal to 1 if firm i was mentioned in the Wall Street Journal on day t, volatility (t-5 to t-1), the standard deviation of abnormal returns over days t-5 to t-1, and cumulative abnormal returns over days t-30 to t-6 and t-5 to t-1. All regressions include date and firm fixed effects. Standard errors are clustered by firm and date. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively (*t*-statistics in parentheses).

Panel A: Using All Messages

	Abnormal Log Volume (t)								
	2013-2014	2013-2014	2010-2018	2013-2014	2013-2014	2010-2021	2013-2014	2013-2014	2010-2021
	100 firms	all firms	all firms	100 firms	all firms	all firms	100 firms	all firms	all firms
Disagreement Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Disagreement 2015 (z)	0.096***								
	(0.008)								
Disagreement 2018 (z)		0.082***	0.068***						
		(0.001)	(0.001)						
Disagreement ST 2021 (z)				0.099***	0.143***	0.100***			
				(0.008)	(0.002)	(0.001)			
Disagreement VADER 2021 (z)							0.088***	0.150***	0.099***
							(0.007)	(0.003)	(0.001)
AbLogVol (t-1)	0.723***	0.555***	0.595***	0.716***	0.551***	0.623***	0.718***	0.553***	0.624***
	(0.015)	(0.005)	(0.003)	(0.015)	(0.005)	(0.003)	(0.015)	(0.005)	(0.003)
Media (t)	0.174***	0.270***	0.200***	0.170***	0.265***	0.171***	0.171***	0.254***	0.164***
	(0.030)	(0.017)	(0.013)	(0.031)	(0.017)	(0.012)	(0.030)	(0.017)	(0.011)
Volatility (t-5 to t-1)	0.194	1.041***	0.991***	0.174	0.924***	0.620***	0.185	0.901***	0.615***
	(0.226)	(0.091)	(0.041)	(0.222)	(0.089)	(0.034)	(0.225)	(0.092)	(0.034)
AbRet (t-5 to t-1)	0.183***	0.166***	0.065***	0.182***	0.167***	0.068***	0.195***	0.196***	0.078***
	(0.052)	(0.021)	(0.009)	(0.052)	(0.021)	(0.007)	(0.052)	(0.021)	(0.007)
AbRet (t-30 to t-6)	0.113***	0.207***	0.130***	0.110***	0.204***	0.111***	0.114***	0.212***	0.114***
	(0.025)	(0.012)	(0.007)	(0.025)	(0.013)	(0.005)	(0.025)	(0.013)	(0.005)
R2	0.642	0.473	0.453	0.646	0.476	0.498	0.644	0.476	0.498
Observations	42,389	751,495	4,534,448	42,389	751,495	7,212,649	42,389	751,495	7,212,649

Panel B: Disagreement using non-missing Approach

	Abnormal Log Volume (t)								
	2013-2014 100 firms	2013-2014 all firms	2010-2018 all firms	2013-2014 100 firms	2013-2014 all firms	2010-2021 all firms	2013-2014 100 firms	2013-2014 all firms	2010-2021 all firms
Disagreement Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Disagreement 2015 (z)	0.096***								
	(0.008)								
Disagreement 2018 (z)		0.093***	0.075***						
		(0.002)	(0.001)						
Disagreement ST 2021 (z)				0.087***	0.128***	0.114***			
				(0.006)	(0.002)	(0.002)			
Disagreement VADER 2021 (z)							0.076***	0.135***	0.119***
							(0.006)	(0.003)	(0.002)
AbLogVol (t-1)	0.723***	0.560***	0.603***	0.715***	0.557***	0.632***	0.717***	0.558***	0.633***
	(0.015)	(0.005)	(0.003)	(0.015)	(0.005)	(0.003)	(0.015)	(0.005)	(0.003)
Media (t)	0.174***	0.285***	0.215***	0.167***	0.276***	0.167***	0.168***	0.265***	0.157***
	(0.030)	(0.018)	(0.014)	(0.030)	(0.018)	(0.012)	(0.030)	(0.018)	(0.012)
Volatility (t-5 to t-1)	0.194	0.884***	0.805***	0.154	0.772***	0.390***	0.174	0.737***	0.367***
	(0.226)	(0.090)	(0.039)	(0.223)	(0.088)	(0.030)	(0.225)	(0.090)	(0.030)
AbRet (t-5 to t-1)	0.183***	0.162***	0.066***	0.183***	0.156***	0.054***	0.196***	0.186***	0.067***
	(0.052)	(0.021)	(0.010)	(0.052)	(0.021)	(0.007)	(0.052)	(0.021)	(0.007)
AbRet (t-30 to t-6)	0.113***	0.199***	0.124***	0.108***	0.195***	0.097***	0.114***	0.203***	0.101***
	(0.025)	(0.013)	(0.007)	(0.025)	(0.013)	(0.005)	(0.025)	(0.013)	(0.005)
R2	0.642	0.488	0.467	0.647	0.491	0.519	0.645	0.491	0.520
Observations	42,389	616,451	3,305,605	42,389	616,451	4,889,937	42,389	616,451	4,889,937

Table 3. **Across- and Within-group disagreement**

AbLogVol(t) is the difference between log volume in period t and the average log volume from trading days t-140 to t-20 (six-month period, skipping a month) for firm i. *Cross-group (z)* is disagreement across different investment philosophies for firm i on day t. *Within-group* is disagreement among investors with the same investment philosophies for firm i on day t. For 2015, sentiment is calculated using MaxEnt method. For 2018, we use sentiment provided by StockTwits, and only keep non-zero and non-missing messages. For 2021, we use the VADER method for sentiment classification, and only keep messages with non-zero sentiment. We drop all messages by authors with a missing investment strategy of who identify as having "Global Macro" as their investment strategy. We standardize the disagreement measure and the number of messages by subtracting the mean and dividing by the standard deviation, calculated over the entire sample period. Since trading volume tends to be autocorrelated, we also control for abnormal trading volume on day t-1. Controls include $Media(t)$, a dummy variable equal to 1 if firm i was mentioned in the Wall Street Journal on day t, volatility (t-5 to t-1), the standard deviation of abnormal returns over days t-5 to t-1, and cumulative abnormal returns over days t-30 to t-6 and t-5 to t-1. All regressions include date and firm fixed effects. Standard errors are clustered by firm and date. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively (t-statistics in parentheses).

	Abnormal Log Volume (t)					
	2013-2014 100 firms	2013-2014 all firms	2010-2018 all firms	2013-2014 100 firms	2013-2014 all firms	2010-2021 all firms
Disagreement Measure	(1)	(2)	(3)	(4)	(5)	(6)
Cross-group 2015 (z)	0.045***					
	(0.008)					
Within-group 2015 (z)	0.176***					
	(0.013)					
Cross-group 2018 (z)		0.007***	0.005***			
		(0.002)	(0.001)			
Within-group 2018 (z)		0.064***	0.059***			
		(0.004)	(0.003)			
Cross-group 2021 (z)				0.025***	0.065***	0.061***
				(0.007)	(0.001)	(0.001)
Within-group 2021 (z)				0.100***	0.177***	0.170***
				(0.007)	(0.005)	(0.003)
AbLogVol (t-1)	0.704***	0.569***	0.609***	0.694***	0.553***	0.627***
	(0.017)	(0.005)	(0.003)	(0.018)	(0.005)	(0.003)
Media (t)	0.135***	0.263***	0.193***	0.110***	0.205***	0.098***
	(0.029)	(0.019)	(0.016)	(0.027)	(0.017)	(0.012)
Volatility (t-5 to t-1)	0.041	0.762***	0.695***	-0.027	0.476***	0.123***
	(0.228)	(0.091)	(0.040)	(0.224)	(0.090)	(0.028)
AbRet (t-5 to t-1)	0.180**	0.168***	0.069***	0.189***	0.183***	0.057***
	(0.053)	(0.021)	(0.010)	(0.055)	(0.021)	(0.007)
AbRet (t-30 to t-6)	0.103***	0.195***	0.120***	0.105***	0.195***	0.086***
	(0.027)	(0.013)	(0.007)	(0.027)	(0.014)	(0.005)
R2	0.655	0.488	0.472	0.663	0.507	0.538
Observations	42,389	557,456	2,944,353	42,389	557,456	4,131,469

Table 4. **Controlling for Attention**

In this table we control for attention - number of messages posted on day t about firm i. $AbLogVol(t)$ is the difference between log volume in period t and the average log volume from trading days t-140 to t-20 (six-month period, skipping a month) for firm i. *Num. Messages* is the number of non-zero and non-missing sentiment messages about firm i on day t. In Panel A, *Disagreement 2015 (z)* is the disagreement among all investors from January 2013 to September 2014, used in Cookson and Niessner (2020), with sentiment classified using MaxEnt method. *Disagreement 2018 (z)* is the disagreement among all investors from January 2010 to December 2018, using StockTwits' sentiment classification. *Disagreement 2021 (z)* is the disagreement among all investors from January 2010 to December 2021 using sentiment from the VADER model. In Panel B, *Cross-group (z)* is disagreement across different investment philosophies for firm i on day t. *Within-group* is disagreement among investors with the same investment philosophies for firm i on day t. We standardize the disagreement measure and the number of messages by subtracting the mean and dividing by the standard deviation, calculated over the entire sample period. Since trading volume tends to be autocorrelated, we also control for abnormal trading volume on day t-1. Controls include $Media(t)$, a dummy variable equal to 1 if firm i was mentioned in the Wall Street Journal on day t, volatility (t-5 to t-1), the standard deviation of abnormal returns over days t-5 to t-1, and cumulative abnormal returns over days t-30 to t-6 and t-5 to t-1. All regressions include date and firm fixed effects. Standard errors are clustered by firm and date. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively (t-statistics in parentheses).

Panel A: Disagreement

	Abnormal Log Volume (t)					
Disagreement Measure	2013-2014 100 firms (1)	2013-2014 all firms (2)	2010-2018 all firms (3)	2013-2014 100 firms (4)	2013-2014 all firms (5)	2010-2021 all firms (6)
Disagreement 2015 (z)	0.086***					
	(0.007)					
Disagreement 2018 (z)		0.080***	0.065***			
		(0.002)	(0.001)			
Disagreement 2021 (z)				0.081***	0.145***	0.095***
				(0.007)	(0.003)	(0.001)
Num. Messages (z)	0.031**	0.063***	0.066***	0.031**	0.057***	0.060***
	(0.009)	(0.019)	(0.011)	(0.009)	(0.017)	(0.011)
AbLogVol (t-1)	0.712***	0.553***	0.592***	0.708***	0.552***	0.621***
	(0.017)	(0.005)	(0.003)	(0.017)	(0.005)	(0.003)
Media (t)	0.125***	0.237***	0.156***	0.122***	0.225***	0.120***
	(0.027)	(0.017)	(0.014)	(0.027)	(0.016)	(0.014)
Volatility (t-5 to t-1)	0.118	0.942***	0.829***	0.107	0.819***	0.493***
	(0.222)	(0.091)	(0.046)	(0.221)	(0.092)	(0.036)
AbRet (t-5 to t-1)	0.144**	0.154***	0.036**	0.155**	0.185***	0.047***
	(0.054)	(0.021)	(0.013)	(0.055)	(0.021)	(0.009)
AbRet (t-30 to t-6)	0.099***	0.201***	0.120***	0.099***	0.207***	0.101***
	(0.029)	(0.013)	(0.007)	(0.028)	(0.013)	(0.005)
R2	0.652	0.476	0.458	0.654	0.478	0.502
Observations	42,389	751,495	4,534,448	42,389	751,495	7,212,649

Panel B: Across- and Within-group Disagreement

	Abnormal Log Volume (t)					
	2013-2014 100 firms	2013-2014 all firms	2010-2018 all firms	2013-2014 100 firms	2013-2014 all firms	2010-2021 all firms
Disagreement Measure	(1)	(2)	(3)	(4)	(5)	(6)
Cross-group 2015 (z)	0.048***					
	(0.008)					
Within-group 2015 (z)	0.151***					
	(0.013)					
Cross-group 2018 (z)		0.013***	0.014***			
		(0.002)	(0.002)			
Within-group 2018 (z)		0.049***	0.035***			
		(0.005)	(0.005)			
Cross-group 2021 (z)				0.031***	0.065***	0.060***
				(0.007)	(0.001)	(0.001)
Within-group 2021 (z)				0.089***	0.167***	0.156***
				(0.007)	(0.005)	(0.004)
Num. Messages (z)	0.029**	0.059**	0.075***	0.025**	0.034**	0.039***
	(0.009)	(0.019)	(0.016)	(0.008)	(0.011)	(0.009)
AbLogVol (t-1)	0.698***	0.567***	0.606***	0.690***	0.553***	0.626***
	(0.018)	(0.005)	(0.003)	(0.018)	(0.005)	(0.003)
Media (t)	0.100***	0.242***	0.158***	0.082**	0.193***	0.080***
	(0.027)	(0.019)	(0.017)	(0.026)	(0.018)	(0.013)
Volatility (t-5 to t-1)	-0.007	0.695***	0.590***	-0.067	0.447***	0.099***
	(0.226)	(0.091)	(0.045)	(0.223)	(0.090)	(0.028)
AbRet (t-5 to t-1)	0.147**	0.158***	0.044**	0.161**	0.176***	0.043***
	(0.055)	(0.021)	(0.014)	(0.057)	(0.021)	(0.008)
AbRet (t-30 to t-6)	0.093**	0.191***	0.114***	0.096**	0.192***	0.082***
	(0.030)	(0.014)	(0.008)	(0.030)	(0.014)	(0.006)
R2	0.662	0.490	0.476	0.668	0.508	0.539
Observations	42,389	557,456	2,944,353	42,389	557,456	4,131,469

Table 5. **Controlling for Attention Flexibly**

In this table, we control for attention flexibly. $AbLogVol(t)$ is the difference between log volume in period t and the average log volume from trading days t-140 to t-20 (six-month period, skipping a month) for firm i. *Num. Messages* Q1 through Q4, is the number of non-zero and non-missing-sentiment messages in a given quartile. The quartiles are generated within a year, to account for the growth of messages over time. *Num. Messages Q1* is the omitted category. In Panel A, *Disagreement 2015 (z)* is the disagreement among all investors from January 2013 to September 2014, used in Cookson and Niessner (2020), with sentiment classified using MaxEnt method. *Disagreement 2018 (z)* is the disagreement among all investors from January 2010 to December 2018, using StockTwits' sentiment classification. *Disagreement 2021 (z)* is the disagreement among all investors from January 2010 to December 2021 using sentiment from the VADER model. In Panel B, *Cross-group (z)* is disagreement across different investment philosophies for firm i on day t. *Within-group* is disagreement among investors with the same investment philosophies for firm i on day t. We standardize the disagreement measure and the number of messages by subtracting the mean and dividing by the standard deviation, calculated over the entire sample period. Since trading volume tends to be autocorrelated, we also control for abnormal trading volume on day t-1. Controls include $Media(t)$, a dummy variable equal to 1 if firm i was mentioned in the Wall Street Journal on day t, volatility (t-5 to t-1), the standard deviation of abnormal returns over days t-5 to t-1, and cumulative abnormal returns over days t-30 to t-6 and t-5 to t-1. All regressions include date and firm fixed effects. Standard errors are clustered by firm and date. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively (t-statistics in parentheses).

Panel A: Disagreement

	Abnormal Log Volume (t)					
Disagreement Measure	2013-2014 100 firms (1)	2013-2014 all firms (2)	2010-2018 all firms (3)	2013-2014 100 firms (4)	2013-2014 all firms (5)	2010-2021 all firms (6)
Disagreement 2015 (z)	0.057***					
	(0.007)					
Disagreement 2018 (z)		0.049***	0.040***			
		(0.001)	(0.001)			
Disagreement 2021 (z)				0.035***	0.051***	0.040***
				(0.005)	(0.002)	(0.001)
Num Messages Q2	0.057**	0.044***	0.028***	0.061**	0.050***	0.029***
	(0.018)	(0.002)	(0.001)	(0.018)	(0.002)	(0.001)
Num Messages Q3	0.077**	0.135***	0.095***	0.058*	0.131***	0.067***
	(0.023)	(0.004)	(0.002)	(0.023)	(0.004)	(0.001)
Num Messages Q4	0.241***	0.391***	0.325***	0.221***	0.381***	0.288***
	(0.028)	(0.007)	(0.004)	(0.027)	(0.007)	(0.003)
AbLogVol (t-1)	0.711***	0.542***	0.582***	0.713***	0.545***	0.616***
	(0.015)	(0.005)	(0.003)	(0.015)	(0.005)	(0.003)
Media (t)	0.162***	0.217***	0.158***	0.167***	0.225***	0.140***
	(0.030)	(0.016)	(0.012)	(0.031)	(0.016)	(0.010)
Volatility (t-5 to t-1)	0.102	0.846***	0.764***	0.146	0.832***	0.514***
	(0.216)	(0.087)	(0.038)	(0.218)	(0.089)	(0.032)
AbRet (t-5 to t-1)	0.180***	0.165***	0.084***	0.183***	0.181***	0.078***
	(0.053)	(0.021)	(0.009)	(0.053)	(0.021)	(0.007)
AbRet (t-30 to t-6)	0.105***	0.202***	0.128***	0.108***	0.207***	0.110***
	(0.026)	(0.013)	(0.007)	(0.025)	(0.013)	(0.005)
R2	0.649	0.489	0.467	0.648	0.487	0.506
Observations	42,389	751,495	4,534,448	42,389	751,495	7,212,649

Panel B: Across- and Within-group Disagreement

	Abnormal Log Volume (t)					
	2013-2014 100 firms	2013-2014 all firms	2010-2018 all firms	2013-2014 100 firms	2013-2014 all firms	2010-2021 all firms
Disagreement Measure	(1)	(2)	(3)	(4)	(5)	(6)
Cross-group 2015 (z)	0.015*					
	(0.007)					
Within-group 2015 (z)	0.143***					
	(0.012)					
Cross-group 2018 (z)		-0.004**	-0.004***			
		(0.002)	(0.001)			
Within-group 2018 (z)		0.054***	0.050***			
		(0.004)	(0.003)			
Cross-group 2021 (z)				-0.005	0.078***	0.033***
				(0.007)	(0.004)	(0.001)
Within-group 2021 (z)				0.085***	0.131***	0.125***
				(0.007)	(0.005)	(0.003)
Num Messages Q2	0.057**	0.037***	0.035***	0.074**	-0.114***	0.004
	(0.018)	(0.003)	(0.002)	(0.023)	(0.007)	(0.002)
Num Messages Q3	0.089***	0.163***	0.120***	0.099***	-0.015	0.064***
	(0.021)	(0.005)	(0.002)	(0.026)	(0.009)	(0.003)
Num Messages Q4	0.194***	0.451***	0.361***	0.142***	0.157***	0.206***
	(0.027)	(0.008)	(0.005)	(0.031)	(0.011)	(0.005)
AbLogVol (t-1)	0.698***	0.549***	0.593***	0.693***	0.547***	0.623***
	(0.017)	(0.005)	(0.003)	(0.018)	(0.005)	(0.003)
Media (t)	0.129***	0.197***	0.145***	0.111***	0.191***	0.096***
	(0.029)	(0.017)	(0.014)	(0.027)	(0.017)	(0.011)
Volatility (t-5 to t-1)	-0.011	0.563***	0.492***	-0.032	0.461***	0.106***
	(0.222)	(0.086)	(0.037)	(0.222)	(0.088)	(0.027)
AbRet (t-5 to t-1)	0.178**	0.156***	0.078***	0.181**	0.171***	0.058***
	(0.054)	(0.021)	(0.010)	(0.055)	(0.021)	(0.007)
AbRet (t-30 to t-6)	0.100***	0.189***	0.114***	0.102***	0.192***	0.085***
	(0.027)	(0.014)	(0.007)	(0.027)	(0.014)	(0.005)
R2	0.659	0.511	0.490	0.664	0.514	0.542
Observations	42,389	557,456	2,944,353	42,389	557,456	4,131,469