Does Disagreement Facilitate Informed Trading? *

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Abstract

Using high-frequency disagreement data from the investor social network StockTwits, we find that greater unsophisticated disagreement facilitates informed buying *and* selling. During periods of overvaluation, the facilitating effect of disagreement on trading is dampened for informed buyers but is amplified for informed sellers. These findings are unexplained by sentiment, news and retail order flow, and they remain when we measure disagreement overnight and disagreement of technical investors, which alleviates concern that disagreement and informed trading respond to a common shock. These findings suggest that informed traders respond meaningfully but differently to valuation changes induced by unsophisticated disagreement.

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1 Introduction

Trading in the presence of disagreement has long been thought to be a behavioral phenomenon. Indeed, most prior work on disagreement focuses on the behavior of less sophisticated traders (e.g., Antweiler and Frank, 2004), or proposes explicitly behavioral explanations for why disagreement leads to trading (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999; Scheinkman and Xiong, 2003). However, this influential perspective is incomplete because it does not account for how *sophisticated* investors react to disagreement in equilibrium. Sophisticated investors trade more when stocks are undervalued and when there is more market liquidity (Peress and Schmidt, 2020). However, disagreement can simultaneously lead to more market liquidity and overvaluation if short selling is costly—effects that can oppose one another. It is, thus, an empirical question whether disagreement encourages or discourages trading by sophisticated investors.[1]

In this paper, we consider how unsophisticated disagreement affects trading by an influential class of sophisticated investors: privately informed traders. To do so, we measure unsophisticated disagreement at the stock-day level using tweets by users on the investor social network StockTwits. We find that disagreement facilitates informed trading across two different classes of identifiable informed traders: activists who are informed buyers and short sellers who are informed sellers. Moreover, our tests shed light on the mechanisms that affect informed trading via an examination of the heterogeneity in how these informed

[1]A segment of the literature considers disagreement in a rational expectations framework (e.g., Banerjee and Kremer, 2010 and Banerjee, 2011), which is useful for understanding disagreement *among* sophisticated individuals. This perspective argues that disagreement ought to carry a risk premium, which in settings with sophisticated disagreement, can lead to greater expected returns (David, 2008). We take a conceptually distinct approach that studies how disagreement among *mostly unsophisticated* investors affects the trading decisions of informed traders.

traders respond to disagreement by mostly unsophisticated investors.

Unosphisticated investor disagreement can affect informed trading through two main channels. First, disagreement may lead to noise trading, creating greater scope for informed traders to buy or sell on their private information (e.g., Kyle, 1985; Collin-Dufresne and Fos, 2015). If disagreement improves liquidity (e.g., Garfinkel, 2009; Cookson and Niessner, 2020), it should encourage informed trading through this liquidity channel irrespective of whether the informed trader buys or sells. Second, investor disagreement can lead to overvaluation because pessimism is not fully incorporated into prices when short-selling is limited (Miller, 1977; Diether, Malloy, and Scherbina, 2002; Berkman, Dimitrov, Jain, Koch, and Tice, 2009). If a stock is overvalued because of disagreement, this should matter for informed traders because informed traders care about trading profits. By contrast to the liquidity channel, this valuation channel affects informed buyers and sellers differently: informed buyers (e.g., activists) are discouraged by overvaluation, whereas informed sellers (e.g., short sellers) are attracted by it.[2] Even though both liquidity and valuation channels may be important, it is an empirical question which channel matters more for informed trading.

We begin by showing our core result that disagreement is positively related to informed trading for both activists and short sellers. This analysis is possible because the StockTwits disagreement measure and informed trading indicators are available at the daily frequency (see Cookson and Niessner (2020) for more details about the disagreement measure). We find that a one standard deviation increase in investor disagreement is associated with a 2.3%

[2]Although the Miller (1977) perspective has empirical support, the literature proposes two other possibilities for the price consequences of disagreement. Disagreement could command a risk premium (Varian, 1985; Carlin, Longstaff, and Matoba, 2014), or idiosyncratic risk may be priced when investors are under-diversified (Boehme, Danielsen, Kumar, and Sorescu, 2009). In our setting, we use broad market tests and sample splits on short selling costs to show that Miller (1977) is a more powerful mechanism for explaining returns and informed trading than these risk-based alternatives.

increase in the likelihood of activist trading, relative to the sample mean. Relating to the competing mechanisms, this positive response is evidence that the liquidity mechanism is more important than the valuation mechanism for activist purchases. However, informed sales respond nearly *three times as much* as informed purchases to investor disagreement—we estimate a 6.2% increase in the likelihood of a spike in short selling. This heterogeneity suggests that the valuation mechanism could also be important for informed trading. Such a mechanism could naturally lead to the heterogeneity we observe because overvaluation from disagreement discourages informed purchases while encouraging informed sales. Indeed, consistent with this idea, we find that activist purchases have *no* significant relation to disagreement when short selling is expensive.

An important empirical concern with the main test is that disagreement and informed trading could each be driven by an omitted factor — e.g., media coverage, corporate announcements, retail attention on social media — such that disagreement itself does not facilitate informed trading directly. To mitigate this concern, our main specifications control for traditional media coverage (capturing traditional news and major corporate announcements), social media attention, recent returns and volatility. We also examine robustness to controlling for other factors that capture the direction of retail trade—retail order imbalances and social media sentiment. Our main findings hold irrespective of whether we control for these characteristics. In addition, we also find that the main findings hold if we consider only disagreement among self-proclaimed technical investors who do not trade on fundamental information. This test also mitigates reverse causality concerns because the factors that influence disagreement among technical investors are plausibly external to the fundamental motivators of informed trade.

Next, we investigate the liquidity and valuation mechanisms behind our main result. First, we verify in the broad sample of firm-day observations that disagreement has both liquidity and valuation effects. Specifically, we estimate that higher investor disagreement is associated with higher daily turnover and a contemporaneous spike in stock returns, followed by a reversion on the following day. A one standard deviation increase in investor disagreement is associated with a 4.24% increase in daily turnover and 3.7% higher contemporaneous stock returns (with a negative return on the following day). Following the literature, we expect the valuation channel to be more pronounced in the sub-sample with high short selling costs (Miller, 1977), and test this using Markit data on short selling utilization as a proxy for the cost of short selling.[3] Consistent with an overvaluation effect, we find the positive relationship between investor disagreement and contemporaneous stock returns is amplified in the high utilization sub-sample relative in the low utilization sub-sample. The coefficient on disagreement at one day lag is negative and is five times larger in magnitude in the high utilization sub-sample.

Guided by this evidence of daily valuation effects of disagreement, we turn to evaluate heterogeneity in *informed trading* by short selling costs, which provides a more precise test of the valuation mechanism. To do this, we split the sample at the median of short selling utilization as well as short lending fees (proxied for by indicative fee measure from Markit being higher than 1%) to contrast stocks with high versus low short selling costs. For the high short-selling costs sub-sample, we find that informed purchases have *no* relation to disagreement while informed sales are strongly related to disagreement. By contrast, in the

[3] Utilization is defined as the ratio of the on-loan value divided by the total gross inventory value of the security.

low short-selling costs sub-sample, we see the opposite pattern: disagreement is strongly related to informed purchases while the relation of informed selling to disagreement weakens. This heterogeneity by short selling costs is novel evidence that the valuation mechanism is important for informed trading decisions. Beyond showing this mechanism is relevant, our finding of no effect on activist purchases when short selling is costly shows that, in some cases, the valuation channel is important enough for informed trading that it can completely offset the liquidity channel.

One possible concern with the main results, which employ contemporaneous measurement of disagreement and informed trading, is that disagreement responds to trading rather than the other way around.[4] To address this concern, we evaluate the relationship between *overnight* disagreement and informed trading. All of our main findings hold just as strongly given overnight measurement of disagreement. This evidence is useful because, in these specifications, disagreement occurs distinctly before trading activity, which helps to rule out the possibility that investor disagreement merely reflects a reaction to heightened trading activity.

Furthermore, the results are robust to alternative specifications, control variables, and sub-sample tests. First, in the case of activist trading, we can measure the intensive margin of informed trading. Even after conditioning on days when an activist trades, we find disagreement predicts more activist trading. Second, our estimates are not sensitive

[4]This concern is less likely to be important for activist trading because these trades are unknown to other market participants. Indeed, activists have strong incentives to keep their trades private until they must disclose their trades for regulatory purposes. All of the activist trades we consider occur *prior* to the disclosure of the activist campaign. As activists accumulate their stakes in target firms, they have strong incentives to keep their purchases private until they are required to disclose their holdings and intentions. We validate this intuition using texts of tweets posted to StockTwits (see Figure 1), which show virtually no mention of activism in the pre-file period followed by a large spike in discussion of the topic.

to controlling for coverage in traditional news media, investor sentiment, and retail order imbalance. Thus, it is likely that the results are due to dispersion of opinion, not directional changes in sentiment. Finally, we obtain the same broad findings, even after focusing on observations in which there are at least two messages about a firm on a particular day, as well as only focusing on messages that were classified as "Bullish" or "Bearish," by the authors of the messages.

Finally, we note that facilitating the trading activities of activists and short sellers is important not only because it affects price efficiency, but also because it can have real effects (e.g., Grullon, Michenaud, and Weston, 2015; Back, Collin-Dufresne, Fos, Li, and Ljungqvist, 2018). To this end, we consider whether activists that face higher investor disagreement during their accumulation stages also tend to accumulate a greater stake in the underlying firm. Specifically, when investors exhibit low disagreement (bottom tercile) about the target firms, activist investors accumulate about 3.3% of shares outstanding during the pre-filing sixty day period. In contrast, during events with high disagreement (top tercile), Schedule 13D filers accumulate about 6% of shares outstanding during the pre-filing sixty day period. As activists have real effects on their target firms and greater effects when they acquire more of a stake in the firm, this finding suggests that disagreement may have important real effects through its effects on sophisticated and informed traders. Indeed, consistent with such real effects, we find that the announcement returns and their treatment component (e.g., following Albuquerque, Fos, and Schroth, 2022) are greater for filings in which there was high disagreement in the 60-day pre-filing period.[5]

[5] Our findings could attract interest from the literature on the real effects of financial markets. Recent work has shown that disagreement affects real estate prices, the valuation of conglomerate firms, and security prices when assets are held in portfolios (Bailey, Cao, Kuchler, and Stroebel, 2018; Reed, Saffi, and Wesep, 2020; Huang, Hwang, You, and Yin, 2020).

Our paper makes several contributions. First, our paper contributes to the literature on the effects of investor disagreement on the trading environment. Trading by informed investors has traditionally been thought of as falling outside of disagreement models (Harris and Raviv, 1993; Kandel and Pearson, 1995; Hong and Stein, 1999; Xiong, 2013). For instance, Harris and Raviv (1993) assume that traders have access to common information but interpret market information differently. Hong and Stein (1999) assume that the same information diffuses gradually through the marketplace. Neither of these perspectives considers the actions of informed traders separately from those of uninformed traders. As we show, however, disagreement among the mostly uninformed has an important effect on informed trading across a variety of sophisticated investor types. This equilibrium response by informed traders provides a fuller understanding the effects of disagreement and suggests modeling avenues for the interactions between sophisticated and unsophisticated market participants.[6]

Second, our results highlight an important tension between the valuation and liquidity effects of disagreement on informed trading. Notably, our results show that informed trading is not completely captured by a pure liquidity perspective like Kyle (1985), nor by a valuation-focused perspective like Miller (1977). To highlight the importance of this contribution, our findings relate to evidence in Fang, Madsen, and Shao (2023), which shows that noise trading is driven by retail attention from weekly recurring advertisements and that these spikes in noise trading facilitate informed trading, providing a test of noise trading models like Kyle

[6]By connecting the actions of sophisticated investors with uninformed trades induced by disagreement, we provide a partial reconciliation between the large disagreement literature and the notion that sophisticated investors play an outsized role in shaping market outcomes (e.g., Koijen, Richmond, and Yogo, 2020). This is related to recent work that identifies uninformed trades by retail investors from Robinhood (e.g., Barber, Huang, Odean, and Schwarz, 2020; Ozik, Sadka, and Shen, 2020; Welch, 2020; Glossner, Matos, Ramelli, and Wagner, 2021; Eaton, Green, Roseman, and Wu, 2021). A unique feature of our setting is that both informed trading and disagreement can be observed explicitly.

(1985) and Collin-Dufresne and Fos (2016). Our findings relate to this work because the liquidity channel of disagreement has similar effects on informed trading as noise trading driven by attention. However, beyond liquidity effects, we show that disagreement exhibits an important overvaluation channel that discourages informed buyers and encourages informed sellers. Thus, our paper emphasizes that informed traders balance an important tension between liquidity and valuation effects on their trading. Indeed, in the high utilization sub-sample, we find disagreement bears *no* relation to informed purchases due to offsetting valuation and liquidity effects. Our findings are not well explained by a pure valuation perspective either. Indeed, the fact that disagreement facilitates informed trading highlights that, on average, the liquidity mechanism is more powerful than the valuation mechanism. This suggests that models of informed trading should incorporate both valuation and liquidity channels, rather than one in isolation.

Finally, our work relates to the growing literature on investor social media (Cookson and Niessner, 2020; Pedersen, 2021), which primarily focuses on its information content and market consequences (Chen, De, Hu, and Hwang, 2014; Farrell, Green, Jame, and Markov, 2021). For example, existing work employs StockTwits data on geography to identify distinct sources of information (Giannini, Irvine, and Shu, 2017), and related research uses social connections and sharing behavior to understand information frictions in financial markets (Chen and Hwang, 2021; Cookson, Engelberg, and Mullins, 2022). Alternatively, other work uses StockTwits data to identify differences in investment philosophies or other ideology (Cookson, Engelberg, and Mullins, 2020). Our work is closest to recent research on the market and informational consequences of social media and retail investors (e.g., Dessaint, Foucault, and Frésard (2021) and Eaton et al. (2021)). Our contribution is to study how privately informed investors − who are unlikely to participate in investor social media − react to disagreement on investor social media. This finding provides evidence that investor disagreement can spill over into decisions made by other market participants.

2 Data

2.1 StockTwits Data

We measure investor disagreement using data from the investor social network StockTwits. StockTwits was founded in 2008 as a social networking 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, 2018. In total, there are 144,641,361 messages posted by 487,265 unique users who mention 13,248 unique assets. 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 assets. For more information about the data, please refer to Cookson and Niessner (2020), who perform a series of validation exercises for using StockTwits data to measure disagreement.

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. Because it will be useful for our decomposition of disagreement into distinct types, we retain StockTwits messages posted by users who select an investment approach, a holding period, and experience in their profile information. Further, to facilitate the link to informed trading data, we focus on firms that are headquartered in the United States and thus make regular filings with the SEC. After these sampling restrictions, our final sample contains 22,475,108 messages posted by 68,284 unique users on 9,306 unique tickers.

We construct our disagreement measure by computing the standard deviation of expressed sentiment across messages for a given $firm \times day$. 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 firm i during time period t equals $1 - AvgSentiment_{it}^2$, where $AvgSentiment_{it}$ is the average sentiment of messages posted about firm i during time period t. Thus our disagreement measure is

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

The $AvgSentiment_{it}$ measure ranges from -1 (all bearish) to $+1$ (all bullish). This 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 particular 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. Our tests consider robustness to this definition by excluding zero and one-message days from the analysis.

2.2 Data on Informed Trades

Our empirical tests rely on measuring informed trades from two types of sophisticated trades: activist investors on the precipice of an activist campaign and discrete increases in short selling activity.

2.2.1 Activist Trades from Schedule 13D filings

We extract information on the timing and size of privately informed trades by activists from the mandated disclosure of beneficial ownership to the SEC. Specifically, Rule 13d-1(a) of the 1934 Securities Exchange Act requires investors to file their status with the SEC within 10 days of acquiring beneficial ownership of more than 5% of a voting class of a company's equity securities registered under Section 12 of the Securities Exchange Act of 1934. We refer to the date when the beneficial ownership crosses the 5% threshold as the "event date" and the date when the filing is sent to the SEC as the "filing date."

Information on trades executed by Schedule 13D filers is reported in Item 5(c). To quote from Item 5(c), filers have to "...describe any transactions in the class of securities reported on that were effected during the past sixty days or since the most recent filing of Schedule 13D, whichever is less,..." Thus, filers are required to report the date, price, and quantity of all trades in the underlying security (common stock) executed during the 60 days that precede the filing date.

The sample of Schedule 13D filings with information on trades is constructed as follows.[7] First, we identify all Schedule 13D filings from 2010 through 2018. Next, we check the sample manually and identify events accompanied by information on trades. Because the trading characteristics of ordinary equities might differ from those of other assets, we retain only assets whose CRSP share codes are 10 or 11. We discard certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks, and REITs. We further exclude stocks whose prices are below $1 or above $1,000. Finally, we exclude Schedule 13D/A filings (i.e., amendments to previously submitted filings) that are mistakenly classified as original Schedule 13D filings. The final sample comprises the universe of all Schedule 13D filings that satisfy the above criteria from 2010 through 2018, which totals 1,409 events. During the sample period, an average of 157 events take place annually.

For each event, we extract the following information from the Schedule 13D filings in our sample: the CUSIP of the underlying security, the transaction date, the transaction type (purchase or sell), the transaction size, and the transaction price. In the vast majority of cases, transaction data are reported at daily frequency. If the transaction data are reported more frequently than daily, we aggregate them to the daily level. Specifically, for each day we calculate the total change in stock ownership and the average purchase price. The average price is the quantity-weighted average of transaction prices.

[7]See Collin-Dufresne and Fos (2015) for a detailed description of the procedure. Ye and Zhu (2020) use Schedule 13D data to study trading avenue choices made by informed traders.

2.2.2 Short Selling Data

We employ Markit data on daily shares on loan as a fraction of shares outstanding, to measure the short seller trading activity. Unlike informed activist trades, we are only able to observe the overall amount of short selling, not identifiable short positions by individual traders. For this reason, we focus on clear cases where daily short selling discretely increases for a firm on a given day. That is, we define an indicator variable *Short Increase Spike* if there is at least a 1 percentage point increase in the fraction of shares on loan from day *t-1* to day *t*.[8]

In addition, we use the short selling utilization information from Markit to split our tests by cases where short selling is costly (high utilization of shares in short selling) versus cases where short selling is not (low short selling utilization). In line with prior literature (Muravyev, Pearson, and Pollet (2022)), we consider high utilization to be utilization above 60%.[9]. These sample splits allow us to focus on cases where the valuation channel is more or less important. We also use stock lending fees as an alternative proxy for the cost of short selling, to show that our main results are robust to using a different cost of short-selling measure.

Although short increase spike and utilization measures are related to short selling, they have distinct purposes in our empirical tests. *Short Increase Spike* is a proxy for informed selling by short sellers of firm i on date t, whereas high versus low *Utilization* is a proxy for how expensive it is to take a short position in a stock. These measures capture different aspects of the trading environment, and though high shorting costs might discourage short selling

[8]In the Online Appendix Table A3, we show that our main results are robust to different cutoffs: 0.5 and 2 percentage point increases.

[9]In the appendix Table A4, we show that our main results are robust to different utilization cutoffs: 50% and 70%

by some less sophisticated investors, empirically, the two measures have a low correlation ($r = 0.0191$). This feature of our data indicates that it is relatively common for both high and low utilization stocks to experience spikes in short selling. Intuitively, this low correlation makes sense: high short selling costs discourage the typical investor from taking a short position, but truly informed short sellers might still find it advantageous to trade on their information, even when it is expensive to borrow shares for short selling (see Engelberg, Evans, Leonard, Reed, and Ringgenberg (2022) for an example).

2.3 Summary Statistics

Table 1 reports summary statistics for all our variables. The full sample contains 15,743,814 firm-day observations. We report *Turnover* and *Return* in percentage units to facilitate exposition of the regression specifications. Consistent with the high degree of daily trading volume observed in other settings (e.g., Hong and Stein (1999)), the sample average of *Turnover* is 1.32%. The *Disagreement* measure ranges from 0 (complete agreement) to 1 (maximal disagreement), with a relatively small mean (0.054) that is driven by a large number of 0 disagreement days. These days in which disagreement is zero are mostly driven by days with 0 or 1 messages in which disagreement is not possible. Naturally, when we drop these days from the sample, we observe a larger mean (0.529). Therefore, we consider robustness of our findings to dropping days with 0 or 1 messages.

For each of the informed trading measures, informed trades are infrequent in the full firm-day panel, irrespective of the type of informed trade: 0.569% (high short increases) and 0.133% (informed activist trades) of firm-day observations correspond to a day with informed trade. However, in the case of activist trading, we can focus on the pre-file window to understand how likely informed trading is, conditional on being informed. We observe that 37.3% of days in the 60-day window prior to a Schedule 13D filing are days when the activist trades. Viewed this way, there is a high likelihood of informed trading during periods when traders are informed.

[Insert Table 1 here]

Before presenting our evidence on the relation between these informed trades and disagreement at the daily level, we present monthly evidence that activist trades and short selling spikes are informed. To do this, we construct indicator measures for whether there was an informed trade (activist purchase or short selling spike) in month t, and we relate these indicators in a monthly panel regression with next-month $t+1$ return as the dependent variable. The results from this exercise are reported in the Appendix (Table A1). Consistent with these trades being informed (as opposed to generating short-term price pressure), activist trade in month t predicts roughly 1.5 percentage points greater stock return in the following month. Similarly, short selling is informed in the opposite direction, a short interest spike is associated with between 0.2 and 0.3 percentage point reduction in next-month returns. These returns results are similar if we look at the return in the next two month period, as well.

3 Disagreement and Informed Trading

In this section, we present our core findings on how disagreement facilitates informed trading, and how liquidity versus valuation channels matter for disagreement's relationship with informed trade.

3.1 Empirical Strategy

Our empirical strategy is to recognize two features of the valuation channel: the asymmetry with respect to purchases versus sales and the importance of short sale constraints.

First, the valuation channel discourages informed purchases but encourages informed sales, while the liquidity channel encourages any type of informed trade. On this logic, we expect that sophisticated and informed selling ought to have a stronger relationship to disagreement than sophisticated and informed purchasing. Indeed, whether informed purchases respond positively or negatively to disagreement is an empirical question about whether valuation or liquidity is more important for informed traders.

Second, the valuation channel should be strongest when short sale constraints are most binding. For this reason, we consider sample splits between high versus low utilization stocks to provide deeper insight into how much valuation versus liquidity mechanisms matter for informed traders.

We implement this empirical strategy by estimating the following panel regression:

$$Y_{it} = \alpha_i + \alpha_t + \beta Disagreement_{it} + X'_{it}\gamma + \varepsilon_{it},, \tag{2}$$

where Y_{it} is an indicator variable for informed trading on day t in firm i, $Disagreement_{it}$ is measured from 4 p.m. on day $t-1$ to 4 p.m. on day t, α_i are firm fixed effects, α_t are date fixed effects, and X is a vector of control variables (contemporaneous and lagged number of messages, lagged disagreement, lagged informed trade, media coverage, lagged volatility, and lagged cumulative abnormal returns). We separately consider specifications with an indicator of informed purchases (*Activist Trade Dummy*) and informed sales (*Short Increase Spike*) as the dependent variable. Our interest in these specifications is in contrasting how much informed purchases respond to disagreement with how much informed sales do.

In this specification, a first-order concern is that an omitted characteristic drives both disagreement and informed trading by activists and short sellers. For example, a major news event might generate both disagreement and informed trade, or in general, drivers of social media attention could lead to more disagreement and informed trade. To mitigate the concern that traditional news drives this relationship, we measure traditional media coverage via the Dow Jones News Wire at the firm-day level. To the extent that drivers of social media attention are not well captured by the media controls, we also directly measure social media attention by counting the number of messages at the firm-day level (in line with social media attention proxies developed in Cookson, Lu, Mullins, and Niessner (2024)). Because of the importance of this attention channel in driving informed trading (e.g., Fang et al., 2023), we estimate our main specifications both with and without the attention control. In addition, we control for other well-known drivers of trading volume at the firm-day level, and could also be driving the informed trades— recent returns, recent volatility, and lagged trading activity. To the extent that we see similar findings with and without these control variables, this strategy bolsters our confidence that disagreement drives informed trading rather than reflecting some omitted background factor.

In a robustness exercise, we conduct an analogous test to our main specification that employs disagreement overnight as a predictor of informed trading on the next day. This overnight disagreement test also helps to alleviate reverse causality concerns that higher trading volume or short selling is driving disagreement among investors.

In addition, we consider an alternative specification that includes disagreement among investors who classify themselves as following a "technical" investment philosophy on StockTwits, and who do not pay attention to fundamental information. Such disagreement is unlikely to reflect fundamental considerations that would usually comprise the informed trader's strategy. Thus, these tests enhance our confidence that disagreement (and not an omitted fundamental factor) drives informed trading.

3.2 Results on Informed Trading

Following the first part of our empirical strategy, we report the estimated relationships between disagreement and informed trading in Table 2.

[Insert Table 2 here]

Irrespective of whether we consider activist purchases or short selling spikes, we estimate a positive and significant relationship between disagreement and informed trade. For informed purchases (column 1 Activist purchases), these results indicate that the liquidity channel is more important for informed trading than the valuation channel, on average. For example, during the 60 day window prior to a Schedule 13D filing, a standard deviation increase in disagreement is associated with 0.84 percentage point greater likelihood that the activist purchases shares on that day. This coefficient reflects an increase of 2.262% of the baseline rate of activist trades during this 60 day window.[10] In columns 1 and 3 we run our main specification without the number of messages control, which proxies for investor attention, and in columns 2 and 4, we add the controls. While the coefficients on Disagreement decrease

[10]The disagreement measure is constructed from the fully classified sample of StockTwits tweets from Cookson and Niessner (2020). We obtain similar findings if we restrict our attention to only self-classified messages. See Table A7 in the Appendix.

in size, slightly, they remain significant, suggesting that disagreement effects on informed trading are different from the effect of attention.

Because the different kinds of informed trades have different base rates, it is most informative to compare the economic magnitude relative to the base rate across columns. When drawing this comparison, we see that the economic magnitude of the disagreement coefficient is much greater for informed sales (column 4) versus informed purchases (column 2). Specifically, the disagreement coefficient is 2.3% of the likelihood of informed purchases, but 6.2% of the likelihood of a short interest spike. This pattern is consistent with the idea that the valuation channel discourages informed purchases, but encourages informed sales.

While we control for contemporaneous media coverage in the last table, there might still be omitted fundamental events that drive both the informed trading as well as disagreement among investors. To address this potential concern further, in Table 3 we repeat our analysis, but focus only on disagreement among investors who self-declare on StockTwits that they follow the "Technical" investment strategy. As we confirm in Figure 1, technical investors are not likely to pay attention to fundamental events (like activist trading), which are the types of events that sophisticated investors tend to base their trading decisions on. In column 1 we regress Activist Trade Dummy and in column 2 Short Increase Spikes on disagreement among technical investors, and the number of messages among technical investors, as well as other controls included in Table 2. While the effects of disagreement are somewhat smaller: 0.831% and 4.747% for informed buying and selling, respectively, we still see the same pattern - that overvaluation channel lessens the effect of disagreement on informed buying but strengthens the effect on informed selling. Therefore, our main results are unlikely to be driven by omitted variables.

[Insert Table 3 here]

3.3 Liquidity and Valuation Channels

The main findings in the previous section show a strong empirical link between StockTwits disagreement and informed trading, and the relative magnitudes suggest that both valuation and liquidity mechanisms could be at play. In this section, we investigate these mechanisms more precisely. Specifically, we show how disagreement gives rise to both a liquidity channel and a valuation channel. This evidence takes the form of panel regressions that relate disagreement at the stock-day level to stock-day stock turnover and returns outcomes. We follow the format of the specifications in equation (2), but instead of informed trading proxies, we include outcome variables related to liquidity and valuation − daily turnover, illiquidity measures, or returns − in a broad panel of firm-day observations.

Using daily turnover as the dependent variable, we obtain the findings in Panel A of Table 4, Panel A, columns 1-3. In columns 1 and 2 we estimate our specification without and with number of messages control, and find that while both disagreement and attention play a role for turnover, the effects are distinct. In column 2 we estimate that a one-standard-deviation increase in *Disagreement* for a given observation ($sd = 0.054$) is associated with 0.22 percentage points greater *Turnover*. In column 3, we find that disagreement at a one-day lag does not predict stock turnover. Thus, we are confident that the estimates do not reflect persistent effects of disagreement and trading from previous days. This estimated magnitude is economically significant, representing approximately one sixth of the average daily turnover, which equals 1.32 percent, and approximately 4.24% of the standard deviation of daily turnover.

[Insert Table 4 here]

These results on daily turnover are consistent with a liquidity channel in which disagreement reduces market illiquidity. To further highlight this liquidity channel, we replace turnover with a variety of explicit illiquidity measures from the literature (e.g., Amihud (2002) illiquidity, as well as different measures of spread and price impact). These results are reported in Table A2 in the Appendix. Across most illiquidity measures (except the Price Impact measure), we find that greater disagreement corresponds to less market illiquidity.

Next, to establish the relevance of the valuation channel, we consider the relationship between disagreement and contemporaneous daily stock returns in an analogous specification. The results are reported columns 4-6 of Table 4, Panel A. The results indicate that disagreement and contemporaneous stock returns are positively related, consistent with a valuation channel. Based on the estimate in column 5, a one-standard-deviation increase in disagreement is associated with higher returns of approximately 9.6 basis points daily. This finding is consistent with Hong and Stein (1999), who posit that disagreement should lead to positive price pressure in the short term. Based on the results in column 6, this estimated coefficient is robust to including lagged measures of disagreement and number of messages. Relative to the daily standard deviation of returns, these estimated coefficients reflect a similar economic magnitude as the turnover results: A standard deviation increase in disagreement is associated with an increase of 3.6% of a standard deviation in returns. The coefficient on lagged disagreement is negative and statistically significant in column 6. This finding is also important evidence of a valuation channel because it suggests that there is some reversion in returns after an initial increase coincident with high disagreement. Such a finding is consistent with the prediction of Miller (1977) model as short sale constraints ease.

To provide further evidence on the valuation channel, we estimate the relation between returns and disagreement separately for stocks with a high fraction of shares on loan (high utilization) versus those with a low fraction of shares on loan (low utilization). These sample splits reveal whether the disagreement-return relationship is stronger in the presence of short sale constraints (high utilization stocks), as predicted by the Miller (1977) model. In line with Muravyev et al. (2022), we consider high utilization to be utilization above 60%. In the Appendix Table A4, we show that our main results are robust to different utilization cutoffs: 50% and 70%.The results from estimating the returns specification on these sub-samples are reported in Panel B of Table 4. Consistent with the Miller hypothesis, we observe a stronger relationship between stock returns and disagreement in the high utilization sub-sample (columns 1-3) than we do in the low utilization sub-sample (columns 4-6). In the specifications that control for lagged disagreement and number of messages (columns 3 versus 6), a standard deviation increase in disagreement is associated with 13.9 basis points greater return in the high utilization sub-sample, but only 8.7 basis points more return in the low utilization sub-sample. The difference in these coefficient estimates is highly statistically significant ($F = 145.93$, $p - value < 0.0001$). Moreover, the estimated coefficient on the lagged term $Disagreement_{t-1}$ is significant and negative in both sub-samples, but its magnitude is more than five times greater in the high utilization channel (-5.45 basis points versus -0.92 basis points). This evidence supports a valuation channel in which future returns are lower in the high utilization sub-sample.

3.4 Liquidity and Valuation Mechanisms for Informed Trading

To more precisely test this valuation mechanism, we appeal to the logic that the valuation channel is strongest when it is difficult to short sell. Specifically, in Table 5, we present results from the same specifications separately for the high utilization sub-sample (columns 1 and 2 of Panel A) versus the low utilization sub-sample (columns 1 and 2 of Panel B). To ensure that our utilization definition is not driving the results, we also use lending fees as another proxy for short selling constraints (columns 3 and 4 of Panels A and B). The lending fees on day t are proxied for by indicative fee measure obtained from Markit data set and high lending fees are defined over days $t-5$ to $t-1$ being greater or equal to 1%. Under the valuation channel, the *ex ante* prediction is that disagreement will be less (more) related to informed purchases (sales) in the high short-selling constraint sub-sample (Panel A). This is precisely what we find. Referring to columns 1 and 3 of Panel A, activist purchases are unrelated to disagreement in the high utilization sub-sample, indicating that the valuation channel and the liquidity channel completely offset one another. Consistent with a valuation channel at play, columns 2 and 4 show that the relationship between disagreement and informed selling becomes much greater in the presence of short sale constraints, with a standard deviation increase in disagreement reflecting an increase in informed selling likelihood of 7.6% and 7% of the baseline rate. Panel C of the table presents these economic magnitudes together with tests for differences in coefficients across specifications.

[Insert Table 5 here]

Turning to the low utilization sub-sample in Panel B, the relationship between disagreement and informed purchasing strengthens in economic magnitude (going from 0.01%

and 0.02% in Panel A to 2.7% and 2.6% in Panel B), whereas the relationship between disagreement and informed selling weakens (going from 7.6% and 7% to 3.6% and 3.9% in Panel B). Taken together, these findings show that disagreement facilitates both informed purchases and informed sales, on average, and that the overall response of informed trading to disagreement reflects both liquidity and valuation channels. Viewed through the lens of the high versus low utilization sample splits, both channels have an economically important effect on informed trading.

For convenience, Panel C of Table 5 presents pairwise tests of differences in coefficients for high versus low short selling utilization (high minus low). For informed buys, the economic magnitude in the low utilization sample is greater by 2.64 percentage points is statistically significant at the 10% level. For informed sales, the economic magnitude is smaller by 3.99 percentage points and is statistically significant at the 5% level. These shifts in the economic effect size that are consistent with there being an important valuation channel at play.

4 Robustness and Implications

In this section, we present several robustness exercises and supplemental results that point to the implications of our main findings.

4.1 Overnight Disagreement and Informed Trading

A first order concern about relating informed trading to investor disagreement is that the two measures are contemporaneous to one another. It is, thus, difficult to tell whether disagreement facilitates informed trading or whether the trading generates disagreement. In the case of activists, the context makes us more confident that those who express disagreement are unaware of informed trading. However, other kinds of trading may be more easily monitored by market participants (e.g., short selling).

To refine our interpretation, we consider specifications that replace the *Disagreement* measure with the sub-daily measure $Disagreement\ Night_{it}$ (the standard deviation of StockTwits message sentiment from the overnight period about firm i, i.e., from 4 p.m. on day $t-1$ to 9 a.m. of day t). Similar to the *Disagreement* measure, we replace one of control variables, the number of messages, with the number of messages during the night. We do this to ensure that the variation in the *Disagreement* measure is not purely reflecting differences in attention. The coefficient of interest is the coefficient on $Disagreement\ Night_{it}$, which occurs distinctly prior to the informed trades on date t.

[Insert Figure 1 here]

Empirically, StockTwits investors seem to be relatively unaware of the actions of informed traders across both measures of informed trade. In support of this, we plot the fraction of mentions to "activist" and "short" in an event window around when these trades are disclosed to the market in Figure 1. In each case, the event window exhibits a spike on the day of the disclosure and a few days following. This confirms that StockTwits users pay attention to the actions of informed traders, but also highlights that StockTwits users do not anticipate these trades. Although the activist trades typically take place weeks before their disclosure with the broader market unaware, there is some contemporaneous attention short selling, which is immediately observable to market participants. Thus, particularly to highlight the differential response of buyers versus sellers to disagreement, it is helpful to evaluate whether disagreement that precedes informed trades predicts informed trading.

Table 6 presents the results of this *overnight disagreement* specification. Analogous to our main findings, we estimate that disagreement overnight facilitates informed trading the next day, irrespective of whether we consider activist purchases or informed short selling. In addition, consistent with our main findings, the economic magnitudes of informed sales response to disagreement are greater than the analogous magnitudes for informed buys. In addition, the evidence of a difference between high and low short selling costs is somewhat stronger in terms of statistical significance. These findings highlight that our general conclusions about whether disagreement facilitates informed trading and the relative weight of valuation versus liquidity channels are not driven by the contemporaneous measurement of disagreement and informed trade.

Similarly in Table 3, we show that disagreement among technical investors has a strong relationship to activist buying a short selling spikes. While these results are less likely to be driven by omitted fundamental variables, there is still the reverse causality concern. Therefore in Table A6, we replicate the results, by focusing only on messages by technical investors written overnight. We find that the results are quantitatively similar (even though we start to lose power as we cut our sample quite a bit by only looking at the overnight messages by a select group of investors).

[Insert Table 6 here]

4.2 Intensive Margin of Informed Trading

One aspect of the main measures of informed trading is that they are indicator measures for whether the sophisticated investor took a position on that day. Such measurement naturally leads one to wonder if there is something special about the days that generate informed trading. To evaluate this possibility, we focus on activist trading because the Schedule 13D disclosures reveal *how much* the activist trades in addition to whether they trade on a given day. Using this intensive margin measurement, we construct a measure *Activist Turnover* that reflects the fraction of shares acquired by the activist in the target firm on a given day (restricting the sample to the 60-day window before disclosure of the activist campaign).

Using this measure, we estimate how disagreement relates to the intensive margin of informed trading by restricting to days in which the activist made at least one purchase. Table 7 reports the results. For reference, column 1 repeats the extensive margin specification. In column 2, we observe a positive and significant relationship of the intensive margin of activist purchasing. Moreover, the economic magnitude is quite a bit stronger than the extensive margin estimate: a standard deviation increase in disagreement is associated with an increase of activist turnover of 17.7% of the average shares traded.

[Insert Table 7 here]

4.3 Other Robustness

We have performed several other robustness tests to account for alternative explanations of our finding.

First, one concern is that, in the case where there are zero messages or one message, the disagreement measure is automatically zero. In Appendix Table A8, we present the main result table without observations in which there are zero messages or only one message about the firm on a given day on StockTwits, and we find very similar results to our main specifications.

A second class of robustness concerns is that the disagreement measure may not reflect pure dispersion of opinion, but directional sentiment and or the directional trading of retail investors. The appendix accounts for this possibility by controlling for average sentiment on StockTwits (Table A9) and controlling for retail trader imbalance using the retail trade classification of Boehmer, Jones, Zhang, and Zhang (2020) (Table A10). Neither of these controls changes the estimates in a quantitatively meaningful fashion.

4.4 Direct Observation of the Liquidity Channel

Next, we use activist setting to show more explicitly the link to liquidity. In this setting, we have the special feature where the activist is truly privately informed about their intentions to engage in activism. By contrast, short sellers may rely on signals that other sophisticated market participants also use. Unlike these market participants, informed activist trading is largely uncorrelated with other traders' information. This allows us to decompose overall stock turnover into the turnover due to activists, and the remainder of (uninformed) ex-activist turnover.

We calculate *Ex-activist trading* by regressing turnover on activist turnover and taking the residual. The results are reported in Table 8, which reports ex-activist turnover as a percentage by multiplying it by 100. For column 1, we focus on the $[t-60, t-1]$ period prior to Schedule 13D filings. We estimate that greater investor disagreement leads to higher ex-activist trading.[11]

[Insert Table 8 here]

The results reported in columns 2 and 3 show that the relationship between investor disagreement and ex-activist trading differs between days when activist investors trade and the days on which they do not trade. Specifically, for activist trading days (column 2), the relationship between disagreement and ex-activist trading on days when activists trade is *stronger* than the relationship between disagreement and ex-activist trading on days when activists do not trade (0.8432 versus 0.1141). The difference in these coefficient estimates is highly statistically significant ($F = 77.37$, $p - value < 0.0001$). Overall, the results are consistent with the idea that activist investors trade on days when uninformed investors react especially strongly to investor disagreement. Because ex-activist trading activity is, by construction, the fraction of daily turnover that is uncorrelated with activist trading activity, this finding provides further evidence consistent with the liquidity channel.

4.5 Real Effects of Disagreement: Activist Stakes in Target Firms

We conclude this section by presenting a result that connects the disagreement and trading results to a potential real effect. This test focuses on the eventual stakes that activists acquire, which are important because greater stakes lead to greater effort on the part of the activist investor (e.g., Back et al., 2018).

[11]These results are robust to using an alternative measure of ex-activist turnover: total turnover minus activist turnover.

For this test, we consider whether activists who target firms that face greater disagreement in their pre-filing periods also acquire greater stakes in their target firms. Using raw data at the event level, we illustrate this relationship by focusing on the mean acquisition stake of activists by comparing whether a targeted firm exhibited low or high levels of disagreement (bottom and top terciles) in the pre-filing period. Consistent with the facilitation of activism by disagreement, Panel (a) of Figure 2 shows that activists acquire significantly higher numbers of shares when shareholder disagreement about a target firm is high. Specifically, when shareholders of target firms exhibit below-median disagreement, activist investors accumulate about 3.3% of shares outstanding.[12] In contrast, during events with above-median levels of messages, Schedule 13D filers accumulate about 6% of shares outstanding. This finding indicates that, when investor disagreement increases, activist investors purchase lager fractions of shares outstanding and therefore are likely to devote more time and energy to activism (Back et al., 2018).

[Insert Figure 2 here]

In Panel (b) Figure 2 we also show that this period of higher disagreement is associated with greater overall stock turnover. Consistent with the liquidity mechanisms we have highlighted throughout the paper, high disagreement appears to be a useful signal about greater trading volume.

Do higher activist stakes lead to real effects on firm value? We next investigate

[12] Our measure of shares accumulated only counts shares acquired after date $t - 60$. Since activists can begin the 60-day period with a non-zero position, they often accumulate less than 5% shares outstanding before crossing the 5% threshold. For example, suppose an activist owns 3% of shares outstanding on March 1. During the following 60-days the activist accumulates 2%, crossing the 5% threshold on April 30. If the activist files a Schedule 13D eight days later on May 8 (within 10-day disclosure period), disclosing a 6.5% position in the stock, our measure of percent shares outstanding accumulated equals 3.5%: 2% in the 60 days before the threshold-crossing date and an additional 1.5% before the filing date.

whether stock prices reflect such effects. Specifically, in Figure 3 we show the relationship between disagreement during the 60-day window and the price reaction to activism campaign announcements (as measured using buy-and-hold abnormal returns around Schedule 13D filing date). Panel (a) shows that when disagreement is high, Schedule 13D filings receive more positive abnormal returns. Consistent with Back et al. (2018), this finding is an important addition to Figure 2 where we show that disagreement leads to larger activist stake.

[Insert Figure 3 here]

Furthermore, we evaluate the relationship between disagreement and the *treatment component of abnormal returns*, which is structurally estimated by Albuquerque et al. (2022) who model the choice between passive investment and activist investment (13G versus 13D filings). In Panel (b) of Figure 3, we restrict attention to this treatment component (a proxy for the real impacts of activism). Consistent with real impacts of disagreement, we find that disagreement is positively associated with the treatment component of abnormal returns.

5 Conclusion

This paper studies how a particular class of sophisticated investors − informed traders − respond to shareholder disagreement. We find that greater investor disagreement facilitates informed trading by activists and short sellers. These findings are unexplained by sentiment, news, and retail order flow, and they remain when we measure disagreement in the overnight period as well as among technical investors, which alleviates concern that disagreement and informed trading respond to a common shock. When short selling is costly, the effect of disagreement is dampened for informed buyers but is amplified for sellers.

Our findings show that disagreement has important effects on both the timing and intensity of informed trading through two distinct mechanisms. On one side, disagreement generates trading by uninformed investors and therefore opens up trading opportunities for informed investors. On the other side, disagreement increases valuation, particularly when short selling is costly, and therefore discourages informed buyers and encourages informed sellers.

Overall, our results highlight the importance of informed and sophisticated market participants to a full understanding of the effects of disagreement in financial markets. Based on our findings, more research is needed to incorporate sophisticated investors' actions into market equilibrium in settings dominated by the actions of behavioral agents.

References

Albuquerque, R., Fos, V., Schroth, E., 2022. Value creation in shareholder activism. Journal of Financial Economics 145 (2, Part A), 153–178.

Amihud, Y., January 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5 (1), 31–56.

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

Back, K., Collin-Dufresne, P., Fos, V., Li, T., Ljungqvist, A., 2018. Activism, strategic trading, and liquidity. Econometrica 86, 1431–1643.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., Dec. 2018. The economic effects of social networks: Evidence from the housing market. Journal of Political Economy 126 (6), 2224–2276.

Banerjee, S., 2011. Learning from prices and the dispersion in beliefs. The Review of Financial Studies 24 (9), 3025–3068.

Banerjee, S., Kremer, I., 2010. Disagreement and learning: Dynamic patterns of trade. The Journal of Finance 65 (4), 1269–1302.

Barber, B. M., Huang, X., Odean, T., Schwarz, C., 2020. Attention induced trading and returns: Evidence from robinhood users. Available at SSRN 3715077.

Berkman, H., Dimitrov, V., Jain, P. C., Koch, P. D., Tice, S., 2009. Sell on the news:

Differences of opinion, short-sales constraints, and returns around earnings announcements. Journal of Financial Economics 92 (3), 376–399.

Boehme, R. D., Danielsen, B. R., Kumar, P., Sorescu, S. M., 2009. Idiosyncratic risk and the cross-section of stock returns: Merton (1987) meets miller (1977). Journal of Financial Markets 12 (3), 438–468.

Boehmer, E., Jones, C. M., Zhang, X., Zhang, X., 2020. Tracking retail investor activity. Journal of Finance, Forthcoming.

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

Chen, H., De, P., Hu, Y. J., Hwang, B.-H., 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. The Review of Financial Studies 27 (5), 1367–1403.

Chen, H., Hwang, B.-H., 2021. Listening in on investors' thoughts and conversations. Journal of Financial Economics.

Collin-Dufresne, P., Fos, V., 2015. Do prices reveal the presence of informed trading? The Journal of Finance 70 (4).

Collin-Dufresne, P., Fos, V., 2016. Insider trading, stochastic liquidity, and equilibrium prices. Econometrica 84 (4), 1441–1475.

Cookson, J. A., Engelberg, J. E., Mullins, W., 2020. Does Partisanship Shape Investor Beliefs: Evidence from the COVID-19 Pandemic. Review of Asset Pricing Studies.

Cookson, J. A., Engelberg, J. E., Mullins, W., 2022. Echo Chambers. Review of Financial Studies, Forthcoming.

Cookson, J. A., Lu, R., Mullins, W., Niessner, M., 2024. The social signal. Journal of Financial Economics 158, 103870.

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

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under-and overreactions. the Journal of Finance 53 (6), 1839–1885.

David, A., 2008. Heterogeneous beliefs, speculation, and the equity premium. The Journal of Finance 63 (1), 41–83.

Dessaint, O., Foucault, T., Frésard, L., 2021. Does alternative data improve financial forecasting? the horizon effect.

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

Eaton, G. W., Green, T. C., Roseman, B., Wu, Y., 2021. Zero-commission individual investors, high frequency traders, and stock market quality. High Frequency Traders, and Stock Market Quality (January 2021).

Engelberg, J., Evans, R. B., Leonard, G., Reed, A. V., Ringgenberg, M. C., 2022. The loan fee anomaly: A short seller's best ideas. In: 2022 American Finance Association Annual Meeting Paper, Kenan Institute of Private Enterprise Research Paper. No. 3707166.

Fang, V. W., Madsen, J., Shao, X., 2023. Is it all noise? the microstructure implications of corporate recurring advertisements. The Microstructure Implications of Corporate Recurring Advertisements*(August 28, 2023).

Farrell, M., Green, T. C., Jame, R., Markov, S., 2021. The democratization of investment research and the informativeness of retail investor trading. Journal of Financial Economics.

Garfinkel, J. A., 2009. Measuring investors' opinion divergence. Journal of Accounting Research 47 (5), 1317–1348.

Giannini, R., Irvine, P., Shu, T., 2017. Nonlocal disadvantage: An examination of social media sentiment. The Review of Asset Pricing Studies.

Glossner, S., Matos, P., Ramelli, S., Wagner, A. F., 2021. Do institutional investors stabilize equity markets in crisis periods? evidence from covid-19.

Grullon, G., Michenaud, S., Weston, J. P., 2015. The real effects of short-selling constraints. The Review of Financial Studies 28 (6), 1737–1767.

Harris, M., Raviv, A., 1993. Differences of opinion make a horse race. Review of Financial Studies 6 (3), 473–506.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of Finance 54 (6), 2143–2184.

Huang, S., Hwang, B.-H., You, D., Yin, C., 2020. Offsetting Disagreement and Security Prices. Management Science 66 (8).

Kandel, E., Pearson, N. D., 1995. Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103 (4), 831–872.

Koijen, R., Richmond, R., Yogo, M., 2020. Which investors matter for equity valuations and expected returns? Working Paper.

Kyle, A. S., Nov 1985. Continuous Auctions and Insider Trading. Econometrica 53 (6).

Miller, E. M., September 1977. Risk, Uncertainty, and Divergence of Opinion. Journal of Finance 32 (4), 1151–1168.

Muravyev, D., Pearson, N. D., Pollet, J. M., 2022. Is there a risk premium in the stock lending market? evidence from equity options. The Journal of Finance 77 (3), 1787–1828.

Ozik, G., Sadka, R., Shen, S., 2020. Flattening the illiquidity curve: Retail trading during the covid-19 lockdown. Available at SSRN 3663970.

Pedersen, L. H., 2021. Game on: Social networks and markets. Available at SSRN 3794616.

Peress, J., Schmidt, D., 2020. Glued to the tv: Distracted noise traders and stock market liquidity. The Journal of Finance 75 (2), 1083–1133.

Reed, A. V., Saffi, P., Wesep, E. D. V., 2020. Short Sales Constraints and the Diversification Puzzle. Management Science, Forthcoming.

Scheinkman, J. A., Xiong, W., 2003. Overconfidence and speculative bubbles. Journal of political Economy 111 (6), 1183–1220.

Varian, H. R., 1985. Divergence of opinion in complete markets: A note. The Journal of Finance 40 (1), 309–317.

Welch, I., 2020. The wisdom of the robinhood crowd. NBER Working Paper (27866).

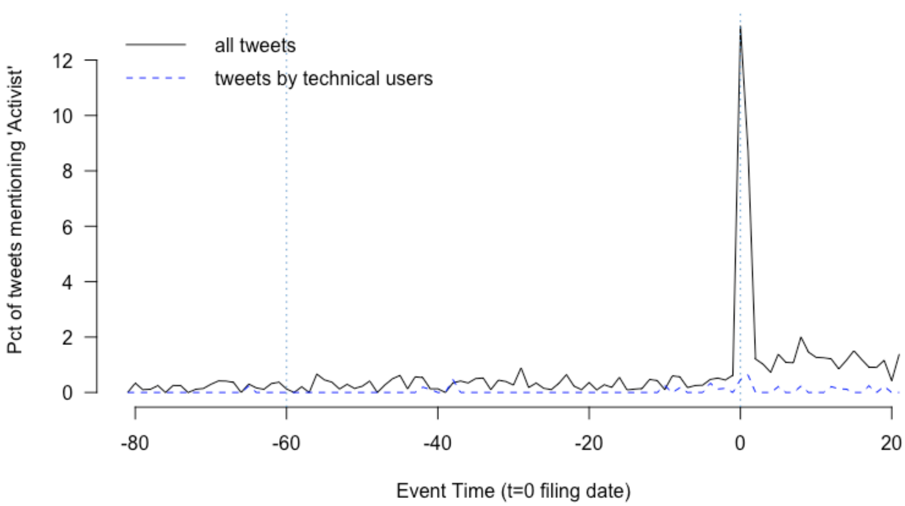
Xiong, W., 2013. Bubbles, crises, and heterogeneous beliefs. Tech. rep., National Bureau of Economic Research.

Ye, M., Zhu, W., February 2020. Strategic informed trading and dark pools, working paper.

Figure 1: Informed Trading and StockTwits Messages About Them

This figure presents two plots of the fraction of messages that refer to each of the informed trading events we study. The first panel presents mentions of "activist" for a window of $t = -80$ to $t = +20$ days around an activist's Schedule 13D filing. This shows the pretrend for the whole pre-filing period, prior to disclosure in the Schedule 13D filing. The continuous line shows the mentions in all tweets, and the dashed line shows the mentions in tweets written by investors that self-classify as having a Technical investment approach. The second plot presents mentions of "short" for a window of $t = -10$ to $t = +10$ days around short sale spike events.

Mentions of "Activist" around 13-D disclosure dates



Mentions of "Short" around short interest spikes

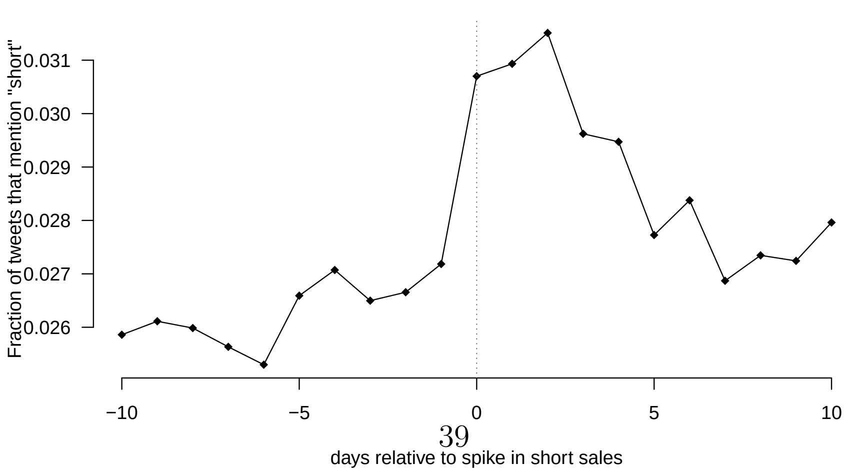
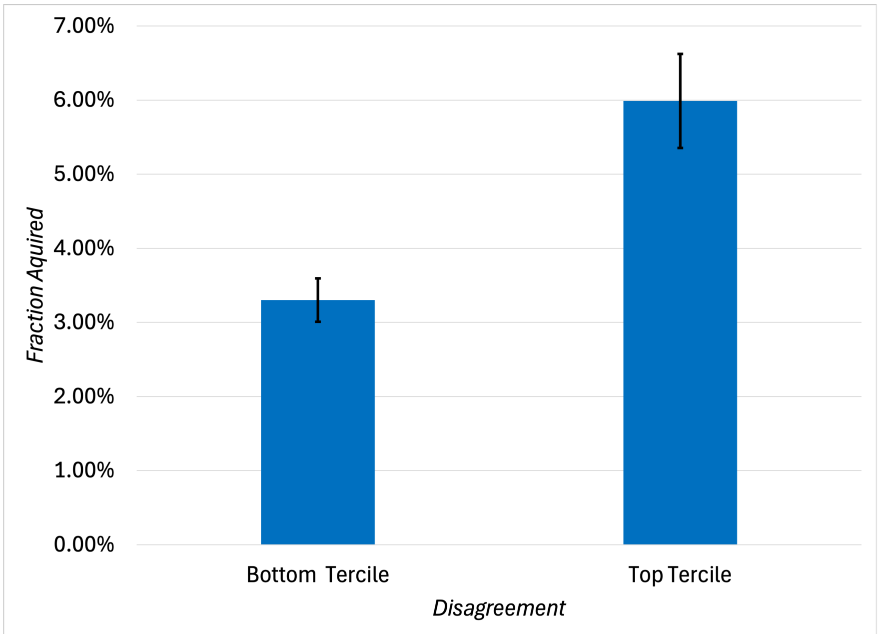


Figure 2: Shares acquired and investor disagreement

Panel (a) plots the fraction of shares outstanding acquired by a focal activist investor during the 60-day period prior to a Schedule 13D filing. Panel (b) plots the average turnover during the 60-day period prior to a Schedule 13D filing. The x-axis represents the average level of disagreement during those 60 days. The level of disagreement is divided into three terciles and we plot the bottom tercile and the top tercile levels of disagreement. The standard error bars represent confidence intervals at the 95% level.

(a) Shares Acquired



(b) Average Turnover

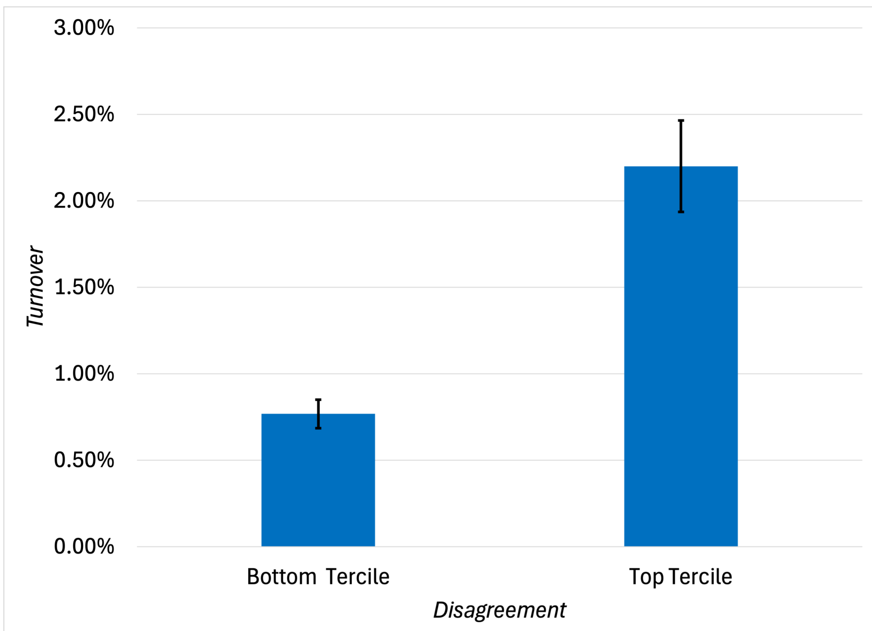
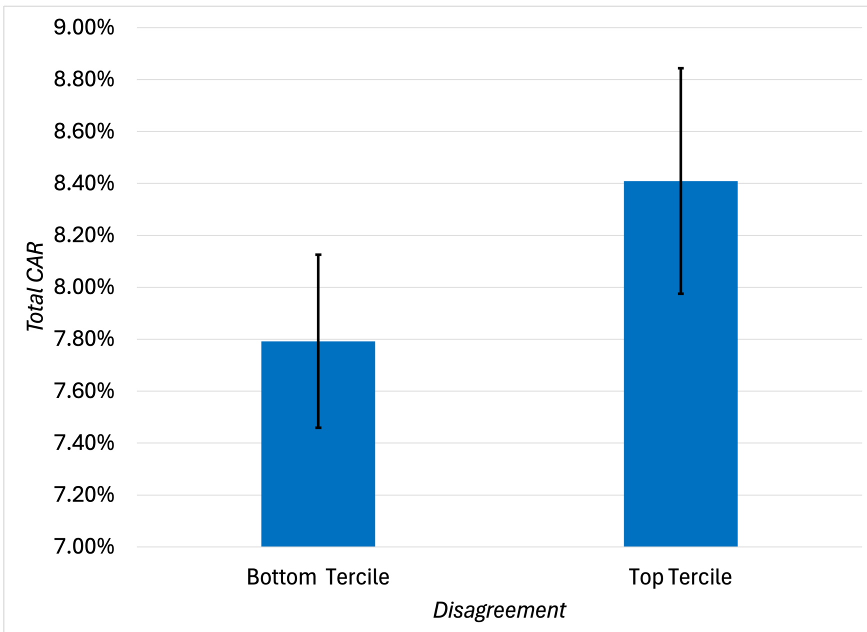


Figure 3: Returns and investor disagreement

Panel (a) plots the average buy-and-hold stock return around Schedule 13D filing date in excess of the Fama-French three-factor model, which is estimated from 360 days through 60 days before the filing date. The abnormal return is calculated from 30 days prior to the filing date to 10 days afterward. Panel (b) uses plots the treatment component of the the average buy-and-hold stock return around Schedule 13D filing date. The treatment component of the abnormal return is calculated using Albuquerque et al. (2022) methodology. The x-axis represents the average level of disagreement during those 60 days. The level of disagreement is divided into three terciles and we plot the bottom tercile and the top tercile levels of disagreement. The standard error bars represent confidence intervals at the 95% level.

(a) Total return



(b) Treatment component of the return

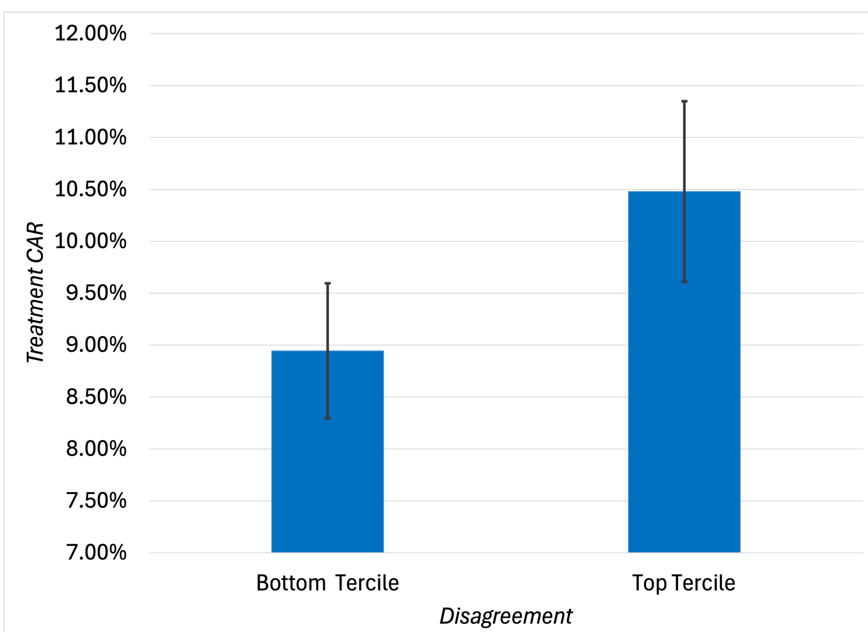


Table 1: Summary Statistics

In this table, we report summary statistics or firm-day-level variables. The sample covers the 2010-2018 period when StockTwits data are available. *Turnover*, *Return*, *Activist Turnover*, and *Ex-Activist Turnover* are expressed in %. *Ex-activist Turnover* is calculated by regressing turnover on activist turnover and taking the residual, and is multiplied by 100. *High Utilization* is defined as the average utilization over days $t-5$ to $t-1$ being greater or equal to 60%. *Short Interest Spike* is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. All potentially unbounded variables are winsorized at 1% and 99%.

	N	mean	sd	min	p25	median	p75	max
Turnover (%)	15,743,814	1.321	4.989	0.000	0.189	0.449	0.966	93.829
Return (%)	15,743,814	0.029	2.682	-17.403	-0.906	0.000	0.916	22.371
Disagreement	15,743,814	0.054	0.215	0.000	0.000	0.000	0.000	1.000
Disagreement | num. messages > 1	1,609,631	0.529	0.450	0.000	0.000	0.771	0.943	1.000
Number of messages	15,743,814	1.292	16.667	0.000	0.000	0.000	0.000	5,769
High Utilization	15,743,814	0.466	0.499	0.000	0.000	0.000	1.000	1.000
Informed Trading Measures								
Short Interest Spike	15,743,814	0.569	7.524	0.000	0.000	0.000	0.000	100.000
Activist Trade Dummy								
... full sample	15,743,814	0.133	3.638	0.000	0.000	0.000	0.000	100.000
... 60 days before filing	55,958	37.282	48.356	0.000	0.000	0.000	100.000	100.000
Activist Turnover (%)								
... full sample	15,743,814	0.000	0.016	0.000	0.000	0.000	0.000	1.790
... 60 days before filing	55,958	0.090	0.260	0.000	0.000	0.000	0.047	1.790
Ex-Activist Turnover (%)								
... full sample	15,743,814	-0.180	4.988	-1.500	-1.311	-1.051	-0.535	92.315
... 60 days before filing	55,958	-0.417	3.715	-1.500	-1.364	-1.085	-0.510	92.315

Table 2: Investor Disagreement and Informed Trading

In this table, we report results pertaining to the relationship between informed trading and disagreement among investors. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. In columns 1 and 2, the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In columns 2 and 3, the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects where indicated. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy		Short Increase Spike	
	(1)	(2)	(3)	(4)
Disagreement (z)	1.0661***	0.8432***	0.0384***	0.0414***
	(0.201)	(0.202)	(0.006)	(0.006)
Number of messages (z)		2.3607***		-0.0330*
		(0.444)		(0.017)
Activist Trade Dummy (t-1)	0.4602***	0.4605***		
	(0.008)	(0.008)		
Short Increase Spike (t-1)			0.0295***	0.0295***
			(0.001)	(0.001)
Turnover (t-1)	0.3275***	0.2992***	0.3850***	0.3879***
	(0.065)	(0.067)	(0.019)	(0.019)
Media	1.4557	1.2240	0.0905***	0.0925***
	(0.960)	(0.959)	(0.016)	(0.016)
Volatility (t-1, t-5)	21.9818**	22.0313**	-1.6320***	-1.6391***
	(8.535)	(8.571)	(0.533)	(0.532)
CAR(t-1, t-5)	8.7870***	8.6800***	-1.4334***	-1.4262***
	(2.887)	(2.868)	(0.114)	(0.114)
CAR(t-30,t-6)	4.7827***	4.8508***	-0.2826***	-0.2797***
	(1.781)	(1.781)	(0.042)	(0.041)
Observations	55,029	55,029	8,614,152	8,614,152
R-squared	0.413	0.413	0.037	0.037
Disagreement effect size	2.860%	2.262%	5.744%	6.193%
Mean	37.281	37.281	0.668	0.668
Firm FEs	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes

Table 3: Informed Trading and Technical Investor Disagreement

In this table, we report results pertaining to the relationship between informed trading and disagreement among technical investors (investors who self-report their investment strategy to be 'Technical' on StockTwits). *Technical Disagreement (z)* and *Technical Num Messages (z)* are measured from 4 p.m. on day $t-1$ to 4 p.m. on day t, and are standardized. In column 1 the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In column 2 the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at firm and date level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy	Short Increase Spike
	(1)	(2)
Technical Disagreement (z)	0.3098***	0.0318***
	(0.117)	(0.006)
Technical Num Messages (z)	0.7903***	-0.0135
	(0.263)	(0.009)
Activist Trade Dummy (t-1)	0.4602***	
	(0.008)	
Short Increase Spike (t-1)		0.0295***
		(0.001)
Turnover (t-1)	0.3406***	0.3868***
	(0.065)	(0.019)
Media	1.8130*	0.1036***
	(0.959)	(0.016)
Volatility (t-1, t-5)	23.3189***	-1.5921***
	(8.565)	(0.534)
CAR(t-1, t-5)	8.6493***	-1.4334***
	(2.875)	(0.114)
CAR(t-30,t-6)	4.7593***	-0.2807***
	(1.783)	(0.042)
Observations	55,029	8,614,152
R-squared	0.412	0.037
Disagreement effect size	0.831%	4.757%
Mean	37.282	0.668
Controls	Yes	Yes
Firm FEs	Yes	Yes
Date FEs	Yes	Yes

Table 4: Liquidity and Valuation Channels

In this table, we report results pertaining to the relationship between turnover, returns and disagreement among investors. Turnover, on day t is multiplied by 100. Returns, is calculated as the close-to-close return obtained from CRSP. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. For Panel B, we split the sample into high and low utilization subsamples. The utilization measure on day t is obtained from Markit data set and high utilization is defined as the average utilization over days $t-5$ to $t-1$ being greater or equal to 60%. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample						
Dependent variable:		Turnover			Returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Disagreement (z)	0.2617***	0.2151***	0.2115***	0.1064***	0.0956***	0.0991***
	(0.007)	(0.012)	(0.013)	(0.003)	(0.004)	(0.004)
Number of messages (z)		0.4119***	0.7752***		0.0958***	0.2143***
		(0.097)	(0.157)		(0.025)	(0.047)
Disagreement (t-1)			-0.0051			-0.0247***
			(0.005)			(0.002)
Number of messages (t-1)			-0.5294***			-0.1713***
			(0.100)			(0.036)
Turnover (t-1)	0.6301***	0.6212***	0.6313***	-0.0088***	-0.0108***	-0.0071***
	(0.014)	(0.014)	(0.014)	(0.001)	(0.001)	(0.001)
Media	0.2194***	0.1913***	0.1703***	0.0493***	0.0428***	0.0371***
	(0.009)	(0.019)	(0.018)	(0.007)	(0.008)	(0.008)
Volatility (t-1, t-5)	1.5271***	0.7445	1.8074***	-0.1741	-0.3560	0.0647
	(0.442)	(0.462)	(0.407)	(0.230)	(0.235)	(0.228)
CAR(t-1, t-5)	-0.0171	-0.2239**	-0.0828	-1.6777***	-1.7257***	-1.6783***
	(0.080)	(0.087)	(0.075)	(0.135)	(0.134)	(0.134)
CAR(t-30,t-6)	0.1779***	0.1283***	0.1606***	-0.1461***	-0.1577***	-0.1449***
	(0.028)	(0.029)	(0.026)	(0.031)	(0.031)	(0.031)
Observations	15,377,819	15,377,819	15,377,819	15,377,869	15,377,869	15,377,869
R-squared	0.683	0.688	0.692	0.111	0.112	0.113
Disagreement effect size	5.25%	4.31%	4.24%	3.97%	3.56%	3.70%
Standard Deviation	4.989	4.989	4.989	2.682	2.682	2.682
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Stock utilization sub-samples						
Dependent variable:	Returns					
Sub-sample:	High Utilization			Low Utilization		
	(1)	(2)	(3)	(4)	(5)	(6)
Disagreement (z)	0.1457***	0.1311***	0.1398***	0.0928***	0.0873***	0.0869***
	(0.010)	(0.010)	(0.010)	(0.003)	(0.004)	(0.005)
Number of messages (z)		0.1220***	0.2138***		0.0643*	0.1292**
		(0.026)	(0.041)		(0.034)	(0.057)
Disagreement (t-1) (z)			-0.0545***			-0.0092***
			(0.006)			(0.002)
Number of messages (t-1) (z)			-0.1429***			-0.0981**
			(0.029)			(0.039)
Turnover (t-1)	-0.0350***	-0.0486***	-0.0319***	-0.0115***	-0.0151***	-0.0068**
	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Media	0.0246	-0.0246	-0.0324	0.0552***	0.0520***	0.0487***
	(0.035)	(0.037)	(0.036)	(0.006)	(0.007)	(0.007)
Volatility (t-1, t-5)	-0.1193	0.0230	0.1914	0.6903***	0.6797***	0.7466***
	(0.401)	(0.394)	(0.390)	(0.254)	(0.254)	(0.254)
CAR(t-1, t-5)	-1.0128***	-1.1088***	-1.1139***	-1.8868***	-1.8908***	-1.8856***
	(0.140)	(0.136)	(0.134)	(0.117)	(0.117)	(0.116)
CAR(t-30,t-6)	-0.2231***	-0.2521***	-0.2433***	-0.1600***	-0.1609***	-0.1593***
	(0.043)	(0.044)	(0.042)	(0.030)	(0.030)	(0.030)
Observations	680,010	680,010	680,010	8,277,558	8,277,558	8,277,558
R-squared	0.093	0.095	0.097	0.141	0.141	0.142
Disagreement effect size	5.31%	4.78%	5.10%	3.53%	3.32%	3.31%
Standard Deviation	2.742	2.742	2.742	2.629	2.629	2.629
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Investor Disagreement and Informed Trading: The Role of Short Selling Constraints

In this table, we report results pertaining to the relationship between informed trading and disagreement among investors, separately for high and low short sale constraints. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. In columns 1 and (3), the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In columns 2 and 4, the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Panel A reports results for observations with high short sale constraints: high utilization or high lending fees, Panel B for low short sale constraints: low utilization and low lending fees, and Panel C the difference in effect sizes. The utilization measure on day t is obtained from Markit data set and high utilization is defined as the average utilization over days $t-5$ to $t-1$ being greater or equal to 60%. The lending fees on day t are proxied for by indicative fee measure obtained from Markit data set and high lending fees are defined over days $t-5$ to $t-1$ being greater or equal to 1%. Controls in all regressions include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)	Activist Trade Dummy (3)	Short Increase Spike (4)
Panel A:	*High Utilization*		*High Fees*	
Disagreement (z)	0.0035	0.0936***	0.0084	0.0449***
	(0.191)	(0.018)	(0.105)	(0.010)
Number of messages (z)	-4.6590	-0.0076	3.6889	0.0147
	(3.433)	(0.017)	(3.297)	(0.030)
Activist Trade Dummy (t-1)	0.3320***		0.3623***	
	(0.045)		(0.044)	
Short Increase Spike (t-1)		0.0207***		0.0135***
		(0.003)		(0.004)
Observations	1,481	640,522	1,430	621,583
R-squared	0.662	0.070	0.617	0.067
Mean	36.290	1.230	37.512	0.639
Panel B:	*Low Utilization*		*Low Fees*	
Disagreement (z)	0.9934***	0.0231***	0.9774***	0.0247***
	(0.234)	(0.005)	(0.233)	(0.006)
Number of messages (z)	3.2030***	-0.0114	3.0488***	-0.0268**
	(0.776)	(0.008)	(0.704)	(0.012)
Activist Trade Dummy (t-1)	0.4614***		0.4609***	
	(0.009)		(0.009)	
Short Increase Spike (t-1)		0.0276***		0.0282***
		(0.002)		(0.002)
Observations	43,602	7,800,485	43,534	7,979,453
R-squared	0.430	0.040	0.433	0.040
Mean	37.473	0.637	37.708	0.672

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)	Activist Trade Dummy (3)	Short Increase Spike (4)
Panel C:	*High minus Low Utilization*		*High minus Low Fees*	
High Utilization/Fee Dis effect size (%)	0.010	7.610	0.022	7.032
Low Utilization/Fee Dis effect size (%)	2.651	3.624	2.588	3.958
Difference in the coefficients	-2.641*	3.986**	-2.566	3.073*
	(1.414)	(2.020)	(1.992)	(1.642)

Table 6: Overnight Investor Disagreement and Informed Trading: The Role of Short Selling Constraints

In this table, we report results pertaining to the relationship between informed trading and disagreement among investors, separately for high and low shortsale cost samples. *Disagreement–Night (z)* and *Number of messages–Night (z)* are measured between 4 p.m. on day $t-1$ and 9 a.m. on day t, and are standardized. In columns 1 and 3, the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In columns 2 and 4, the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Panel A reports results for observations with high short sale constraints: high utilization or high lending fees, Panel B for low short sale constraints: low utilization and low lending fees, and Panel C the difference in effect sizes. The utilization measure on day t is obtained from Markit data set and high utilization is defined as the average utilization over days $t-5$ to $t-1$ being greater or equal to 60%. The lending fees on day t are proxied for by indicative fee measure obtained from Markit data set and high lending fees are defined over days $t-5$ to $t-1$ being greater or equal to 1%. Controls in all regressions include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)	Activist Trade Dummy (3)	Short Increase Spike (4)
Panel A:	*High Utilization*		*High Fees*	
Disagreement - Night (z)	0.002	0.0686***	0.0044	0.0300***
	(0.132)	(0.017)	(0.070)	(0.006)
Number of messages - Night (z)	-4.6823	-0.0150	2.3165	0.0083
	(6.513)	(0.015)	(3.597)	(0.029)
Activist Trade Dummy (t-1)	0.3713		0.3644***	
	(0.477)		(0.044)	
"Short Increase Spike (t-1)"		0.1454***		0.0135***
		(0.012)		(0.004)
Observations	1,481	640,522	1,430	621,583
R-squared	0.662	0.07	0.617	0.067
Mean	36.290	1.230	37.512	0.639
Panel B:	*Low Utilization*		*Low Fees*	
Disagreement - Night (z)	1.0278***	0.0087*	0.9932***	0.0063
	(0.242)	(0.005)	(0.243)	(0.005)
Number of messages - Night (z)	3.8763***	-0.0111*	3.7908***	-0.0213**
	(0.926)	(0.007)	(0.939)	(0.010)
Activist Trade Dummy (t-1)	0.3450***		0.4611***	
	(0.064)		(0.009)	
"Short Increase Spike (t-1)"		0.5768***		0.0282***
		(0.025)		(0.002)
Observations	43,602	7,800,485	43,534	7,979,453
R-squared	0.430	0.039	0.433	0.040
Mean	37.473	0.637	37.708	0.672

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)	Activist Trade Dummy (3)	Short Increase Spike (4)
Panel C:	*High minus Low Utilization*		*High minus Low Fees*	
High Utilization/Fee Dis effect size (%)	0.006	5.577	0.012	4.698
Low Utilization/Fee Dis effect size (%)	2.743	1.365	2.634	0.938
Difference in the coefficients	-2.737**	4.212***	-2.622**	3.761*
	(1.257)	(1.521)	(1.291)	(1.9795)

Table 7: Effects of Investor Disagreement on Activist Trading

In this table we reports results pertaining to the relationship between activist trading and disagreement among investors. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. In column 1, the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In column 2, the dependent variable is activist turnover for firm i on day t, multiplied by 100. The sample covers days on which activists trade during the 60-day period prior to Schedule 13D filings during 2010-2018. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed-effects. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Activist Trade Dummy	Activist Turnover
	(1)	(2)
Disagreement (z)	0.8432***	0.0426***
	(0.202)	(0.004)
Number of messages (z)	2.3607***	0.0399***
	(0.444)	(0.012)
Activist Trade Dummy (t-1)	0.4605***	
	(0.008)	
Activist Turnover (t-1)		0.1499***
		(0.015)
Observations	55,029	20,479
R-squared	0.413	0.429
Disagreement effect size	2.262%	17.694%
Mean	37.282	0.241
Controls	Yes	Yes
Firm FEs	Yes	Yes
Date FEs	Yes	Yes

Table 8: Investor Disagreement on Ex-activist Turnover

In this table, we report the relationship between ex-activist trading and disagreement among investors. The dependent variable, ex-activist turnover, is calculated by regressing turnover on activist turnover and taking the residual, and is multiplied by 100. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. In column 1 the sample covers the 60-day periods prior to a Schedule 13D filing. In column 2 the sample covers days during the 60-day periods prior to Schedule 13D filings, during which some activist turnover occurs. In columns 3 the sample covers days during the 60-day periods prior to Schedule 13D filings, during which no activist turnover occurs. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Ex-activist Turnover		
Sample:	60-day period	Days with Activist Trading	Days without Activist Trading
	(1)	(2)	(3)
Disagreement (z)	0.4590***	0.8432***	0.1141*
	(0.053)	(0.094)	(0.061)
Number of messages (z)	2.7805***	2.4599***	3.5376***
	(0.466)	(0.410)	(0.824)
Activist Turnover (t-1)	-0.5589***	-0.7649***	-0.2288
	(0.119)	(0.180)	(0.147)
Observations	55,029	20,479	34,525
R-squared	0.362	0.440	0.539
Disagreement effect size	12.359%	16.871%	4.279%
Standard deviation	3.714	4.998	2.667
Controls	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes

Internet Appendix to : "Does Disagreement Facilitate Informed Trading?"

Table A1: Informed Trading and Returns

In this table, we report monthly results pertaining to the relationship between activist and short sellers' trading and future returns. The dependent variable is next month's returns multiplied by 100. *Trade Dummy* is an indicator variable that equals 100 if there was activist trading for firm i in month m, and zero otherwise. *Short Increase Spike* is 100 if there was at least a 1% daily increase in fraction of shares on loan in month m, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include *Media prior month*, equals 1 if the company had at least one story on Dow Jones News Wire in month m, *Volatility prior month* is the standard deviation of abnormal returns over the calendar month m, *Return prior month* is the return over the calendar month m, and *Return prior year*, is the return from month $m-12$ through month $m-1$. Regressions include month fixed effects, where noted. Heteroskedasticity-robust standard errors reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Returns (m+1)			
	(1)	(2)	(3)	(4)
Trade Dummy	1.4277***	1.5851***		
	(0.254)	(0.258)		
Short Increase Spike			-0.3272***	-0.2143***
			(0.069)	(0.070)
Media prior month		-0.0273		-0.2034***
		(0.036)		(0.041)
Volatility prior month		-5.5139***		-3.2706***
		(0.755)		(1.000)
Return prior month		-0.0282***		-0.0303***
		(0.001)		(0.002)
Return prior year		0.0023***		0.0012***
		(0.000)		(0.000)
Observations	747,018	685,478	448,571	424,348
R-squared	0.000	0.009	0.000	0.009
Month FEs		Yes		Yes

Table A2: Alternative Liquidity Measures

In this table we consider alternative measures of liquidity to turnover. Amihud illiquidity measure is based on Amihud (2002), Quote Spread, Effective Spread, Realized Spread, and Price Impact are constructed from high-frequency TAQ data. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Amihud (1)	Bid-Ask Spread (2)	Quoted Spread (3)	Effective Spread (4)	Realized Spread (5)	Price Impact (6)
Disagreement (z)	-0.0604***	-0.0623***	-0.0516***	-0.0118**	-0.0994***	0.0679***
	(0.005)	(0.003)	(0.010)	(0.006)	(0.005)	(0.004)
Number of messages (z)	-0.0317*	-0.0390***	-0.0164	0.0004	-0.0174*	0.0150
	(0.017)	(0.012)	(0.028)	(0.016)	(0.010)	(0.010)
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	14,994,105	15,377,784	10,094,747	10,061,924	10,059,288	10,058,521
R-squared	0.117	0.515	0.690	0.646	0.326	0.174
Disagreement effect size	-0.58%	-1.60%	-0.21%	-0.07%	-0.55%	0.66%
Standard Deviation	10.444	3.901	24.515	16.788	18.033	10.277
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table A3: Informed Trading and Short Interest Spike Cutoffs

In this table, we report results pertaining to the relationship between short interest spikes and disagreement among investors, for different spike cutoffs. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. The dependent variable, *Short Increase Spike*, is 100 if the increase in fraction of shares on loan from day $t-1$ to t was at least 2% in column 1, at least 1% in column 2 and at least 0.5% in column 3. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5,t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at firm and date level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Short Increase Spike		
Cutoff:	2%	1%	0.5%
	(1)	(2)	(3)
Disagreement (z)	0.0060**	0.0414***	0.1518***
	(0.003)	(0.006)	(0.011)
Number of messages (z)	-0.0112	-0.0330*	-0.0467*
	(0.008)	(0.017)	(0.026)
Short Increase Spike (t-1)	0.0209***	0.0295***	0.0414***
	(0.002)	(0.001)	(0.001)
Observations	8,614,152	8,614,152	8,614,152
R-squared	0.024	0.037	0.059
Disagreement effect size	3.774%	6.193%	6.851%
Mean	0.159	0.668	2.216
Firm FEs	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes

Table A4: Different Utilization Cutoffs

In this table, we report results pertaining to the relationship between returns and disagreement for high- and low-utilization samples for different definitions of high vs. low utilization. Returns, is calculated as the close-to-close return obtained from CRSP. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. We split the sample into high and low utilization subsamples. The utilization measure on day t is obtained from Markit data set and high utilization is defined as the average utilization over days $t-5$ to $t-1$ being greater or equal to 50% in columns 1 and 4, 60% in columns 2 and 5, and 70% in columns 3 and 6. Controls include disagreement and number of messages on day $t-1$, turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Returns					
Sub-sample:	High Utilization			Low Utilization		
Cutoffs:	50%	60%	70%	50%	60%	70%
	(1)	(2)	(3)	(4)	(5)	(6)
Disagreement (z)	0.1348***	0.1398***	0.1457***	0.0859***	0.0869***	0.0881***
	(0.009)	(0.010)	(0.012)	(0.005)	(0.005)	(0.004)
Number of messages (z)	0.2092***	0.2138***	0.2444***	0.1251**	0.1292**	0.1297**
	(0.046)	(0.041)	(0.042)	(0.059)	(0.057)	(0.052)
Disagreement (t-1) (z)	-0.0480***	-0.0545***	-0.0644***	-0.0086***	-0.0092***	-0.0100***
	(0.005)	(0.006)	(0.007)	(0.002)	(0.002)	(0.002)
Number of messages (t-1) (z)	-0.1422***	-0.1429***	-0.1636***	-0.0944**	-0.0981**	-0.0977***
	(0.033)	(0.029)	(0.028)	(0.041)	(0.039)	(0.036)
Turnover (t-1)	-0.0308***	-0.0319***	-0.0339***	-0.0041	-0.0068**	-0.0085***
	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)
Media	-0.0309	-0.0324	-0.0296	0.0507***	0.0487***	0.0473***
	(0.028)	(0.036)	(0.047)	(0.007)	(0.007)	(0.007)
Volatility (t-1, t-5)	0.0849	0.1914	0.4895	0.8376***	0.7466***	0.6478***
	(0.357)	(0.390)	(0.455)	(0.257)	(0.254)	(0.249)
CAR(t-1, t-5)	-1.0812***	-1.1139***	-1.1862***	-1.9631***	-1.8856***	-1.8171***
	(0.127)	(0.134)	(0.146)	(0.118)	(0.116)	(0.115)
CAR(t-30,t-6)	-0.2333***	-0.2433***	-0.2412***	-0.1660***	-0.1593***	-0.1623***
	(0.039)	(0.042)	(0.046)	(0.030)	(0.030)	(0.030)
Observations	883,286	680,010	508,510	8,074,291	8,277,558	8,449,063
R-squared	0.103	0.097	0.092	0.143	0.142	0.140
Disagreement effect size	3.45%	5.10%	3.63%	3.31%	3.31%	3.31%
Standard Deviation	3.903	2.742	4.014	2.598	2.629	2.660
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table A5: Informed Trading and Overnight Investor Disagreement

In this table, we report results pertaining to the relationship between informed trading and disagreement among investors between market close on day $t-1$ and market open on day t. *Disagreement - Night (z)* and *Number of Messages - Night (z)* are measured between 4 p.m. on day $t-1$ and 9 a.m. on day t, and are standardized. In column 1 the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In column 2 the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at firm and date level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)
Disagreement - Night (z)	0.9113***	0.0211***
	(0.207)	(0.006)
Number of messages - Night (z)	2.1353***	-0.0286**
	(0.639)	(0.014)
Activist Trade Dummy (t-1)	0.4607***	
	(0.008)	
Short Increase Spike (t-1)		0.0295***
		(0.001)
Observations	55,029	8,614,152
R-squared	0.413	0.037
Disagreement effect size	2.444%	3.156%
Mean	37.282	0.668
Controls	Yes	Yes
Firm FEs	Yes	Yes
Date FEs	Yes	Yes

Table A6: Informed Trading and Technical Overnight Investor Disagreement

In this table, we report results pertaining to the relationship between informed trading and disagreement among investors who classify themselves as having a technical approach between market close on day $t-1$ and market open on day t. *Technical Disagreement Night (z)* and *Technical Num Messages Night(z)* are measured between 4 p.m. on day $t-1$ and 9 a.m. on day t for investors who self-classify themselves as having a "Technical" approach, and are standardized. In column 1 the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In column 2 the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at firm and date level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)
Technical Disagreement Night (z)	0.4770*	0.0107*
	(0.250)	(0.006)
Technical Num Messages Night (z)	2.0706***	-0.0197*
	(0.473)	(0.012)
Activist Trade Dummy (t-1)	0.4606***	
	(0.008)	
Short Increase Spike (t-1)		0.0295***
		(0.001)
Observations	55,029	8,614,152
R-squared	0.413	0.037
Disagreement effect size	1.279%	1.601%
Mean	37.282	0.668
Controls	Yes	Yes
Firm FEs	Yes	Yes
Date FEs	Yes	Yes

Table A7: Informed Trading and Self-classified Disagreement

In this table, we report results pertaining to the relationship between informed trading and disagreement among investors based on messages where investors self-classified the sentiment of the message. *Self-classified Disagreement (z)* and *Self-classified Num. Messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t and we only consider messages where the author of the tweet either classified it as "Bearish" or "Bullish." Both measures are standardized. In column 1 the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In column 2 the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects. Heteroskedasticity-robust standard errors are double-clustered at firm and date level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)
Self-classified Disagreement (z)	0.7940***	0.0295***
	(0.259)	(0.008)
Self-classified Num. Messages (z)	1.0766***	-0.0521***
	(0.398)	(0.019)
Activist Trade Dummy (t-1)	0.4604***	
	(0.008)	
Short Increase Spike (t-1)		0.0295***
		(0.001)
Observations	55,029	8,614,152
R-squared	0.412	0.037
Disagreement effect size	2.130%	4.413%
Mean	37.282	0.668
Controls	Yes	Yes
Firm FEs	Yes	Yes
Date FEs	Yes	Yes

Table A8: Days with at least Two Messages

In this table, we report results pertaining to the relationship between informed trading and disagreement among investors on days with at least two messages on StockTwits about the firm. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. In column 1 the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In column 2 the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 firm and date fixed effects where indicated. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)
Disagreement (z)	0.3459*	0.0247***
	(0.185)	(0.006)
Number of messages (z)	2.1464***	0.0034
	(0.421)	(0.010)
Activist Trade Dummy (t-1)	0.3728***	
	(0.019)	
Short Increase Spike (t-1)		0.0394***
		(0.003)
Observations	5,514	1,108,120
R-squared	0.605	0.051
Disagreement effect size	0.844%	1.880%
Mean	41	1.314
Controls	Yes	Yes
Firm FEs	Yes	Yes
Date FEs	Yes	Yes

Table A9: Controlling for Investor Sentiment

In this table we report results pertaining to the relationship between informed trading and disagreement among investors while controlling for investor sentiment. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. In column 1 the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In column 2 the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 $t-1$. *Avg. Sentiment* is the average sentiment of messages posted about firm i on day t. All regressions include firm and date fixed effects where indicated. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)
Disagreement (z)	0.8401***	0.0423***
	(0.203)	(0.006)
Number of messages (z)	2.3722***	-0.0336**
	(0.445)	(0.017)
Activist Trade Dummy (t-1)	0.4605***	
	(0.008)	
Short Increase Spike (t-1)		0.0295***
		(0.001)
Avg. Sentiment	-0.189	0.0506***
	(0.454)	(0.009)
Observations	55,029	8,614,152
R-squared	0.413	0.037
Disagreement effect size	2.253%	6.328%
Mean	37.281	0.668
Controls	Yes	Yes
Firm FEs	Yes	Yes
Date FEs	Yes	Yes

Table A10: Controlling for Retail Order Imbalance

In this table we report results pertaining to the relationship between informed trading and disagreement among investors while controlling for retail order imbalance. *Disagreement (z)* and *Number of messages (z)* are measured between 4 p.m. on day $t-1$ and 4 p.m. on day t, and are standardized. In column 1 the dependent variable is an indicator variable that equals 100 if there was activist trading for firm i on day t, and zero otherwise. The sample covers the 60-day period prior to Schedule 13D filings during 2010-2018. In column 2 the dependent variable is 100 if there was at least a 1% increase in fraction of shares on loan from day $t-1$ to t, and zero otherwise. Fraction of shares on loan is calculated as the number of shares on loan divided by the number of shares outstanding. Controls include turnover on day $t-1$, $Media$, equals 1 if the company had at least one story on Dow Jones News Wire on day t, $Volatility(t-5, t-1)$, is 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 $t-1$. *Retail order imbalance* is calculated as the difference between retail buying and selling volume, divided by the total retail trading volume. All regressions include firm and date fixed effects where indicated. Heteroskedasticity-robust standard errors are double-clustered at the firm and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Activist Trade Dummy (1)	Short Increase Spike (2)
Disagreement (z)	0.7525***	0.0421***
	(0.204)	(0.006)
Number of messages (z)	2.6466***	-0.0296*
	(0.471)	(0.017)
Activist Trade Dummy (t-1)	0.4685***	
	(0.008)	
Short Increase Spike (t-1)		0.0285***
		(0.001)
	(0.008)	(0.001)
Retail Order Imbalance	-0.7184*	0.0133*
	(0.383)	(0.007)
Observations	51,275	7,983,559
R-squared	0.419	0.037
Disagreement effect size	2.018%	6.298%
Mean	37.281	0.668
Controls	Yes	Yes
Firm FEs	Yes	Yes
Date FEs	Yes	Yes