Strategic Informed Trades and Tiny Trades

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Advisor: Vivian Fang

May, 2024

Acknowledgements

I am deeply indebted to my advisor, Vivian Fang, for her unwavering support, insightful guidance, and constant encouragement during my doctoral studies. I am also grateful to my dissertation committee members and references, Salman Arif, Zhi Da, Pervin Shroff, and Gaoqing Zhang for their helpful suggestions and support.

I am thankful for the advice and support from many other faculty members and friends: Stephaine Dong, Mike Iselin, Nan Li, Josh Madsen, Xinyuan Shao, Shuyan Wang, Da Xu, Mengjie Xu, Johnny Yoon, Helen Zhang, Yang Zhang, and Zhiyu Zhang. I also appreciate the feedback and suggestions from seminar participants at the Chinese University of Hong Kong (SZ), Singapore Management University, University of Hong Kong, and University of Minnesota.

I am lucky to have had the company and support of the faculty at the University of Minnesota as well as my fellow Ph.D. students (past and present) at the Carlson School and the Department of Economics.

I would also like to thank Ningzhong Li, Jieying Zhang, Jianming Ye, and Feng Xiong for introducing me to an academic career in accounting during my undergraduate studies.

Finally, I am incredibly grateful to my parents for their love and support in helping me pursue my academic dream. I could not have done it without them.

Dedication

To my family.

Abstract

This paper studies how institutional investors strategically respond to an anticipated surge in tiny retail trades. Exploiting positive 8-K filings as informational events, I present three findings. First, stocks exposed to intense fractional trading exhibit substantial price pressure and volatility following filings, displaying an initial overshoot and subsequent reversal. Second, institutional investors leverage such price pressure and volatility by delaying immediate sales upon filing and even accumulating additional stakes to ride the mispricing post-filing. Third, increased post-filing trading profits incentivize information acquisition. These results suggest that institutional investors adapt to the evolving landscape of retail trading in today's markets, albeit leading to delayed price discovery.

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Chapter 1

Introduction

The landscape of retail trading in the U.S. stock market has undergone a transformation in recent years. We observe increased participation by a new generation of retail traders who are young, inexperienced in investing, and capital-constrained. These new retail traders are shown to have important implications for the financial markets. They engage in more attention-induced trading than other retail traders (Barber et al., 2022) and herd in stocks that were recently discussed on social media platforms (Eaton et al., 2022; Hu et al., 2021). Despite small individual investments, attention-coordinated tiny retail trades drive the stock price to deviate from its fundamental value for longer periods and induce more price volatility (van der Beck and Jaunin, 2023).[1] Sophisticated informed (often institutional) investors might hesitate to correct the mispricing and even profit from mimicking the bets made by the less sophisticated crowd (Zhou and Zhou, 2023; Wall Street Journal, 2022), thereby amplifying price pressure and volatility. This paper studies the strategic interaction between informed investors and tiny traders and its implication for the price discovery of accounting disclosures.

In a competitive financial market, informed investors would act as "*rational arbitrageurs*", actively engaging in private information acquisition and quickly capitalizing on the short-lived information advantages.[2] Specifically, around the disclosure event,

[1] The average account size for a Robinhood investor was approximately $3,500 in 2021 compared to $127,000, $234,000 or $279,000 for E-Trade, Charles Schwab and Fidelity, respectively (Forbes Advisor, 2021). The median account balance was only $240 (SEC, 2021). Additionally, van der Beck and Jaunin (2023) show that, despite representing about 0.2% of the market share, Robinhood traders contribute to 10% of the cross-sectional variation in stock returns during the second quarter of 2020.

[2] The trading immediacy among informed investors is primarily driven by competition from other

informed investors who acquire information early usually trade aggressively on their private information before the information is publicly disclosed. These informed traders then sell immediately on the news and earn extra trading profits by exploiting overreaction to the public disclosure by less sophisticated investors (Brunnermeier, 2005; Ben-Rephael et al., 2022; Callen et al., 2022). Alternatively, informed traders may act as "*opportunity takers*", trading with retail investors and potentially exacerbating mispricing and price volatility following the disclosure. There are trading frictions due to limits of arbitrage (Shleifer and Vishny, 1997) and noise trader risk (De Long et al., 1990a), which deters informed traders from correcting the mispricing. Additionally, prior theories show the benefits of riding the mispricing in the presence of predictable sentiment (De Long et al., 1990b; Abreu and Brunnermeier, 2003).[3] There are also plenty of anecdotes of smart money taking advantage of dumb retail flows by riding the bubble, but large sample firm-level empirical evidence remains limited (Brunnermeier and Nagel, 2004; Griffin et al., 2011).

I exploit the introduction of fractional trading, which facilitates tiny retail trades, to study how informed investors strategically respond to the anticipated surge of tiny retail trades following disclosure events. From an empirical perspective, tiny retail trades capture extremely uninformed retail trading flows, complementing the general retail trading measure by Boehmer et al. (2021). Boehmer et al. (2021) measure may include informed retail trades and even a considerable proportion of institutional trades (Barber et al., 2023; Battalio et al., 2023).

As part of an ongoing strategy to attract retail clientele, several US brokers introduced fractional trading services to allow investors to trade less than a whole share of equity. Retail investors can enter dollar- or cent-based trades rather than only share-based trades on mobile-based applications (Wall Street Journal, 2021). Fractional trading increases the general willingness to enter and trade stocks, leading to a surge in tiny retail trades (Da et al., 2023).[4] Fractional orders are executed internally by retail

informed investors and the potential benefits of being early profit takers. Informed traders engage in competition for bounded liquidity alongside other informed traders. Immediacy is desirable as their profits vanish with the introduction of additional trading rounds (Holden and Subrahmanyam, 1992; Foster and Viswanathan, 1993).

[3] Previous theory work suggests that the incentive for informed investors to ride the mispricing emanates from predictable "sentiment": such as the extent to which they can predict feedback trader's demand in De Long et al. (1990b) and bubble growth in Abreu and Brunnermeier (2003).

[4] The introduction of fractional trading spurs a larger increase of tiny trades in stocks as it not only

brokers rather than being routed to market makers. Executing brokers are required to make additional public disclosures for these fractional trades, which are subsequently recorded in FINRA's OTC Transparency dataset on a weekly basis. Utilizing the public fractional trade reporting, I calculate the total number of fractional trades during the post-FT period for each stock and define high-FT stocks as stocks in the top FT-decile.[5] This indicates that high-FT stocks exhibit a high level of uninformed trading intensity.

I use 8-K filings as informational events. These events are *unanticipated* since most 8-K forms are not pre-scheduled.[6] Thus, trading in the pre-filing period (the gap between the event day and the filing day) demands more costly information acquisition, often beyond the reach of retail traders.[7] This provides an empirical advantage for measuring informed trading activities. The pre-filing window is well-defined and directional trades within this period are more likely to be informed trades. Moreover, post-filing retail trades are more prone to being uninformed as textual contents in 8-K filings are challenging to process (Blankespoor et al., 2019, 2020), thereby carrying the potential to introduce an abundance of noise trader risk after the disclosure.

I begin by examining patterns of stock returns surrounding positive 8-K events. Figure 5.3 shows that, during the pre-FT period, high-FT stocks exhibit a downward-drifting return pattern after the filing day, consistent with informed traders selling immediately on the news. In the post-FT period, high-FT stocks display a larger price reaction on the filing day, with an upward drifting pattern after the filing day, followed

makes stock ownership more accessible for budget-constrained marginal investors (a direct effect) but also arguably elicits their general willingness to enter and trade stocks (an indirect effect) (Da et al., 2023).

[5] I set post-FT period to be years 2021 and 2022. There is a sequential introduction of fractional trading at different retail brokers during 2019 and 2020. Specifically, Interactive Brokers first announced fractional trading offerings on November 25, 2019, joined by Robinhood on December 12, 2019, Fidelity on January 29, 2020, and then Charles Schwab on June 9, 2020. In addition, two major fractional brokers Robinhood and DriveWealth (a back-end brokerage firm) started to report fractional trades to FINRA TRFs in 2021.

[6] By "unanticipated", I refer to Form 8-K events other than those reporting business operations and preliminary earnings, because the latter is likely to be anticipated by investors. Specifically, I exclude Item 2.02 from the analyses.

[7] Institutional investors have earlier access to 8-K event information pre-filing through press releases or journalist findings from expensive professional services like Bloomberg. They could also acquire information from alternative data such as web data, satellite images, credit card transactions, or even private channels. For example, Li and Venkatachalam (2022) show that cell phone pings help unravel material events such as refinery outages.

by a significant return reversal. The post-FT return pattern suggests that the post-filing price pressure is more pronounced and the timing of the return reversal is delayed compared to the pre-FT pattern. Informed traders do not effectively correct the price overreaction immediately following the disclosure. In addition, the increase in the daily tiny trades is positively correlated with contemporaneous stock price change and the number of social media mentions in the post-filing window, confirming that coordinated tiny trades exert price pressure and volatility on high-FT stocks.

Next, I investigate whether informed investors change their trading behavior around 8-K events in response to the price pressure and heightened volatility induced by tiny traders. These excessive noise trader risks may potentially discourage informed traders from correcting the post-filing mispricing and even profit from riding the mispricing for a while. I hypothesize that informed traders are less likely to unwind their positions on the filing day. I follow Bogousslavsky et al. (2023) to measure the occurrence of abnormal short spikes on the filing day. I find that there is a significant reduction in short spikes on the filing day for high-FT stocks after fractional trading, supporting the conjecture that informed traders delay immediate sales upon filing. In addition, for the subset of stocks displaying pre-filing abnormal institutional attention (Ben-Rephael et al., 2017), informed traders engage in significantly more net buys on the filing day, which exacerbates price pressure.

I further analyze how informed traders could be strategically positioned to "ride the bubble" to capture the upturn after the disclosure and benefit from the correction of the mispricing. First, consistent with theory work positing that the incentive to "ride the bubble" arises from predictable signals, I present empirical evidence demonstrating how informed traders can predict and contribute to the post-filing price run-up. Due to unsophistication, tiny traders may struggle to make effective use of the value-relevant information in 8-K filings and heavily rely on the relevant positive social media discussions upon filing, continuing to chase returns (Blankespoor et al., 2019). Figure 5.4 depicts a positive correlation between post-filing returns and social media activities. Informed traders would effectively track real-time sentiment (The Washington Post, 2021) and mimic the bets made by tiny traders, which contributes to the further price run-up.[8] Specifically, I find that when there is a higher number of concurrent tiny

[8] Survey evidence suggests that 42% of hedge fund respondents said they presently use social media

trades, informed traders are more likely to buy shares during the price run-up after the 8-K event is filed.

Second, I show that informed traders correct the mispricing when there is a shift in tiny trader sentiment or noise trader risk in De Long et al. (1990a). I observe that social media activities decline significantly around the price peak. For high-FT stocks, I also document relatively more short interest accumulated around the price peak than low-FT stocks after fractional trading is available. These findings suggest that informed traders leverage their knowledge to generate extra trading profits by driving up the price and subsequently correcting the mispricing at the expense of unsophisticated traders around accounting disclosures (Blankespoor et al., 2020). Cross-sectional analyses indicate that this trading pattern is more pronounced when the 8-K event signals a stronger underlying fundamental change and when traders are more exposed to the common signal, consistent with the theory predictions from the adapted coordination model in Fang et al. (2022).

In the final set of analyses, I explore whether higher expected trading profits resulting from the increased participation by less sophisticated tiny traders lead to more costly information acquisition by informed investors (Grossman and Stiglitz, 1980). Ben-Rephael et al. (2022) document that institutional attention as measured by Bloomberg news searching and reading activities spikes on both the event day and the filing day for 8-K events. Building on their study, I find that high-FT stocks exhibit significantly higher abnormal institutional attention on the event day compared to low-FT stocks after fractional trading is available. These empirical findings suggest higher expected trading profits incentivize pre-filing information acquisition.

I also provide suggestive evidence of how informed traders respond to the post-filing uncertainty during the pre-filing window.[9] While the surge in tiny retail trades after the disclosure is anticipated, the extent of the price overreaction, the timing of the shift of noise trader sentiment, and the response of other institutional investors are ex-ante uncertain. In contrast to Ben-Rephael et al. (2022), higher event day institutional

data in 2022 (Hedge Fund Law Report, 2022). They obtain social media data from data providers such as Quiver Quantitative, Thinknum, and Context Analytics whose major clients are asset managers and hedge funds.

[9] Informed traders would be able to learn more about market conditions and trade accordingly post-filing.

attention does not always lead to more pre-filing price discovery.

My study makes three main contributions. First, I contribute to the growing literature on retail trading and fractional trading. Barber et al. (2022) and Eaton et al. (2022) study the herding behavior of Robinhood investors and its implication for market quality. Meanwhile, Bartlett et al. (2022a) and Bartlett et al. (2022b) develop a methodology for identifying fractional trades on tape and show that this specific type of retail order predicts market liquidity, distinct from the general retail order flow. Da et al. (2023) study the impact of fractional trading on retail trading in high-priced stocks, as well as how the coordinated tiny trades by fractional traders affect the return patterns of these stocks. In addition, recent accounting literature provides rich evidence of how retail investors react to earnings announcements (Michels, 2023; Friedman and Zeng, 2022), ESG news (Moss et al., 2023; Li et al., 2023), and corporate advertisements (Fang et al., 2023) via exploiting data on Robinhood holdings, exogenous broker outages, and general retail trade measures. My study complements previous work by identifying the extremely unsophisticated retail order flow to document the impact of tiny traders on the return patterns around 8-K events and provide insights on informed trading dynamics.

Second, my paper speaks to the literature on bubbles, herding behaviors, and coordination. Informed traders might not act effectively as "rational arbitrageurs" due to noise trader risk (De Long et al., 1990a) and might find it optimal to ride the mispricing based on predictable sentiment (De Long et al., 1990b; Abreu and Brunnermeier, 2003). Additionally, bubbles could happen if there is a speculative component in asset prices (Scheinkman and Xiong, 2003). To analyze how retail traders coordinate on social media platforms, Fang et al. (2022) incorporate a strategic social media disclosure component into the coordination model and provide insights on how the interaction between social media leaders and followers affects coordination success. Informed traders could capitalize on inter-investor differences in disclosure processing or information acquisition post-filing at the expense of unsophisticated traders(Blankespoor et al., 2020). My paper provides empirical support for such a trading pattern and suggests that institutional traders exacerbate the price pressures and volatility induced by tiny traders following disclosures.

Finally, my paper is closely related to the literature on the role of information

acquisition by institutional investors and their trading strategies around accounting disclosure events. Information acquisition by sophisticated traders measured by institutional EDGAR searching activity (Drake et al., 2020) or news reading activity on Bloomberg terminals (Ben-Rephael et al., 2017) facilitates price discovery. At the same time, there is a heightened demand for trading immediacy among institutional investors and large empirical research finds supporting evidence for pre-announcement informed trading. For instance, Christophe et al. (2004) document a positive association between pre-announcement abnormal short-selling and announcement-period price reaction, consistent with the presence of informed traders. Likewise, Truong and Corrado (2014) find high options trading volume prior to earnings announcements. Ben-Rephael et al. (2022) and Callen et al. (2022) also find significant institutional trading prior to 8-K filings. Furthermore, Rogers et al. (2017) and Bolandnazar et al. (2020) show profitable pre-filing trading when institutional traders have early access to regulatory filings. My paper finds that institutional investors alter their trading strategy around 8-K events for firms that are exposed to more tiny trades. I provide evidence that institutional investors leverage the price pressure and volatility by delaying immediate sales upon filing and even accumulating additional shares post-filing. While there is more information acquisition, we observe more price volatility around the disclosure event. Overall, institutional investors adapt their trading strategy to evolving retail trading in today's markets at the expense of delayed price discovery.

Chapter 2

Data and Variable Measurement

2.1 Aggregate Fractional Trades and Tiny Trades

Most retail brokers who offer direct fractional trading services, such as Robinhood, Fidelity, Charles Schwab, Interactive Brokers, and the back-end brokerage firm Drivewealth, execute a fractional share trade on a principal basis.[10] This means that the broker executes a fractional share trade against its own inventory, and therefore each fractional share trade must be reported separately to a FINRA trade reporting facility (TRF) and OTC Transparency platform by the executing broker. To see this, consider a fractional trader submits a dollar-based order of $200 to invest in a stock trading at $160 per share. This trade which involves both whole shares and fractional share trades will be split into a whole share component (1 share) and a fractional share component (0.25 share). The whole share would be executed on an agency basis (be routed to market markers) while the fractional share component would be internalized by the executing broker and be reported to the consolidated tape and OTC Transparency platform as a one-share trade as per the "rounding-up rule".[11]

The one-share trades which appear in the consolidated tape include both rounded-up fractional share trades and one-whole-share trades. Distinguishing between these two

[10] Some small brokerage firms such as SoFi and Betterment execute fractional trades using Apex, which is similar to an accounting entry on the books and therefore not a trade. This results in no public reporting for the fractional component separately.

[11] FINRA guidance requires rounding quantities up to one if less than one share and truncating the fractional quantity for transactions that involve both a whole-share and fractional-share quantity.

trade types in TAQ is challenging. I use the OTC Transparency data to estimate the aggregate frequency of fractional trading for each stock. In 2016, FINRA launched an initiative to enhance the transparency of non-exchange trade reporting. As part of this program, FINRA releases weekly overviews of the overall count of shares and trades executed by each broker on a per-stock basis. Two pieces of evidence substantiate why OTC Transparency data yields reliable estimates of fractional shares. First, brokers began appearing in these trade disclosures after commencing their fractional trading services.[12] This further supports that retail brokers execute fractional components on a principal basis while executing the whole-share components on an agency basis. Second, the average trade size (calculated as the total number of weekly shares divided by the total number of weekly trades) for trades reported by these brokers is close to one, indicating that these reported one-share trades primarily represent fractional trades. Appendix B provides a snapshot of trade reporting for Tesla for different FINRA-registered brokers during the first week of March 2021. Notably, the average trade size for major brokers offering fractional trading is close to one, while this number is greater than 60 for market makers such as Citadel Securities and Virtu.

I manually collect these weekly summary documents from January 2021 to December 2022 (the post-FT period). For each weekly document, I gathered the symbol name for each security, the name of the market participant, and the quantity of total weekly shares and trades at the stock-broker level. To detect fractional trades, I focus on the trades reported by the five major retail brokers: Robinhood, DriveWealth, Fidelity, Charles Schwab, and Interactive Brokers. Then I calculate the average trade size at the stock-broker level, excluding observations with a trade size greater than 1.1. Finally, I aggregate the stock-broker-week observation to the stock level to estimate the aggregate frequency of fractional trading for each stock during the post-FT period.

Figure 5.1 shows the cumulative density of the total number of fractional trades detected from the OTC Transparency data. The number of fractional trades is not uniformly distributed across stocks; instead, the distribution exhibits a highly right-skewed pattern. Remarkably, the top-decile stocks alone account for more than 97% of all reported fractional share trades of the sample firms. Tesla emerged as the most

[12] High-frequency market markers such as Citadel and Virtu dominated the trade reporting by the end of 2019.

popular stock among fractional traders. Although stocks at the bottom rank suffer from an underestimation of fractional trades due to the missing broker-specific information, this is less of a concern as my focus is on stocks with a total number of fractional trades above the 90th percentile. As per FINRA rules, detailed security-related data for firms with "de minimis" volume is aggregated and published in a non-attributed manner. Specifically, weekly trades are reported under the category of "De Minimis Firms" rather than being attributed to a specific broker if the broker does not execute an average of 200 or more transactions per day for that particular security during the week.

In addition, Bartlett et al. (2022b) introduce a novel approach to differentiate between rounded one-share trades and one-whole-share trades. They find that the reporting for the fractional share trades executed by Robinhood and Drivewealth, which are observed in TAQ, display distinct broker-specific characteristics (BMO measure in short). Notably, these trades would be reported to one of the three FINRA TRFs and exhibit noticeably longer trade reporting latencies.[13] Details about the detecting algorithms are included in Appendix E. I further show that the main results are robust to using BMO measure in Figure E.1 and Figure E.2.

To measure the daily-level tiny trades, I use the off-exchange one-share trades in TAQ. As is indicated by Da et al. (2023), this measure includes only one-whole-share trades pre-FT but both fractional trades (reported as one-share trades) and one-whole-share trades post-FT, which helps document FT-facilitated shifts in tiny trades. As an illustrating example, the number of off-exchange one-share trades as a percentage of total trades closely followed the movements of Tesla's stock price during the recent Nasdaq bubble period in late 2021 (Figure 5.2), suggesting the collective price impact of these tiny traders.

[13] Bartlett et al. (2022b) specifically focus on Robinhood and Drivewealth because these two brokers are the largest in terms of executing fractional trades, accounting for approximately 80 percent of the reported volume in FINRA's OTC Transparency data. While the majority of the market experiences reporting latencies of less than 20 milliseconds, Robinhood and Drivewealth have a reporting latency exceeding 20 milliseconds.

2.2 Other Variables

To identify informed (or institutional) trading, I apply a trade size cutoff of over $50,000 to separate informed and uninformed trades following Lee and Radhakrishna (2000) and Barber et al. (2008). In addition, I use the daily securities borrowing data from Markit. Markit gathers information from over 100 participants in the equity loan market, collectively representing about 85% of US securities loans. I focus on the short interest ratio and borrower concentration. The short interest ratio is calculated as the quantity of shares borrowed (`QuantityOnLoan`) divided by the number of total shares outstanding. Borrower concentration is a metric ranging from 0 to 1, providing insight into the distribution of borrower demand.[14] As the original `datadate` in Markit reflects the settlement date, I calculate the transaction date as `datadate` -3 before September 7, 2017 and `datadate` -2 after September 7, 2017.[15] Option trading volume data is from Option Metrics.

To measure institutional attention, I follow Ben-Rephael et al. (2017) to create a measure of abnormal institutional attention (AIA) based on Bloomberg's daily attention score. *AIA* is a dummy variable that has a value of 1 if Bloomberg's daily attention score is greater than or equal to 3 and 0 otherwise.

To measure the social media mention of each stock, I collect all submissions (posts) and comments on Reddit's WallStreetBets between January 2017 and December 2022 using the Pushshift API.[16] Following Bryzgalova et al. (2023), I collect both original submissions and comments under the "Daily Discussion" category. To count the ticker mentions at the daily level, I start from CRSP tickers and search for them in all the comments. Specifically, I use regular expressions to extract all capitalized words from the full text, given the common practice among the Reddit users to use capitalized tickers. Each matching word is counted as one mention if it corresponds to any CRSP tickers. I also exclude tickers whose names coincide with commonly used words in the

[14] A low value of Borrower Concentration indicates numerous borrowers with relatively small borrowed amounts, whereas a value of 1 signifies a single borrower accounting for all the broker demand. When the Borrower Concentration is 0, it implies an absence of borrower demand.

[15] On September 5, 2017, SEC adopted the amended rule which shortens the settlement cycle for securities transactions from three business days ($T+3$) to two business days ($T+2$).

[16] According to Baumgartner et al. (2020), Pushshift is a social media data collection, analysis, and archiving platform that since 2015 has collected Reddit data and made it available to researchers. We use `PSAW` (Python Pushshift API Wrapper) to search public Reddit submissions via the Pushshift API.

WallStreetBets forum or carry special meanings. Details are included in Appendix F.

I also include a list of firm- and market-characteristic control variables in the regression analyses. These controls are the log of market capitalization at the end of previous trading day $t-1$ ($ln(Market\ Cap)_{t-1}$), book-to-market at the end of previous year ($Book\ to\ Market_{y-1}$), return-on-asset at the end of previous year ($Return\ on\ Asset_{y-1}$), institutional ownership at the end of previous quarter ($Institutional\ Ownership_{q-1}$), the standard deviation of the stock's daily returns over the past month ($Past\ Month\ Volatility_t$), the stock's maximum daily return over the past month ($Past\ Month\ Max\ Return_t$), and the stock's cumulative return of the past month and year (labeled $Past\ Month\ Return_t$ and $Past\ Year\ Return_t$).

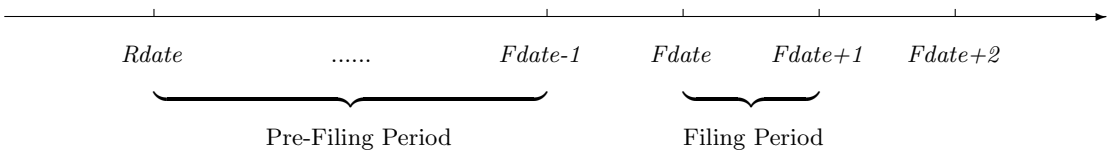
2.3 8-K Events

The Securities and Exchange Commission (SEC) mandates Form 8-K as a filing requirement for public companies, in addition to their annual reports on Form 10-K and quarterly reports on Form 10-Q. This filing is designed to promptly report material corporate events, providing shareholders with timely information on significant developments. Recognizing the increasing demand for real-time information from investors, the SEC proposed a rule in 2002 to enhance reporting efficiency, reducing the time gaps and expanding the scope of events that companies must report. Effective on August 23, 2004, the SEC increased the types of events to be reported on an 8-K form from 12 to 21, while also shortening the filing deadline for non-voluntary items from 15 calendar days to 4 business days.

The majority of 8-K forms are not pre-scheduled. But there are some exceptions. The SEC requires companies to furnish earnings releases and similar announcements to the SEC on Form 8-K under Item 2.02. The majority of 8-Ks filed under Item 2.02 are related to earnings announcements. Since I am interested in unanticipated disclosure events, I exclude from my analysis 8-K forms that contain Item 2.02.

I download the entire population of 8-K filings via SEC EDGAR for the years 2017 to 2022. The filing data includes the filing form type (i.e., 8-K or 8-K/A), the event date (also called the reported date or Rdate), the filing date to the SEC (Fdate), the filing time (Secatime), and the filer (firm) CIK number. Importantly, each filing has a

specific identifier, called the "accession number," or file name (Fname).



The above figure illustrates the timeline associated with an 8-K event. I define the pre-filing period from the event date (*Rdate*) to one day prior to the filing date (*Fdate-1*). The filing period is the two-day window surrounding the filing date: *Fdate* and *Fdate+1*. Trading days after the filing period are assigned to the post-filing period.

Appendix G provides an illustrative example of how 8-K events trigger social media discussions after the disclosure and attract tiny trades to drive up the stock price.

2.4 Summary Statistics

To build the sample, I start with the universe of stocks in the CRSP/Compustat Merged database with no missing daily returns between January 2017 and December 2022. I exclude penny stocks (i.e., those with closing price of $1 or less before the event date) to alleviate the impact of market microstructure noise on return analysis. I follow Ben-Rephael et al. (2022) to focus on single-item 8-K filings in the main analyses because it is difficult to attribute outcome variables such as investor attention and market reaction to any particular item for the multiple-item filings. I further exclude events with another 8-K event in the 10-day window. To ensure the informativeness of 8-K events and classify them into positive events, I also require that events be associated with filing-period returns equal to or greater than 2%.[17] Detailed sample construction process is reported in Appendix C.

The sample used in the baseline analyses linking 8-K filing data to market data,

[17] The results remain qualitatively similar when applying the 1%, 3% or 5% cutoff. The results are also robust to using textual sentiment of 8-K filings, based on Loughran-McDonald dictionary and sentiment word lists (Loughran and McDonald, 2011). I report this robustness test in Figure H.2 of Appendix H.

which merges the daily measure of off-exchange one-share trades, informed trades, investor attention, social media discussions, and controls, consists of 5,187 positive 8-K events during the sample period. Table 5.1 Panel A reports descriptive statistics for the number of 8-K events in the full sample, conditioning on the filing gap. The filing gap is the number of business days between the calendar event day and the calendar filing day, as stated in the 8-K filing. Nearly 40% of 8-K events have a filing gap of 1 trading day. Table 5.1 Panel B reports descriptive statistics for the number of 8-K events in the full sample, conditioning on the item type. The five major 8-K items for more than 90 percent of all observations. These items are: Item 5.02 (Departure of Directors or Principal Officers; Election of Directors; Appointment of Principal Officers), Item 8.01 (Other Events), Item 5.07 (Submission of Matters to a Vote of Security Holders), Item 1.01 (Entry into a Material Definitive Agreement), and Item 7.01 (Regulation FD Disclosure). Table 5.1 Panel C reports summary statistics of the continuous variables used in the regression analyses.

Chapter 3

Main Results

3.1 Return Patterns around 8-K Events

I begin the analysis by investigating the cumulative abnormal returns (CARs) around 8-K events for the high- and low-FT stocks before and after the introduction of fractional trading during the sample period. Starting with the high-FT stocks, which comprise the top FT-decile stocks in terms of the total number of fractional trades reported by the OTC Transparency dataset in the post-FT period within the sample stock universe, Panel A of Figure 5.3 illustrates a significantly positive price reaction on the filing day in both pre-and post-FT period. In addition, the magnitude of this positive price movement is larger after fractional trading was introduced, as indicated by the red line which represents CARs post-FT. Following the filing period, the red line keeps drifting upwards until 8 trading days after the filing day while the blue line representing CARs pre-FT keeps drifting downwards. Furthermore, there is a significant return reversal after the price peak day post-FT.[18] Then focusing on the remaining stocks, low-FT stocks, Panel B of Figure 5.3 displays similar return patterns both pre- and post-FT. Specifically, both pre- and post-FT periods exhibit a notably substantial increase in stock prices during the filing period, with no significant difference in the magnitude of the increase. However, the subsequent trading days manifest a relatively stabilized

[18] As is shown in Panel A of Figure H.1 of Appendix H, if we extend the x-axis to the 60 trading days after the filing day, the two lines representing pre- and post-FT returns converge, suggesting a price overreaction to the positive 8-K filings during the post-FT period.

price trend, in contrast to the pronounced price overshot and reversals for high-FT stocks during the post-FT period.

The pre-FT return patterns for high-FT stocks suggest that informed traders sell immediately on the news day to correct the overreaction by unsophisticated traders. This is discussed in the theory work such as Hirshleifer et al. (1994) and Brunnermeier (2005), and further substantiated by the empirical evidence documented by Ben-Rephael et al. (2022) and Callen et al. (2022) that institutional abnormal attention and trading spike on both event day and filing day. Specifically, during the pre-FT period, sophisticated informed traders leverage their information advantages regarding unexpected 8-K events against retail investors (or uninformed traders) by establishing stock positions prior to public disclosure. Retail investors, on the other hand, react to the stale information on the filing day, and informed investors exploit this price pressure via opportunistic liquidity provision (or reversing their established positions), which causes the return to revert shortly after the filing period.

However, the distinctly different post-FT return patterns observed in high-FT stocks during the filing and post-filing period imply that tiny traders induce price pressure and volatility. Barber et al. (2022) and Eaton et al. (2022) show that Robinhood traders engage in more attention-induced trading than other retail traders and are more likely to herd into stocks that were recently discussed on Reddit WallStreetBets, generating short-run positive returns. Likewise, Da et al. (2023) find that tiny trades exert large price pressure on stocks and can even fuel meme stock-like trading frenzies. For positive 8-K events, high-FT stocks exhibit coordinated short-run price pressure, with the price continuing to drift upwards until 8 trading days after the filing day. At the same time, there is a heightened volume of social media discussions during the post-filing period. As depicted in Figure 5.4, the average number of stock mentions on Reddit WallStreetBets exhibits an upward trend until the day of the peak return, and returns start to revert when the sentiment on social media begins to weaken.

The post-FT return patterns following the filing day appear to be inconsistent with informed traders selling immediately on the news, possibly due to the noise trader risk and the potential trading profits from riding the mispricing. Therefore, the dynamics of price patterns for high-FT stocks in the post-filing period are different, and informed

traders may be adopting alternative strategies to capitalize on the information advantages provided by unscheduled 8-K events. While Niessner (2015) suggest that firms may strategically time the disclosure of 8-K events, I do not find a significant difference in the filing gap and disclosure complexity for high-FT stocks relative to low-FT stocks post-FT. The results are reported in Table H.1 in Appendix H.[19] In the next section, I explore the informed trading dynamics around 8-K events.

To complement the findings presented in the figures, I conduct regression analyses to first investigate how high-FT stocks experience price overshoot and reversal around positive 8-K events compared to low-FT stocks in the post-FT period. I measure $BHAR_{[D_1,D_2]}$, a stock's buy-and-hold abnormal return over day D_1 to day D_2, as the stock's raw daily return compounded over day D_1 to D_2 minus the corresponding market return compounded over the same period, i.e., $\prod_{\tau=D_1}^{\tau=D_2}(1+r_\tau)-\prod_{\tau=D_1}^{\tau=D_2}(1+r_{m\tau})$. I estimate the following ordinary least squares (OLS) model:

$$BHAR_{[D_1,D_2]} = \alpha + \beta High\ FT \times Post\ FT + \gamma Controls_t + \epsilon_t. \tag{3.1}$$

The sample is at the firm-event level, with subscript t indexing the event day and the subscript for firm omitted for brevity. The dependent variable is the buy-and-hold abnormal return $BHAR_{[D_1,D_2]}$. The key regressor is the interaction term between *High FT*, an indicator denoting whether the firm is in the high-FT group which comprises the top-decile stocks in terms of the total number of fractional trades reported by the OTC Transparency data in the post-FT period within the sample universe, and *Post FT*, an indicator denoting whether the 8-K event is in the post-FT period. $Controls_t$ includes those discussed in Section 2.2 (measured right before the event day t), 8-K item fixed effects to control for item-specific variations, filing-gap fixed effects to control for reporting lag variations, firm fixed effects to control for firm-level heterogeneity, day-of-week fixed effects, and year, month fixed effects to control for the market conditions and intertemporal variation in trading activity due to common shocks. With the inclusion of these fixed effects, two standalone variables *High FT* and *Post FT* drop out from the regression outputs. In all regressions henceforth, I cluster standard errors at the firm level to account for within-firm serial correlation in the error term.

[19] The empirical analyses are robust to using other regression specifications for count variables, such as the Poisson regression model for the filing gap.

Given that fractional trades are only observable in the post-FT period, I follow Bartlett et al. (2022b) to use the ex-post measure to assign high- and low-FT stocks. This group assignment captures the time-invariant portion of uninformed trading intensity at the stock level. In addition, the *Post FT* indicator representing the introduction of fractional trading, along with the fixed-effect structure helps to control for firm-specific and time-varying omitted correlated variables. Moreover, the empirical strategy is built upon the causal evidence documented by Da et al. (2023) that the introduction of fractional trading leads to more tiny trades and Eaton et al. (2022) that these tiny trades are more likely to herd and harm market quality. This observed surge in tiny trades during the post-FT period is likely ascribed to the exogenous introduction of fractional trading through direct and indirect effects.

Table 5.2 Panel A reports the regression results of equation (3.1) with *BHAR* during the event period, filing period, and post-filing period for positive 8-K events as the dependent variable without including controls and fixed effects. Column (1) shows that there is no significant difference in the pre-filing *BHAR*, measured over the time interval spanning from five days preceding the event date to one day prior to the filing day, for both high- and low-FT stocks in the post-FT period compared to the pre-FT period. The coefficient estimates on the interaction term, *High FT*$\times$*Post FT*, are positive and significant in columns (2) and (3), which measure filing-period and post-filing period returns. This confirms the return patterns shown in Panel A of Figure 5.3 that, relative to low-FT stocks, high-FT stocks exhibit a significant price overshoot until 8 trading days after the filing day around positive 8-K events post-FT. The magnitude of the interaction term in column (2) suggests that high-FT stocks experience greater 1.3% buy-and-hold abnormal returns compared to low-FT stocks post-FT during the two-day filing period. Additionally, the magnitude of the interaction term in column (3) implies a greater average price overshoot of 2.5% at its peak for high-FT stocks relative to low-FT stocks post-FT. The significantly negative coefficient estimates in column (4) suggest a price reversal of 1.2% in the 5-day window following the price peak. The results are robust to including controls and fixed effects as is shown in Table 5.2 Panel B.

Among the controls, I find that stocks with greater volatility in the past are more likely to have less positive pre-filing returns while it is the opposite for stocks with

greater past returns. Firm size is negatively associated with *BHAR* in columns (2) and (3) while the association is positive for past stock volatility, suggesting that smaller and more volatile firms tend to experience more price overshoot in the filing and post-filing period.

Further, to examine whether coordinated tiny trades contribute to the price run-up following the disclosure of positive 8-K events in the post-FT period, I estimate the following OLS model to quantify the association between stock daily returns and the percentage change of the number of the tiny trades:

$$\begin{aligned} Return_t = \alpha &+ \beta_1 \%\Delta\ Tiny\ Trades_t + \beta_2 High\ FT \times Post\ FT \\ &+ \beta_3 High\ FT \times \%\Delta\ Tiny\ Trades_t + \beta_4 Post\ FT \times \%\Delta\ Tiny\ Trades_t \\ &+ \beta_5 High\ FT \times Post\ FT \times \%\Delta\ Tiny\ Trades_t + \gamma Controls_t + \epsilon_t. \end{aligned} \tag{3.2}$$

For each 8-K event, I set the event period to start from the filing day and end 8 trading days after the filing date (the peak day) in the regression analyses. $Return_t$ is the daily return of the stock, $\%\Delta\ Tiny\ Trades_t$ represents the daily percentage change of the number of the tiny trades, and *High FT* is as defined in equation (3.1). The controls are the same as in Table 5.2. The sample is at the firm-event-trading day level, with subscript t indexing trading day.

Table 5.3 Panel A reports the regression results of equation (3.2). I measure tiny trades using the off-exchange one-share trades as in Da et al. (2023) and label the variable $\%\Delta$ *One-Share Trades*$_t$. The coefficient estimate for this variable is positive and marginally significant at 10%, indicating that the percentage change of tiny trades weakly aligns with daily price movements following positive 8-K events. The coefficient estimate on the triple interaction term is positive and significant at the 5% level in column (1), suggesting that tiny traders are more likely to contribute to the price run-up for high-FT stocks post-FT. The observed significance remains robust even after incorporating event fixed effects into the analysis, as indicated in column (2). I also validate that social media activity is positively correlated with a contemporaneous increase in tiny trades. Table 5.3 Panel B documents a significantly positive association between *# of WSB Mentions*$_t$, the natural log of the number of stock mentions on Reddit WallStreetBets on day t, and the daily percentage change of the number of tiny trades. Overall, tiny traders who orchestrate their trading via social media platforms

contribute to the short-run positive movement in the post-filing window of positive 8-K events.

3.2 Informed Trading Dynamics around 8-K Events

Results thus far show that coordinated tiny trades exert significant price pressure and volatility for high-FT stocks post-FT and make the timing of the return reversal less predictable. These post-FT return patterns also indicate that informed traders do not effectively function as "rational arbitrageurs" to correct the price overreaction immediately on the news day. In this section, I study how informed investors change their trading behavior around 8-K events in response to the surge in tiny retail trades.

There are situations in which informed traders hesitate to correct the mispricing due to trading frictions. These frictions include short-sale restrictions (Scheinkman and Xiong, 2003), noise trader risks (De Long et al., 1990a), and capital constraints (Shleifer and Vishny, 1997). Uninformed tiny retail trades introduce excessive noise trader risks following the disclosure, which may potentially discourage informed traders from correcting the mispricing immediately. An arbitrageur opting to sell short during instances where noise traders have inflated the asset price must be aware of the risk of a potential further increase in price should noise traders exhibit an even more bullish view in the future. At the same time, sophisticated investors may even ride the bubble to earn extra profits if they are able to predict the sentiment (De Long et al., 1990b; Abreu and Brunnermeier, 2003).

I start by analyzing whether informed traders are less likely to sell short on the filing day. I leverage Markit daily shorting interest data and follow Bogousslavsky et al. (2023) to measure the occurrence of abnormal short spikes in the pre-filing trading window (*[Rdate,Fdate-1]*) and the two-day filing trading window (*[Fdate,Fdate-1]*). I construct an indicator, $\mathcal{I}(\textit{Short Spike})$, to denote the abnormal short spike. Specifically, this variable indicates whether the maximum daily change in short interest during the pre-filing or filing period exceeds the 90th percentile for the full sample. I reestimate equation (3.1) using pre-filing- and filing-period $\mathcal{I}(\textit{Short Spike})$ as the dependent variables. Table 5.4 reports the regression results. The coefficient estimate on the interaction term $\textit{High FT} \times \textit{Post FT}$ is insignificant in column (1), indicating that there

is no significant change in the occurrence of short spikes for high-FT stocks pre-filing. However, the coefficient estimate on the interaction term becomes negative and significant at the 5% level in column (2), consistent with the conjecture that informed traders are less likely to correct the price overreaction immediately on the news day.

Next, I study whether informed traders exhibit more net buys upon filings. I focus on the set of stocks displaying pre-filing abnormal institutional attention. I explore whether this specific set of stocks experiences more net buys during the filing period. I estimate the following regression:

$$\begin{aligned} \textit{Inst BSI}_t = \alpha &+ \beta_1 \textit{Pre-Filing AIA} + \beta_2 \textit{High FT} \times \textit{Post FT} \\ &+ \beta_3 \textit{High FT} \times \textit{Pre-Filing AIA} + \beta_4 \textit{Post FT} \times \textit{Pre-Filing AIA} \\ &+ \beta_5 \textit{High FT} \times \textit{Post FT} \times \textit{Pre-Filing AIA} + \gamma Controls_t + \epsilon_t. \end{aligned} \tag{3.3}$$

Inst BSI$_t$ is the institutional buy-sell imbalance in the number of institutional trades, shares, and dollar volumes.

Table 5.5 reports the regression results of equation (3.3) for the two-day and five-day filing period trading results. Panel A reports the results using AIA indicator, denoting whether the Bloomberg news searching and reading score is greater than or equal to 3. Columns (1), (3) and (5) report the two-day trading window results and columns (2), (4) and (6) report the five-day trading window results. In Panel A, the coefficient estimate on the interaction term *High FT* $\times$ *Pre-Filing AIA* is significantly negative in all six columns, suggesting that institutional investors tend to unwind their positions immediately after the disclosure for high-FT stocks before fractional trading is available. This is consistent with Ben-Rephael et al. (2022) that pre-filing AIA facilitates less filing-period price discovery. Consistently, the significantly negative coefficient estimate on *Post FT* $\times$ *Pre-Filing AIA* suggests that institutional investors sell immediately on the news for low-FT stocks post-FT. However, the coefficient estimate on the triple interaction term *High FT* $\times$ *Post FT* $\times$ *Pre-Filing AIA* is positive and significant at 5% for all six columns, suggesting that informed traders are exhibiting more net buys or less likely to reverse their trades for the set of stocks that receive more pre-filing institutional attention. I also check the robustness of the results using continuous variable *Pre-Filing AIA Score*. The results are similar and reported in Panel B. Overall, results in Tables 5.4–5.5 show that informed traders adapt to the increased price pressure and volatility

by delaying immediate sales and even accumulating additional shares upon filing.

I then conduct several additional analyses to explore how informed traders could strategically ride the mispricing to further contribute to the price runup after the disclosure and benefit from correcting the mispricing at a later stage. Previous theory literature suggests that the incentive for informed investors to ride the mispricing arises from the predictable market signal. I propose that one such signal could be real-time social media volume. Due to unsophistication, these tiny traders cannot effectively use readily available value-relevant information contained in 8-K filings and are likely to be misled by social media discussions, continuing to chase returns following the positive events. Figure 5.4 shows that social media volume tracks the post-filing return pattern closely. Anecdotal evidence also suggests that, during the Gamestop trading frenzy, some hedge funds effectively tracked real-time social media sentiment (The Washington Post, 2021) and earned substantial profits by mimicking the bets made by Reddit renegades (Wall Street Journal, 2022).

To provide a large sample firm-level support for informed traders trading with the social media-coordinated tiny retail trading flows, I document that there is a positive association between the probability of daily institutional net buying and the percentage change of number of tiny trades during the price run-up. The window starts from the filing day (*Fdate*) and ends 8 trading days after the filing date (*Fdate+8*) in the regression analyses. I construct indicators based on whether there is a positive buy-sell imbalance of trades, shares, and dollar volume. The key independent variable, $\%\Delta$ *One-Share Trades*$_t$, is the daily percentage change of number of off-exchange one-share trades on day t relative to day $t-1$. Table 5.6 reports the regression results of the relation between the probability of informed net buying and daily contemporaneous change of the number of tiny trades. Columns (1), (3) and (5) report the results for the post-FT period. The coefficient estimate on $\%\Delta$ *One-Share Trades*$_t$ is positively significant at the 1% level in all three columns, which suggests that the probability of net informed buying is positively associated with an increase in tiny trades. However, I do not observe such a positive relation pre-FT, as the coefficient estimates on $\%\Delta$ *One-Share Trades*$_t$ are insignificant in columns (2), (4) and (6).

To rule out the alternative that this trading pattern is primarily driven by short covering, I test whether there are more abnormal shorting activities when the 8-K event

is disclosed. Table 5.7 columns (1) and (3) report the regression results of equation (3.1) with the daily average short interest ratio and borrower concentration during the filing period, respectively, as dependent variables. The coefficient estimate on the interaction term *High FT* $\times$ *Post FT* is insignificant in both columns (1) and (3), suggesting that the more institutional net buying post-filing is not entirely due to short covering.

In the next step, I turn to investigating informed trading patterns around the price peak. Figure 5.4 shows that social media activities decline significantly around the price peak. This indicates that there is a shift in tiny trader sentiment or noise trader risk in De Long et al. (1990a). I study whether informed traders effectively act as arbitrageurs when the noise trade risk is low. Specifically, I examine whether sophisticated informed traders accumulate more short positions around the price peak for high-FT stocks post-FT. Table 5.7 columns (2) and (4) report the regression results of equation (3.1) with the daily average short interest ratio and borrower concentration around the price peak $[Fdate + 7, Fdate + 9]$, respectively, as dependent variables. The coefficient estimate on the interaction term *High FT* $\times$ *Post FT* is positive and significant in both columns (2) and (4), suggesting that informed traders step in when noise trader risk is low and leverage their sophistication to generate extra trading profits from correcting mispricing.

Having established the empirical fact that informed traders take advantage of unsophisticated tiny trades post-filing by creating a more pronounced price run-up and benefiting from correcting the mispricing, I further explore the underlying economic driving forces in the context of a coordination model. Fang et al. (2022) extend the canonical model of investment beautify contest (Angeletos and Pavan (2004)) to analyze how retail traders coordinate on social media platforms, leading to trading frenzies. While their focus is on the interaction between social media leaders and the followers, I simplify the model setup in Fang et al. (2022) to derive a static trading equilibrium for both the informed trader and tiny trader without focusing on the role of strategic information disclosure in the coordination game. The detailed model setup and equilibrium analyses are included in Appendix D.

Similar to Fang et al. (2022), the final payoff hinges not only on the state variable but also on the collective investment decisions of all market participants. The equilibrium trading strategy reveals that the informed trader is incentivized to prioritize the public signal over the private signal due to strategic complementarity. Therefore, they trade

more aggressively when they are more exposed to the common signal. This is consistent with anecdotal evidence that many hedge funds track real-time social media sentiment and profit from taking advantage of unsophisticated traders. It also aligns with real-world instances such as the technology bubble of the early 2000s and the recent meme-stock trading frenzies. In addition, I define mispricing as the extent to which the final price exceeds the intrinsic value of the state variable. The comparative statics analyses reveal that the magnitude of mispricing is positively correlated with the magnitude of the state variable and the exposure to the common signal.

I conduct cross-sectional analyses to see whether the predictions fit the empirical patterns. First, I use the filing period return to measure the value of the state variable. I augment regression analysis in Table 5.7 with *Filing-Period Return*$_t$, its respective interactions with *High FT* and *Post FT*, and the triple interaction. Column (1) of Table 5.8 reports the results. The highly positive coefficient estimate on the triple interaction term *High FT* $\times$ *Post FT* $\times$ *Filing-Period Return*$_t$ suggests that mispricing becomes more pronounced as the value of the state variable increases. Second, I use the total number of stock mentions on Reddit WallStreetBets during the window $[Fdate, Fdate+8]$ to measure the exposure to the common signal. This is consistent with Goldstein et al. (2013) that the number of social media discussions indicates the extent to which traders are exposed to the common signal. Likewise, I add this new variable *Total WSB Mentions*$_t$ into the regression to interact with *High FT* and *Post FT*. Column (2) of Table 5.8 reports the results. The coefficient estimate on *High FT* $\times$ *Post FT* $\times$ *Total WSB Mentions*$_t$ is positive and significant, consistent with the exposure of the common signal leading to more mispricing.

3.3 Information Acquisition around 8-K Events

In this section, I study informed investors' information acquisition around 8-K events. Higher expected trading profits resulting from the involvement of a greater number of less sophisticated traders could lead to an increase in costly private information acquisition (Grossman and Stiglitz, 1980). Previous research documents heightened information acquisition activity by sophisticated institutional investors around accounting disclosure events, such as increased EDGAR searching or news reading activity on

Bloomberg terminals. Typically, Ben-Rephael et al. (2022) document that institutional attention spikes on both the event day and the filing day for 8-K events. Building on their study, I investigate whether there is a significant difference in pre-filing- or filing-period abnormal institutional attention (AIA) between high- and low-FT stocks post-FT relative to pre-FT.

Table 5.9 reports the regression results of equation (3.1) with pre-filing- and filing-period AIA as the dependent variables. AIA is an indicator that denotes the maximum Bloomberg's daily attention score during the pre-filing period or filing period is greater than or equal to 3. The coefficient estimate on the interaction term $High\ FT \times Post\ FT$ is positive and significant at the 1% level in column (1), but it becomes insignificant in column (2), suggesting that informed traders tend to display more information acquisition during the pre-filing period for high-FT stocks post-FT. This finding is consistent with the hypothesis that informed traders increase their pre-filing information acquisition due to higher expected trading profits. Interestingly, institutional attention remains high even post-filing as indicated in column (3), suggesting informed traders intentionally trade and take advantage of tiny traders after the disclosure. The empirical results are also robust to using to continuous version of AIA measure, *AIA Score*, as shown in columns (4) – (6).

In addition, I study whether informed traders tend to pay more attention to 8-K filings with high disclosure linguistic complexity. Previous studies find that disclosure filings with less readable content are associated with less investor processing and investor interest in the company. For example, disclosure complexity is negatively related to institutional ownership (Lundholm et al., 2014). While institutional investors pay less attention to complex 8-K filings previously, higher expected trading profits may increase their information acquisition for complex filings. I use smog index and fog index to measure the disclosure complexity of 8-K filings and construct *High Complexity* to indicate whether smog index or fog index exceeds the sample 90th percentile. I add this indicator to the above regression.

Table 5.10 reports the regression results with filing-period AIA and *AIA Score* as dependent variables. The coefficient estimate on the interaction term $High\ FT \times High\ Complexity$ is negative and significant for all the columns, suggesting that informed traders pay less attention to 8-K filings with high disclosure complexity for high-FT

stocks pre-FT. However, the triple interaction term *High FT* × *Post FT* ×*High Complexity* is positive and significant at the in all columns. This result suggests that for high-FT stocks post-FT, informed traders would engage in more information acquisition for 8-K filings with high disclosure complexity relative to low-FT stocks. Together, results in Tables 5.9–5.10 show that higher expected trading profits incentivize pre-filing information acquisition in general and post-filing information acquisition for complex 8-K filings.

3.4 Pre-Filing Trading

In this section, I provide suggestive evidence on how informed traders strategically engage in pre-filing trading in response to the post-filing uncertainty induced by the tiny traders. While we observe increased pre-filing information acquisition, this does not necessarily lead to more pre-filing price discovery. An extensive body of literature in market microstructure theory suggests that informed investors have an incentive to time their trades based on the market condition (Kyle, 1985; Collin-Dufresne and Fos, 2016). In addition, although the surge in tiny retail trades after the disclosure is anticipated, the extent of the price overreaction, the timing of the shift of noise trader sentiment, and the response of other institutional investors are ex-ante uncertain. Informed traders may alter their pre-filing trading strategy in response to the post-filing uncertainty.

I reestimate equation (3.1) with abnormal call and put option trading volume as the dependent variables. The abnormal trading volume is defined as the pre-filing period mean daily trading volume net of the daily trading volume during *[Rdate-30,Rdate-5]*. The regression results are reported in Table 5.11. Interestingly, I did not find a significant increase in pre-filing call option trading volume as indicated by the insignificant coefficient estimate on the interaction term *High FT* × *Post FT* in the first three columns. This suggests that informed traders do not chase for the upside potential pre-filing possibly due to uncertainty. Instead, I found abnormally high put option trading volume pre-filing. The coefficient estimate on the interaction term *High FT* × *Post FT* is positive and significant at 1% in the last three columns. Informed traders use put option to protect their established positions from the post-filing uncertainty.[20]

[20] As an additional note, the uncertainty does not just come from higher interday stock price volatility,

I provide one additional test on the association between pre-filing abnormal institutional attention and pre-filing price discovery. Ben-Rephael et al. (2022) find that pre-filing AIA leads to more pre-filing price discovery. I analyze whether this association still holds or not when informed traders anticipate higher post-filing uncertainty.

Blankespoor et al. (2020) propose a measure of price responsiveness to accounting disclosure, Intra-Period Efficiency (IPE). Specifically, IPE is calculated as the average of $\left[1 - \frac{|AR_T - AR_t|}{|AR_T|}\right]$ during the window $[0, T]$, where AR_t is the abnormal return over the window $[0, t]$. Building on their measure, I measure the pre-filing price discovery as the intra-period efficiency of event-period price discovery during the window $[R, F+60]$, $IPE_{[R,F+60]}$, which is $\left[1 - \frac{|AR_{[R,F+60]} - AR_{[R,F-1]}|}{|AR_{[R,F+60]}|}\right]$. I choose a longer window of $[R, F + 60]$ due to the post-filing overreaction. I did not take the average because this measure captures to what extent information has been incorporated into the stock price during the event period.

I find that pre-filing abnormal institutional attention is associated with less pre-filing price discovery. I reestimate equation (3.3) with $IPE_{[R,F+60]}$ as the dependent variable. Panel A column (1) of Table 5.12 show that the coefficient estimate on the triple interaction term *High FT* $\times$ *Post FT* $\times$ *Pre-Filing AIA* is negative and significant at 5% level for the full sample. I found the results concentrated on 8-K events with longer filing gaps. This is suggested by Callen et al. (2022) that longer filing gaps give more advantages to informed traders to establish early positions. These results are robust to using the continuous AIA measure as shown in Panel B. In addition, the positive coefficient estimate on *High FT* $\times$ *Pre-Filing AIA Score* in column (1) Panel B suggests pre-filing abnormal institutional attention facilitates price discovery before the filing day for high-FT stocks pre-FT, consistent with Ben-Rephael et al. (2022). While institutional investors engage in more pre-filing information acquisition, such institutional effort need not lead to more pre-filing price discovery.

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but also intraday price volatility (See Table H.2 in Appendix H).

Chapter 4

Conclusion

Recent trading innovation among U.S. retail brokers helps democratize financial markets and makes stock ownership more accessible to budget-constrained tiny retail investors. Their participation in the stock market introduces uncertainty as well as extra trading profits for sophisticated traders to leverage. This paper delves into the dynamics between strategic informed trades and uninformed tiny trades. It sheds light on the adaptive strategies of institutional investors in response to evolving retail trading trends in today's stock market and the implication on price discovery of accounting disclosure events.

Specifically, utilizing unanticipated positive 8-K events, I investigate how sophisticated informed traders strategically trade on their private information in anticipation of a surge in tiny retail trades following the filing. The findings in the paper indicate that the coordinated tiny trades induce substantial price pressure and volatility following 8-K filings and the timing of the return reversal is less predictable. Informed investors adapt to such price pressure and volatility by delaying immediate sales upon filing. At the same time, informed traders are motivated to exploit inter-investor differences in disclosure processing to ride the mispricing and make additional trading profits. Moreover, higher post-filing trading profits incentivize costly information acquisition, but informed traders' strategic response leads to delayed price discovery of 8-K filings.

My paper has several implications for accounting literature. First, this evolving retail trading trend affects the price discovery process of informational events through institutional investors' strategic response. While we observe more information acquisition,

such institutional effort exacerbates price pressure and volatility around the disclosure. Second, the disclosure event may trigger coordinated uninformed retail trading. This effect could be amplified due to the recent trading innovation and use of social media platforms. Institutional investors strategically take advantage of these retail investors, who are likely "on the lower end of the sophistication spectrum"(Blankespoor et al., 2019).

Chapter 5

Tables and Figures

Table 5.1: Summary Statistics

Panel A: Breakdown by Filing Gap

This panel reports the number of positive 8-K events in the sample conditioning on the filing gap. Filing gap is the number of business days between the calendar event day and the calendar filing day, stated in the 8-K filing. For example, a filing gap of 1 means that the filing occurred on the next business day after the event date.

Filing Gap	# of Cases	Percentage
1	2,037	39.27%
2	1,219	23.50%
3	1,018	19.63%
4	913	17.60%
Total	5,187	

Panel B: Breakdown by Item Number

This panel reports the number of positive 8-K events in the sample conditioning on the item type. The five major 8-K items are Item 5.02 (Departure of Directors or Principal Officers; Election of Directors; Appointment of Principal Officers), Item 8.01 (Other Events), Item 5.07 (Submission of Matters to a Vote of Security Holders), Item 1.01 (Entry into a Material Definitive Agreement), and Item 7.01 (Regulation FD Disclosure).

Item Number	# of Cases	Percentage
5.02	1,968	37.94%
8.01	1,051	20.26%
5.07	960	18.51%
1.01	509	9.81%
7.01	236	4.55%
5.03	139	2.68%
4.01	72	1.39%
1.02	45	<1%
3.01	45	<1%
2.01	37	<1%
2.03	35	<1%
3.02	35	<1%
2.05	20	<1%
Others	35	<1%

Table 5.1: Summary Statistics - Cont'd

Panel C: Variables in Regression Analyses

This panel reports summary statistics of the continuous variables used in the regression analyses for both the event-level observations and daily-level observations. Detailed variable definitions are in Appendix A. All variables are winsorized at the top and bottom 1%.

Variable	Obs	Mean	SD	P25	P50	P75
Event-Level Observations						
$BHAR_{[R-5,F-1]}$	5,187	-0.001	0.09	-0.042	-0.004	0.034
$BHAR_{[F,F+1]}$	5,187	0.046	0.049	0.020	0.032	0.054
$BHAR_{[F,F+8]}$	5,187	0.045	0.104	-0.009	0.031	0.081
$BHAR_{[F+9,F+13]}$	5,187	-0.002	0.070	-0.029	-0.002	0.026
$Inst\ BSI_{Trades[F,F+1]}$	5,187	0.006	0.422	-0.087	0.000	0.105
$Inst\ BSI_{Trades[F,F+4]}$	5,187	-0.002	0.373	-0.091	0.000	0.091
$Inst\ BSI_{Shares[F,F+1]}$	5,187	-0.002	0.463	-0.157	0.000	0.149
$Inst\ BSI_{Shares[F,F+4]}$	5,187	-0.007	0.414	-0.146	0.000	0.139
$Inst\ BSI_{DV[F,F+1]}$	5,187	-0.002	0.463	-0.156	0.000	0.150
$Inst\ BSI_{DV[F,F+4]}$	5,187	-0.006	0.414	-0.145	0.000	0.140
$Short\ Interest\ Ratio_{[F,F+1]}$	5,187	0.037	0.048	0.005	0.018	0.049
$Short\ Interest\ Ratio_{[F+7,F+9]}$	5,187	0.039	0.055	0.005	0.018	0.050
$Borrower\ Concentration_{[F,F+1]}$	5,187	0.305	0.186	0.171	0.248	0.384
$Borrower\ Concentration_{[F+7,F+9]}$	5,187	0.303	0.188	0.170	0.247	0.381
Abnormal Call	5,187	-0.153	2.401	-0.107	-0.001	0.000
Abnormal Put	5,187	0.689	3.489	-0.008	0.000	0.071
$IPE_{[R,F+60]}$	5,187	-0.202	1.185	-0.154	0.012	0.169
$ln(Market\ Cap)_{t-1}$	5,187	13.811	2.161	12.198	13.795	15.278
$Book\ to\ Market_{y-1}$	5,187	0.645	0.340	0.360	0.636	0.913
$Return\ on\ Asset_{y-1}$	5,187	-0.103	0.342	-0.119	0.008	0.050
$Institutional\ Ownership_{q-1}$	5,187	0.636	0.364	0.353	0.718	0.892
$Past\ Month\ Volatility_t$	5,187	0.031	0.020	0.018	0.026	0.039
$Past\ Month\ Max\ Return_t$	5,187	0.068	0.059	0.033	0.050	0.082
$Past\ Month\ Return_t$	5,187	0.003	0.156	-0.084	-0.004	0.071
$Past\ Year\ Return_t$	5,187	0.300	0.888	-0.194	0.117	0.510
Daily-Level Observations						
$Return_t$	44,593	0.006	0.035	-0.011	0.004	0.021
$\%\Delta\ One\text{-}share\ Trades_t$	44,593	0.274	1.237	-0.332	0.000	0.424
$\#\ of\ WSB\ Mentions_t$	26,046	0.048	0.240	0.000	0.000	0.000

Table 5.2: Return Patterns around 8-K Events

Panel A: Univariate Analyses

This panel reports the ordinary least squares (OLS) regression results on differences in high- and low-FT firms' pre-filing period, filing period, and post-filing period buy-and-hold abnormal returns (BHAR) around positive 8-K events before and after the availability of fractional trading. $BHAR_{[D_1,D_2]}$ is the stock's raw return compounded over $[D_1,\ D_2]$ minus the corresponding market return compounded over the same window. Column (1) shows the results for the window from 5 trading days before the event date (labeled *R-5*) to 1 trading day before the filing date (labeled *F-1*). Column (2) shows the results for the window from the filing date (labeled *F*) to 1 trading day after the filing date (labeled *F+1*). Column (3) shows the results for the window from the filing date (labeled *F*) to 8 trading days after the filing date (labeled *F+8*). Column (4) shows the results for the window from 9 trading days after the filing date (labeled *F+9*) to 13 trading days after the filing date (labeled *F+13*). *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the interaction term between the two. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. *t* statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	BHAR			
	(1)	(2)	(3)	(4)
	[R-5,F-1]	*[F,F+1]*	*[F,F+8]*	*[F+9,F+13]*
High FT	0.012**	-0.002	-0.007	0.004
	(2.07)	(-0.75)	(-1.04)	(1.21)
Post FT	0.004	-0.002	0.002	0.001
	(1.56)	(-1.60)	(0.58)	(0.54)
High FT × *Post FT*	-0.005	0.013***	0.025**	-0.012**
	(-0.55)	(2.75)	(2.38)	(-2.05)
Observations	5,187	5,187	5,187	5,187
Adjusted R^2	0.001	0.002	0.002	0.000

Table 5.2: Return Patterns around 8-K Events - Cont'd

Panel B: Multivariate Analyses

This panel reports the OLS regression results on differences in high- and low-FT firms' pre-filing period, filing period, and post-filing period buy-and-hold abnormal returns (BHAR) around positive 8-K events before and after the availability of fractional trading. Controls include $ln(Market\ Cap)_{t-1}$, $Book\ to\ Market_{y-1}$, $Return\ on\ Asset_{y-1}$, $Institutional\ Ownership_{q-1}$, $Past\ Month\ Volatility_t$, $Past\ Month\ Max\ Return_t$, $Past\ Month\ Return_t$ and $Past\ Year\ Return_t$ as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	BHAR			
	(1)	(2)	(3)	(4)
	[R-5,F-1]	*[F,F+1]*	*[F,F+8]*	*[F+9,F+13]*
High FT × Post FT	0.004	0.011***	0.022**	-0.011*
	(0.37)	(2.68)	(2.31)	(-1.92)
$ln(Market\ Cap)_{t-1}$	-0.004	-0.004***	-0.004***	0.000
	(-0.76)	(-8.69)	(-3.66)	(0.17)
$Book\ to\ Market_{y-1}$	0.017	-0.001	0.001	0.003
	(1.06)	(-0.32)	(0.16)	(0.66)
$Return\ on\ Asset_{y-1}$	-0.007	-0.005	-0.006	0.003
	(-0.58)	(-1.49)	(-0.72)	(0.61)
$Institutional\ Ownership_{q-1}$	0.001	-0.006***	0.000	0.001
	(0.14)	(-2.75)	(0.04)	(0.33)
$Past\ Month\ Volatility_t$	-0.825**	0.528***	0.520**	0.182
	(-2.42)	(5.11)	(2.00)	(1.08)
$Past\ Month\ Max\ Return_t$	0.238**	-0.019	-0.058	-0.025
	(2.18)	(-0.55)	(-0.69)	(-0.47)
$Past\ Month\ Return_t$	0.185***	0.007	0.036**	0.001
	(8.81)	(0.99)	(1.96)	(0.11)
$Past\ Year\ Return_t$	-0.000	0.001	0.003	-0.005**
	(-0.10)	(0.62)	(1.14)	(-2.48)
Year Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes
Item Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Filing Gap Fixed Effects	Yes	Yes	Yes	Yes
Observations	4,402	4,402	4,402	4,402
Adjusted R^2	0.097	0.182	0.039	0.005

Table 5.3: Coordinated Tiny Trades around 8-K Events

Panel A: Daily Percentage Change of Tiny Trades

This panel reports the OLS regression results on differences in high- and low-FT firms' relation between the daily return and the percentage of change of the number of tiny trades following the disclosure of 8-K events after the availability of fractional trading. For each 8-K event, I set the event period to start from the filing day (*Fdate*) and end 8 trading days after the filing date (*Fdate+8*) in the regression analyses. $Return_t$ is the stock's daily raw return of trading day t in the percentage. $\%\Delta$ *One-Share Trades*$_t$ is the daily percentage change of number of off-exchange one-share trades on day t relative to day $t-1$. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the triple interaction term. Column (1) reports the results without additionally using event-fixed effects, and column (2) reports the results using event-fixed effects. Controls include the log of market cap on the previous trading day (*ln(Market Cap)*$_{t-1}$), book-to-market of prior year (*Book to Market*$_{y-1}$), ROA of prior year (*Return on Asset*$_{y-1}$), institutional ownership of prior quarter (*Institutional Ownership*$_{q-1}$), stock price volatility of past month (*Past Month Volatility*$_t$), the stock's maximum daily return of past month (*Past Month Max Return*$_t$), and the stock's cumulative return of past month and year (*Past Month Return*$_t$ and *Past Year Return*$_t$) as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Return$_t$	
	(1)	(2)
$\%\Delta$ *One-share Trades*$_t$	0.170*	0.180*
	(1.80)	(1.68)
High FT × *Post FT*	0.368**	0.891***
	(2.26)	(2.62)
High FT × $\%\Delta$ *One-share Trades*$_t$	-0.147	-0.154
	(-1.54)	(-1.42)
Post FT × $\%\Delta$ *One-share Trades*$_t$	0.230*	0.216
	(1.84)	(1.55)
High FT × *Post FT* × $\%\Delta$ *One-share Trades*$_t$	0.737**	0.792**
	(2.41)	(2.44)
Controls	Yes	Yes
Year Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes
Item Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Filing Gap Fixed Effects	Yes	Yes
Event Fixed Effects	No	Yes
Observations	44,584	44,558
Adjusted R^2	0.071	0.002

Table 5.3: Coordinated Tiny Trades around 8-K Events - Cont'd

Panel B: Daily Social Media Discussions

This panel reports the OLS regression results on the association between the daily percentage change in tiny trades and the social media activities following the disclosure of 8-K events after the availability of fractional trading. For each 8-K event, I set the event period to start from the filing day (*Fdate*) and end 8 trading days after the filing date (*Fdate+8*) in the regression analyses. %Δ *One-Share Trades*$_t$ is the daily percentage change of number of off-exchange one-share trades on day t relative to day $t-1$. *# of WSB Mentions*$_t$ is the natural log of total times of a stock being mentioned on Reddit WallStreetBets on day t. Column (1) reports the results without additionally using event-fixed effects, and column (2) reports the results using event-fixed effects. Controls include the log of market cap on the previous trading day (*ln(Market Cap)*$_{t-1}$), book-to-market of prior year (*Book to Market*$_{y-1}$), ROA of prior year (*Return on Asset*$_{y-1}$), institutional ownership of prior quarter (*Institutional Ownership*$_{q-1}$), stock price volatility of past month (*Past Month Volatility*$_t$), the stock's maximum daily return of past month (*Past Month Max Return*$_t$), and the stock's cumulative return of past month and year (*Past Month Return*$_t$ and *Past Year Return*$_t$) as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	%Δ *One-share Trades*$_t$	
	(1)	(2)
# of WSB Mentions$_t$	0.519**	0.549**
	(2.26)	(2.25)
Controls	Yes	Yes
Year Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes
Item Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Filing Gap Fixed Effects	Yes	Yes
Event Fixed Effects	No	Yes
Observations	25,906	25,906
Adjusted R^2	0.002	0.000

Table 5.4: Abnormal Short Spike around 8-K Events

This table reports the OLS regression results on differences in high- and low-FT firms' short spikes around positive 8-K events before and after the availability of fractional trading. Column (1) reports the pre-filing-period results, with $\mathcal{I}(\textit{Short Spike})$ indicating the maximum daily change in short interest during the window *[R,F-1]* exceeds the 90th percentile for the full sample. Column (2) reports the filing-period results, with $\mathcal{I}(\textit{Short Spike})$ indicating the maximum daily change in short interest during the the window *[F,F+1]* exceeds the 90th percentile for the full sample. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the interaction term between the two. Controls include $\textit{ln(Market Cap)}_{t-1}$, $\textit{Book to Market}_{y-1}$, $\textit{Return on Asset}_{y-1}$, $\textit{Institutional Ownership}_{q-1}$, $\textit{Past Month Volatility}_t$, $\textit{Past Month Max Return}_t$, $\textit{Past Month Return}_t$ and $\textit{Past Year Return}_t$ as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	$\mathcal{I}(\textit{Short Spike})$	
	(1)	(2)
	Pre-Filing Period	*Filing Period*
High FT × *Post FT*	0.017	-0.085**
	(0.34)	(-2.00)
$\textit{ln(Market Cap)}_{t-1}$	0.013	-0.032**
	(0.67)	(-2.10)
$\textit{Book to Market}_{y-1}$	-0.017	-0.168***
	(-0.28)	(-3.47)
$\textit{Return on Asset}_{y-1}$	-0.078**	0.044
	(-2.16)	(1.42)
$\textit{Institutional Ownership}_{q-1}$	0.063	0.014
	(1.40)	(0.39)
$\textit{Past Month Volatility}_t$	2.887***	1.231
	(2.80)	(1.49)
$\textit{Past Month Max Return}_t$	-0.335	0.093
	(-1.04)	(0.33)
$\textit{Past Month Return}_t$	-0.006	-0.030
	(-0.10)	(-0.52)
$\textit{Past Year Return}_t$	0.025**	0.006
	(2.05)	(0.62)
Year Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes
Item Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Filing Gap Fixed Effects	Yes	Yes
Observations	4,402	4,402
Adjusted R^2	0.146	0.061

Table 5.5: Pre-Filing AIA and Post-Filing Directional Institutional Trading

This table reports the OLS regression results on differences in high- and low-FT firms' relation between filing-period institutional buy-sell imbalance and pre-filing attention around positive 8-K events before and after the availability of fractional trading. Panel A uses AIA indicator and Panel B uses the continuous AIA score. In each panel, Columns (1) and (2) use *Inst BSI* $_{Trades}$, buy-sell imbalance in the number of institutional trades. Columns (3) and (4) use *Inst BSI* $_{Shares}$, buy-sell imbalance in the number of institutional shares. Columns (5) and (6) use *Inst BSI* $_{DV}$, buy-sell imbalance in the number of institutional dollar volume. Columns (1), (3), and (5) focus on the window *[F,F+1]*, and columns (2), (4), and (6) focus on the window *[F,F+4]*. *Pre-Filing AIA* indicates whether the maximum Bloomberg's daily attention score during the pre-filing period is greater than or equal to 3. *Pre-Filing AIA Score* is the maximum Bloomberg's daily attention score during the pre-filing period. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the interaction term of the three. Controls include *ln(Market Cap)* $_{t-1}$, *Book to Market* $_{y-1}$, *Return on Asset* $_{y-1}$, *Institutional Ownership* $_{q-1}$, *Past Month Volatility* $_t$, *Past Month Max Return* $_t$, *Past Month Return* $_t$ and *Past Year Return* $_t$ as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: AIA Indicator

	Inst BSI $_{Trades}$		*Inst BSI* $_{Shares}$		*Inst BSI* $_{DV}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	[F,F+1]	*[F,F+4]*	*[F,F+1]*	*[F,F+4]*	*[F,F+1]*	*[F,F+4]*
Pre-Filing AIA	0.047	0.035	0.093**	0.035	0.093**	0.035
	(1.34)	(1.29)	(2.17)	(1.06)	(2.18)	(1.06)
High FT × Post FT	-0.042	-0.006	-0.070	-0.040	-0.070	-0.039
	(-0.89)	(-0.15)	(-1.31)	(-0.90)	(-1.31)	(-0.89)
High FT × Pre-Filing AIA	-0.164**	-0.086**	-0.198***	-0.116*	-0.198***	-0.115*
	(-2.56)	(-2.02)	(-2.59)	(-1.94)	(-2.59)	(-1.93)
Post FT × Pre-Filing AIA	-0.109**	-0.108***	-0.186***	-0.107**	-0.186***	-0.107**
	(-2.33)	(-2.87)	(-3.31)	(-2.34)	(-3.31)	(-2.34)
High FT × Post FT × Pre-Filing AIA	0.198**	0.120**	0.293***	0.158**	0.292***	0.157**
	(2.44)	(2.09)	(3.04)	(2.12)	(3.04)	(2.10)
Controls & Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,402	4,402	4,402	4,402	4,402	4,402
Adjusted R^2	0.007	0.002	0.014	0.001	0.014	0.001

Table 5.5: Pre-Filing AIA and Post-Filing Directional Institutional Trading - Cont'd

Panel B: Continuous AIA Score

	Inst BSI $_{Trades}$		*Inst BSI* $_{Shares}$		*Inst BSI* $_{DV}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	[F,F+1]	*[F,F+4]*	*[F,F+1]*	*[F,F+4]*	*[F,F+1]*	*[F,F+4]*
Pre-Filing AIA Score	0.009	0.009	0.024**	0.014	0.024**	0.014
	(0.95)	(1.21)	(2.06)	(1.53)	(2.06)	(1.54)
High FT × Post FT	-0.052	-0.005	-0.086	-0.043	-0.086	-0.042
	(-0.96)	(-0.13)	(-1.44)	(-0.87)	(-1.44)	(-0.86)
High FT × Pre-Filing AIA Score	-0.044**	-0.024**	-0.052**	-0.033**	-0.052**	-0.032**
	(-2.50)	(-1.98)	(-2.46)	(-1.99)	(-2.46)	(-1.98)
Post FT × Pre-Filing AIA Score	-0.022*	-0.022**	-0.046***	-0.030**	-0.046***	-0.030**
	(-1.85)	(-2.25)	(-3.16)	(-2.45)	(-3.16)	(-2.45)
High FT × Post FT × Pre-Filing AIA Score	0.050**	0.026	0.080***	0.041**	0.079***	0.041**
	(2.25)	(1.58)	(3.07)	(2.03)	(3.07)	(2.01)
Controls & Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,402	4,402	4,402	4,402	4,402	4,402
Adjusted R^2	0.007	0.002	0.014	0.001	0.014	0.001

Table 5.6: Institutional Buys and Tiny Trades around 8-K Events

This table reports the OLS regression results on the relation between the probability of institutional net buying and the daily percentage change of number of tiny trades following positive 8-K events before and after the availability of fractional trading. Columns (1) and (2) use $\mathcal{I}(Inst\ BSI_{Trades} > 0)_t$, an indicator that equals one if the daily buy-sell imbalance in the number of institutional trades on day t is positive. Columns (3) and (4) use $\mathcal{I}(Inst\ BSI_{Shares} > 0)_t$, an indicator that equals one if the daily buy-sell imbalance in the number of institutional shares on day t is positive. Columns (5) and (6) use $\mathcal{I}(Inst\ BSI_{DV} > 0)_t$, an indicator that equals one if the daily buy-sell imbalance in institutional dollar volume on day t is positive. $\%\Delta$ *One-Share Trades*$_t$ is the daily percentage change of number of off-exchange one-share trades on day t relative to day $t-1$. For each 8-K event, I set the event period to start from the filing day (*Fdate*) and end 8 trading days after the filing date (*Fdate+8*) in the regression analyses. Controls include the log of market cap on the previous trading day (*ln(Market Cap)*$_{t-1}$), book-to-market of prior year (*Book to Market*$_{y-1}$), ROA of prior year (*Return on Asset*$_{y-1}$), institutional ownership of prior quarter (*Institutional Ownership*$_{q-1}$), stock price volatility of past month (*Past Month Volatility*$_t$), the stock's maximum daily return of past month (*Past Month Max Return*$_t$), and the stock's cumulative return of past month and year (*Past Month Return*$_t$ and *Past Year Return*$_t$) as well as year, month, day-of-week, item, firm, filing-gap and event-fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	$\mathcal{I}(Inst\ BSI_{Trades} > 0)_t$		$\mathcal{I}(Inst\ BSI_{Shares} > 0)_t$		$\mathcal{I}(Inst\ BSI_{DV} > 0)_t$	
	(1)	(2)	(3)	(4)	(5)	(6)
	Post-FT	*Pre-FT*	*Post-FT*	*Pre-FT*	*Post-FT*	*Pre-FT*
$\%\Delta$ *One-share Trades*$_t$	0.015***	0.002	0.010***	0.003	0.010***	0.003
	(4.75)	(0.88)	(3.02)	(1.54)	(3.04)	(1.41)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Item Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Filing Gap Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,906	19,194	25,906	19,194	25,906	19,194
Adjusted R^2	0.056	0.060	0.061	0.076	0.063	0.077

Table 5.7: Short Interest Ratio around Price Peak

This table reports the OLS regression results on differences in high- and low-FT firms' short interest and borrower concentration around positive 8-K events before and after the availability of fractional trading. Columns (1) and (2) use *Short Interest Ratio*, the short interest ratio, calculated as the quantity of shares on loan divided by the number of total shares outstanding. Columns (3) and (4) use *Borrower Concentration*, the borrower concentration, which measures the distribution of borrower demand. Columns (1) and (3) focus on the window *[F,F+1]* and columns (2) and (4) focus on the window *[F+7,F+9]*. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the interaction term between the two. Controls include $ln(Market\ Cap)_{t-1}$, $Book\ to\ Market_{y-1}$, $Return\ on\ Asset_{y-1}$, $Institutional\ Ownership_{q-1}$, $Past\ Month\ Volatility_t$, $Past\ Month\ Max\ Return_t$, $Past\ Month\ Return_t$ and $Past\ Year\ Return_t$ as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Short Interest Ratio$_t$		*Borrower Concentration*$_t$	
	(1)	(2)	(3)	(4)
	[F,F+1]	*[F+7,F+9]*	*[F,F+1]*	*[F+7,F+9]*
High FT × *Post FT*	0.010	0.016*	0.015	0.032**
	(1.39)	(1.86)	(1.00)	(2.23)
$ln(Market\ Cap)_{t-1}$	0.005*	0.005	-0.046***	-0.051***
	(1.85)	(1.48)	(-6.02)	(-6.74)
$Book\ to\ Market_{y-1}$	-0.001	-0.002	0.016	0.043*
	(-0.22)	(-0.26)	(0.64)	(1.71)
$Return\ on\ Asset_{y-1}$	0.001	0.005	0.002	-0.003
	(0.19)	(0.66)	(0.11)	(-0.19)
$Institutional\ Ownership_{q-1}$	0.020***	0.021***	-0.004	-0.009
	(3.87)	(3.52)	(-0.26)	(-0.56)
$Past\ Month\ Volatility_t$	0.216**	0.313***	-0.648*	-0.163
	(2.22)	(2.60)	(-1.92)	(-0.50)
$Past\ Month\ Max\ Return_t$	-0.010	-0.038	0.016	-0.092
	(-0.35)	(-1.12)	(0.15)	(-0.86)
$Past\ Month\ Return_t$	0.000	-0.002	0.040*	0.057***
	(0.05)	(-0.24)	(1.94)	(2.69)
$Past\ Year\ Return_t$	-0.003**	-0.004**	0.010**	0.010**
	(-2.40)	(-2.26)	(2.55)	(2.43)
Year Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes
Item Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Filing Gap Fixed Effects	Yes	Yes	Yes	Yes
Observations	4,402	4,402	4,402	4,402
Adjusted R^2	0.617	0.600	0.447	0.434

Table 5.8: Short Interest Ratio around Price Peak: Cross-Sectional Analyses

This table reports cross-sectional analyses of the OLS regression results on differences in high- and low-FT firms' short interest around positive 8-K events before and after the availability of fractional trading. Column (1) uses *Filing-Period Return*$_t$, the daily cumulative returns over the filing period. Column (2) uses *Total WSB Mentions*$_t$, the total number of stock mentions on Reddit's WallStreetBets during the period from F to $F + 8$. *Short Interest Ratio* is the short interest ratio on time period *[F+7,F+9]*. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the triple interaction term in each column. Controls include *ln(Market Cap)*$_{t-1}$, *Book to Market*$_{y-1}$, *Return on Asset*$_{y-1}$, *Institutional Ownership*$_{q-1}$, *Past Month Volatility*$_t$, *Past Month Max Return*$_t$, *Past Month Return*$_t$ and *Past Year Return*$_t$ as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Short Interest Ratio$_t$	
	(1)	(2)
	State Variable	*Common Signal*
High FT × *Post FT*	-0.000	0.018**
	(-0.03)	(2.11)
Filing-Period Return$_t$	0.040***	
	(3.14)	
High FT × *Filing-Period Return*$_t$	-0.192	
	(-1.64)	
Post FT × *Filing-Period Return*$_t$	-0.028*	
	(-1.67)	
High FT × *Post FT* × *Filing-Period Return*$_t$	0.285**	
	(2.34)	
Total WSB Mentions$_t$		0.069**
		(2.49)
High FT × *Total WSB Mentions*$_t$		-0.068**
		(-2.48)
Post FT × *Total WSB Mentions*$_t$		-0.061**
		(-2.14)
High FT × *Post FT* × *Total WSB Mentions*$_t$		0.060**
		(2.09)
Controls	Yes	Yes
Year Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes
Item Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Filing Gap Fixed Effects	Yes	Yes
Observations	4,402	4,402
Adjusted R^2	0.603	0.602

Table 5.9: Abnormal Institutional Attention around 8-K Events

This table reports the OLS regression results on differences in high- and low-FT firms' abnormal institutional attention (AIA) around positive 8-K events before and after the availability of fractional trading. Columns (1) and (4) report the pre-filing-period results. Columns (2) and (5) report the filing-period result. Columns (3) and (6) report the post-filing-period result. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the interaction term between the two. Controls include $ln(Market\ Cap)_{t-1}$, $Book\ to\ Market_{y-1}$, $Return\ on\ Asset_{y-1}$, $Institutional\ Ownership_{q-1}$, $Past\ Month\ Volatility_t$, $Past\ Month\ Max\ Return_t$, $Past\ Month\ Return_t$ and $Past\ Year\ Return_t$ as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	AIA			*AIA Score*		
	(1)	(2)	(3)	(4)	(5)	(6)
	[R,F-1]	*[F,F+1]*	*[F+2,F+8]*	*[R,F-1]*	*[F,F+1]*	*[F+2,F+8]*
High FT × Post FT	0.116***	0.004	0.099*	0.421***	0.072	0.339*
	(2.64)	(0.10)	(1.94)	(2.80)	(0.46)	(1.95)
$ln(Market\ Cap)_{t-1}$	0.005	0.005	0.035**	0.040	0.059	0.118**
	(0.40)	(0.47)	(2.49)	(0.93)	(1.41)	(2.43)
$Book\ to\ Market_{y-1}$	0.013	0.037	0.003	0.017	0.153	0.012
	(0.40)	(1.18)	(0.09)	(0.13)	(1.24)	(0.09)
$Return\ on\ Asset_{y-1}$	-0.021	-0.006	-0.007	-0.014	0.051	0.028
	(-1.05)	(-0.31)	(-0.28)	(-0.18)	(0.64)	(0.29)
$Institutional\ Ownership_{q-1}$	0.046	0.071**	0.050	0.138	0.269**	0.209*
	(1.53)	(2.43)	(1.55)	(1.19)	(2.42)	(1.92)
$Past\ Month\ Volatility_t$	-0.545	-0.623	-1.135*	-0.836	-1.862	-3.426
	(-0.98)	(-1.16)	(-1.82)	(-0.41)	(-1.00)	(-1.55)
$Past\ Month\ Max\ Return_t$	-0.011	-0.029	0.331	-0.271	-0.002	1.062
	(-0.07)	(-0.16)	(1.49)	(-0.44)	(-0.00)	(1.43)
$Past\ Month\ Return_t$	0.036	-0.014	-0.074*	0.100	-0.091	-0.212
	(1.04)	(-0.39)	(-1.91)	(0.78)	(-0.69)	(-1.56)
$Past\ Year\ Return_t$	0.007	0.011*	0.001	0.025	0.035	0.035
	(1.01)	(1.66)	(0.17)	(0.98)	(1.43)	(1.22)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Item Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Filing Gap Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,402	4,402	4,402	4,402	4,402	4,402
Adjusted R^2	0.303	0.248	0.385	0.408	0.377	0.494

Table 5.10: Abnormal Institutional Attention and 8-K Disclosure Complexity

This table reports the OLS regression results on differences in high- and low-FT firms' filing-period abnormal institutional attention (*AIA* or *AIA Score*) for 8-K filings with high disclosure complexity before and after the availability of fractional trading. Columns (1) and (3) report the results using *Smog Index* to measure disclosure complexity. Columns (2) and (4) report the results using *Fog Index* to measure disclosure complexity. *AIA* indicates whether the maximum Bloomberg's daily attention score during the filing period is greater than or equal to 3. *AIA Score* is the maximum Bloomberg's daily attention score during the filing period. *High Complexity* indicates whether *Smog Index* or *Fog Index* exceeds the sample 90th percentile respectively. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the interaction term of the three. Controls include the log of market cap on the previous trading day ($ln(Market\ Cap)_{t-1}$), book-to-market of prior year ($Book\ to\ Market_{y-1}$), ROA of prior year ($Return\ on\ Asset_{y-1}$), institutional ownership of prior quarter ($Institutional\ Ownership_{q-1}$), stock price volatility of past month ($Past\ Month\ Volatility_t$), the stock's maximum daily return of past month ($Past\ Month\ Max\ Return_t$), and the stock's cumulative return of past month and year ($Past\ Month\ Return_t$ and $Past\ Year\ Return_t$) as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	AIA		*AIA Score*	
	(1)	(2)	(3)	(4)
	Smog Index	*Fog Index*	*Smog Index*	*Fog Index*
High Complexity	-0.019	-0.027	-0.058	-0.087
	(-0.84)	(-1.20)	(-0.72)	(-1.05)
High FT × *Post FT*	-0.021	-0.017	-0.075	-0.064
	(-0.41)	(-0.33)	(-0.45)	(-0.39)
High FT × *High Complexity*	-0.120*	-0.108*	-0.405*	-0.379*
	(-1.78)	(-1.65)	(-1.88)	(-1.76)
Post FT × *High Complexity*	0.018	0.034	0.059	0.108
	(0.49)	(0.91)	(0.45)	(0.82)
High FT × *Post FT* × *High Complexity*	0.267**	0.250**	0.830**	0.791*
	(2.10)	(1.97)	(1.97)	(1.87)
Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes
Item Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Filing Gap Fixed Effects	Yes	Yes	Yes	Yes
Observations	4,402	4,402	4,402	4,402
Adjusted R^2	0.338	0.338	0.379	0.379

Table 5.11: Pre-Filing Option Trading

This table reports the OLS regression results on differences in high- and low-FT firms' pre-filing option trading volume around positive 8-K events before and after the availability of fractional trading. The left panel reports the call option trading results and the right panel reports the put option trading results. Columns (1) and (4) use the full sample, columns (2) and (5) use the subsample with filing gap less than or equal to one trading day, and columns (3) and (6) use the subsample with filing gap more than one trading day. *Abnormal Call* is the abnormal call option trading volume in thousands, calculated as the mean of call option trading volume during the pre-filing period *[R,F-1]* net of the mean of call option trading volume during *[R-30,R-5]*. *Abnormal Put* is the abnormal put option trading volume in thousands, calculated as the mean of put option trading volume during the pre-filing period *[R,F-1]* net of the mean of put option trading volume during *[R-30,R-5]*. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the interaction term of the two. Controls include the log of market cap on the previous trading day ($ln(Market\ Cap)_{t-1}$), book-to-market of prior year ($Book\ to\ Market_{y-1}$), ROA of prior year ($Return\ on\ Asset_{y-1}$), institutional ownership of prior quarter ($Institutional\ Ownership_{q-1}$), stock price volatility of past month ($Past\ Month\ Volatility_t$), the stock's maximum daily return of past month ($Past\ Month\ Max\ Return_t$), and the stock's cumulative return of past month and year ($Past\ Month\ Return_t$ and $Past\ Year\ Return_t$) as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Abnormal Call			*Abnormal Put*		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full	*Gap* ≤ 1	*Gap* > 1	*Full*	*Gap* ≤ 1	*Gap* > 1
High FT × *Post FT*	-0.048	0.881	-0.747	4.413***	6.298***	3.643***
	(-0.09)	(0.65)	(-1.13)	(5.42)	(3.10)	(3.74)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
High FT × *Post FT*	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Item Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Filing Gap Fixed Effects	Yes	No	No	Yes	No	No
Observations	4,402	1,189	2,269	4,402	1,189	2,269
Adjusted R^2	0.194	0.210	0.218	0.411	0.303	0.482

Table 5.12: Pre-Filing AIA and Pre-Filing Price Discovery

This table reports the OLS regression results on differences in high- and low-FT firms' relation between pre-filing price discovery and pre-filing abnormal institutional attention around positive 8-K events before and after the availability of fractional trading. Panel A uses AIA indicator and Panel B uses the continuous AIA score. In each panel, column (1) uses the full sample, column (2) uses the subsample with filing gap less than or equal to one trading day, and column (3) uses the subsample with filing gap more than one trading day. $IPE_{[R,F+1]}$ is the intra-period efficiency of event-period price discovery during the window $[R, F + 60]$. *Pre-Filing AIA* indicates whether the maximum Bloomberg's daily attention score during the event period is greater than or equal to 3. *Pre-Filing AIA Score* is the maximum Bloomberg's daily attention score during the event period. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the triple interaction term. Controls include the log of market cap on the previous trading day ($ln(Market\ Cap)_{t-1}$), book-to-market of prior year ($Book\ to\ Market_{y-1}$), ROA of prior year ($Return\ on\ Asset_{y-1}$), institutional ownership of prior quarter ($Institutional\ Ownership_{q-1}$), stock price volatility of past month ($Past\ Month\ Volatility_t$), the stock's maximum daily return of past month ($Past\ Month\ Max\ Return_t$), and the stock's cumulative return of past month and year ($Past\ Month\ Return_t$ and $Past\ Year\ Return_t$) as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: AIA Indicator

	$IPE_{[R,F+60]}$		
	(1) *Full Sample*	(2) *Filing Gap* ≤ 1	(3) *Filing Gap* > 1
Pre-Filing AIA	-0.186	-0.517	-0.051
	(-1.39)	(-1.48)	(-0.26)
High FT × *Post FT*	0.101	-0.265	0.260
	(0.73)	(-1.49)	(1.42)
High FT × *Pre-Filing AIA*	0.270	0.488	0.256
	(1.29)	(1.12)	(0.89)
Post FT × *Pre-Filing AIA*	0.235	0.533	0.209
	(1.37)	(1.54)	(0.80)
High FT × *Post FT* × *Pre-Filing AIA*	-0.551**	-0.561	-0.714*
	(-2.13)	(-1.40)	(-1.92)
Controls & Fixed Effects	Yes	Yes	Yes
Observations	4,402	1,189	2,269
Adjusted R^2	0.004	0.012	0.004

Table 5.12: Pre-Filing AIA and Pre-Filing Price Discovery - Cont'd

Panel B: Continuous AIA Score

	$IPE_{[R,F+60]}$		
	(1) *Full Sample*	(2) *Filing Gap* ≤ 1	(3) *Filing Gap* > 1
Pre-Filing AIA Score	-0.069*	-0.158	-0.028
	(-1.70)	(-1.41)	(-0.50)
High FT $\times$ *Post FT*	0.119	-0.274	0.278
	(0.82)	(-1.52)	(1.50)
High FT $\times$ *Pre-Filing AIA Score*	0.108*	0.124	0.129
	(1.69)	(0.91)	(1.47)
Post FT $\times$ *Pre-Filing AIA Score*	0.076	0.164	0.058
	(1.57)	(1.46)	(0.81)
High FT $\times$ *Post FT* $\times$ *Pre-Filing AIA Score*	-0.173**	-0.152	-0.219**
	(-2.18)	(-1.25)	(-2.02)
Controls & Fixed Effects	Yes	Yes	Yes
Observations	4,402	1,189	2,269
Adjusted R^2	0.004	0.010	0.004

Figure 5.1: Distribution of Total Number of Fractional Trades

This picture plots the cumulative density function of the total number of fractional trades reported to FINRA OTC Transparency Dataset by major brokers executed fractional-share orders (including Robinhood, DriveWealth, Fidelity, Charles Schwab, and Interactive Brokers) during the sample period from January 2021 to December 2022 for each stock. X-axis indicates the rank of the total number of fractional trades and Y-axis indicates the cumulative density. The green vertical indicates the top decile.

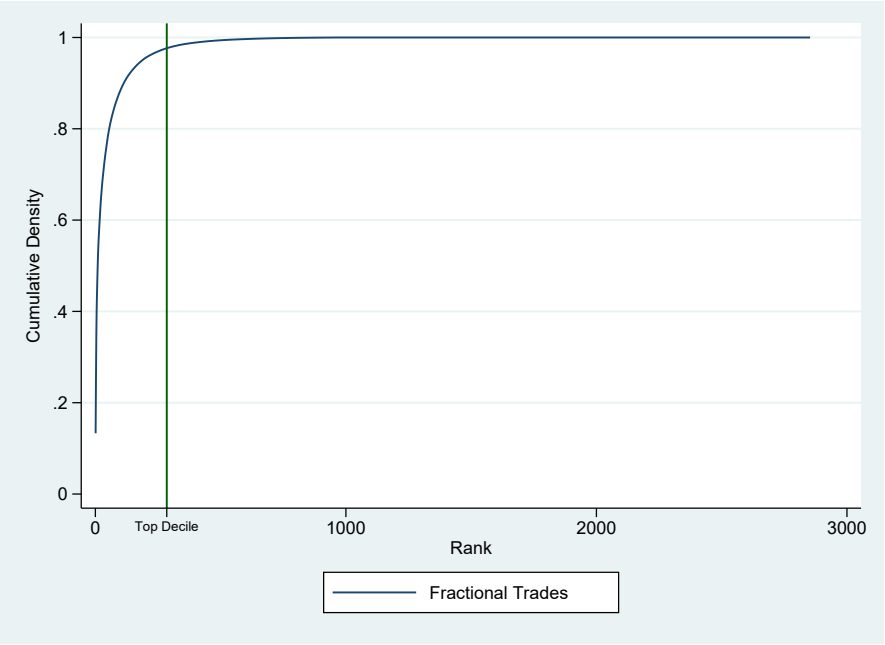


Figure 5.2: Tesla Bubble Example – Percentage of Number of Tiny Trades

This figure plots Tesla's daily closing price along with the daily number of off-exchange one-share trades (as a percentage of total number of trades) during the recent Nasdaq bubble sample period from September 2021 to December 2021. The blue solid line indicates the daily closing price and the red dashed line indicates the daily number of off-exchange one-share trades as a percentage of total number of trades.

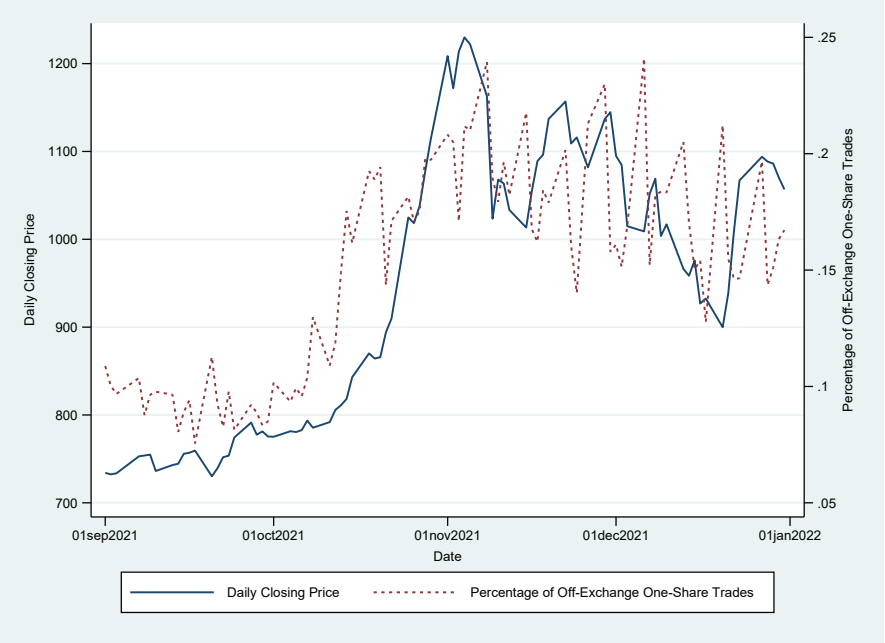
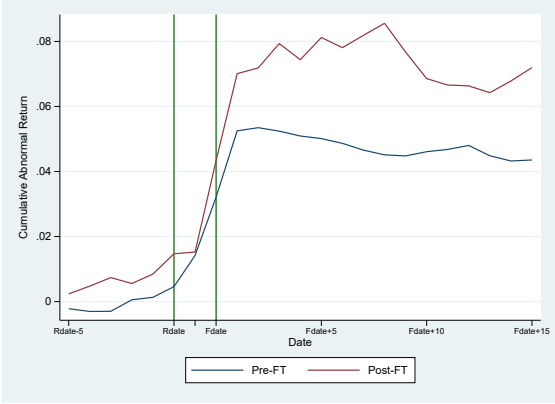


Figure 5.3: Cumulative Abnormal Return around 8-K Events

This figure plots the cumulative abnormal return around positive 8-K events for the high-FT stocks in Panel A and low-FT stocks in Panel B. For each 8-K event, I set the event period to start from 5 trading days before the event date (labeled *Rdate*) and end 15 trading days after the filing date (labeled *Fdate*). For each day t on the x-axis, the cumulative abnormal return (CAR) is calculated as the daily abnormal return compounded over the window [*Rdate-5*, t], with daily abnormal return being the difference between the stock's raw return and the corresponding return on the CRSP value-weighted index. The blue line represents the average CAR across events in the pre-FT period (2017-2019) and the red line represents the average CAR across events in the post-FT period (2021-2022). The two green vertical lines indicate the event date and filing date, and the point in-between indicates CAR averaged over [*Rdate+1*, *Fdate-1*].

Panel A: High–FT Stocks



Panel B: Low–FT Stocks

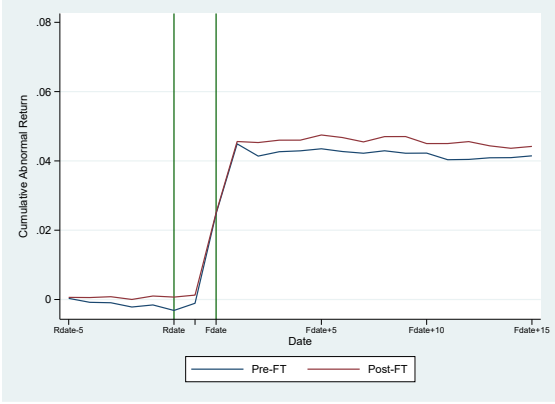
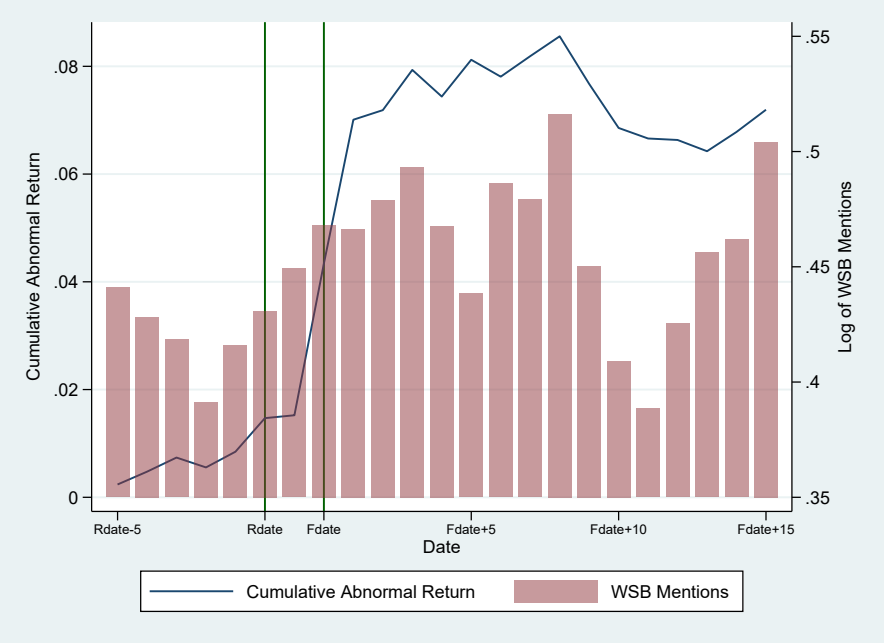


Figure 5.4: Social Media Discussions around 8-K Events

This figure plots the number of social media mentions on Reddit WallStreetBets for the high-FT stocks around positive 8-K events in the post-FT period (2021-2022). For each event, I set the event period to start from 5 trading days before the event date (labeled *Rdate*) and end 15 trading days after the filing date (labeled *Fdate*). For each day t on the x-axis, the cumulative abnormal return (CAR) is calculated as the daily abnormal return compounded over the window [*Rdate-5*, t], with daily abnormal return being the difference between the stock's raw return and the corresponding return on the CRSP value-weighted index. The number of social media mentions is the natural log of total times of a stock being mentioned on Reddit WallStreetBets on day t. The blue line represents the average CAR across events in the post-FT period (2021-2022). The red bar represents the average social media mentions across events in the post-FT period (2021-2022). The two green vertical lines indicate the event date and filing date, and the point in-between indicates CAR or the number of mentions averaged over [*Rdate+1*, *Fdate-1*].



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Appendix A

Variable Definitions

This appendix describes the calculation of variables used in the core analyses. Underlined variables refer to variable names within Compustat or CRSP. t indexes trading day, q indexes the quarter to which trading day t belongs, and y indexes the fiscal year.

Table A.1: Variable Definitions

Variable	**Definition**
Key Outcome Variables	
$BHAR_{[D_1,D_2]}$	Buy and hold abnormal return over the trading window $[D_1, D_2]$, calculated as the firm's raw daily return compounded from day D_1 to day D_2 minus the corresponding daily return on the CRSP value-weighted index compounded over the same window, $\prod_{\tau=D_1}^{\tau=D_2}(1+r_\tau) - \prod_{\tau=D_1}^{\tau=D_2}(1+r_{m\tau})$.
$Return_t$	The stock's daily raw return on trading day t in the percentage.

Continued on next page

Table A.1 – continued from previous page

Variable	Definition
$\mathcal{I}(Short\ Spike)$	An indicator that equals one the maximum daily change in short interest during the pre-filing period or filing period exceeds the 90th percentile for the full sample, and zero otherwise.
$Inst\ BSI_{Trades}$	Buy-sell imbalance in the number of institutional trades during a specific window, the difference between institutional buys and sells, scaled by the sum of institutional buys and sells.
$Inst\ BSI_{Shares}$	Buy-sell imbalance in the number of institutional shares during a specific window, the difference between institutional buy shares and sell shares, scaled by the sum of institutional buy shares and sell shares.
$Inst\ BSI_{DV}$	Buy-sell imbalance in the number of institutional dollar volume during a specific window, the difference between institutional buy dollar volume and sell dollar volume, scaled by the sum of institutional buy dollar volume and sell dollar volume.
$\mathcal{I}(Inst\ BSI_{Trades}, {}_{Shares}$ or $_{DV} > 0)_t$	An indicator that equals one if the daily buy-sell imbalance in the number of institutional trades, shares, or dollar volumes on day t is positive, and zero otherwise.
$Short\ Interest\ Ratio_t$	Short interest ratio, calculated as the quantity of shares borrowed/loaned by Markit borrowers/lenders (QuantityOnLoan) divided by the number of total shares outstanding.

Continued on next page

Table A.1 – continued from previous page

Variable	Definition
Borrower Concentration$_t$	Borrower Concentration is a value between 0 and 1, which measures the distribution of borrower demand. A very small value of Borrower Concentration indicates a large number of borrowers with low borrowed values and 1 indicates a single borrower with all the broker demand. 0 means no borrower demand.
AIA	An indicator that equals one if the maximum Bloomberg's daily attention score during the pre-filing period or filing period is greater than or equal to 3, and zero otherwise.
AIA Score	The maximum Bloomberg's daily attention score during the pre-filing period or filing period.
Abnormal Call	The abnormal call option trading volume in thousands, calculated as the mean of call option trading volume during the pre-filing period *[R,F-1]* net of the mean of call option trading volume during *[R-30,R-5]*.
Abnormal Put	The abnormal put option trading volume in thousands, calculated as the mean of put option trading volume during the pre-filing period *[R,F-1]* net of the mean of put option trading volume during *[R-30,R-5]*.
$IPE_{[D_1,D_2]}$	The intra-period efficiency of pre-filing-period price discovery during the window $[D_1, D_2]$.
Key Independent Variables	
High FT	An indicator that equals one if the firm is included in the high-FT group, and zero otherwise.
Post FT	An indicator that equals one if the 8-K event happened in the post FT period (2021-2022).
$\%\Delta$ *One-Share Trades*$_t$	The daily percentage change of number of off-exchange one-share trades on day t relative to day $t-1$.

Continued on next page

Table A.1 – continued from previous page

Variable	Definition
# of WSB Mentions$_t$	The daily number of stock mentions on Reddit's WallStreetBets on day t, collected following the method of Bryzgalova et al. (2023).
Pre-Filing AIA	An indicator that equals one if the maximum Bloomberg's daily attention score during the pre-filing period is greater than or equal to 3, and zero otherwise.
Pre-Filing AIA Score	The maximum Bloomberg's daily attention score during the pre-filing period.
High Complexity	An indicator that equals one if *Smog Index* or *Fog Index* exceeds the sample 90th percentile.
Filing-Period Return$_t$	The cumulative returns over the filing period.
Total WSB Mentions$_t$	The total number of stock mentions on Reddit's WallStreetBets during the period from F to $F+8$.
Control Variables	
ln(Market Cap)$_{t-1}$	Natural logarithm of market capitalization (PRC $\times$ SHROUT) on trading day $t-1$.
Book to Market$_{y-1}$	Book value of assets (AT) divided by market value of assets (PRCCF $\times$ CSHO + LT) at the end of year $y-1$.
Return on Asset$_{y-1}$	Income before extraordinary items (IB) divided by book value of assets (AT) at the end of year $y-1$.
Institutional Ownership$_{q-1}$	The percentage of institutional holding of prior quarter $q-1$.
Past Month Volatility$_t$	The standard deviation of the stock's daily returns over the past 30 calendar days.
Past Month Max Return$_t$	The stock's maximum daily return over the past 30 calendar days, calculated following the method of Bali et al. (2011).

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Table A.1 – continued from previous page

Variable	Definition
Past Month Return$_t$	The stock's cumulative return of the past month by compounding the stock's daily returns over the past 30 calendar days.
Past Year Return$_t$	The stock's cumulative return of the past year by compounding the stock's daily returns over the past 360 calendar days.

Appendix B

Trade Reporting for TSLA in OTC Transparency Data

Table B.1: Trade Reporting for TSLA in OTC Transparency Data

This appendix shows the trade reporting for TSLA for each FINRA-registered broker during the first week of March 2021. The information is sourced from OTC Transparency Data. The first column indicates the symbol name. The second column indicates the market participant name. The third and fourth columns indicate the quantity of total weekly shares and the number of total weekly trades respectively. The major brokers who offer direct fractional trading services are in bold.

Symbol	Market Participant	Total Weekly Share	Total Weekly Trade
TSLA	CANACCORD GENUITY LLC	140380	4514
TSLA	**CHARLES SCHWAB & CO., INC.**	**3120**	**1082**
TSLA	CITADEL SECURITIES LLC	32099050	480695
TSLA	COMHAR CAPITAL MARKETS, LLC	1003695	25234
TSLA	DRIVEWEALTH INSTITUTIONAL LLC	102315	17270
TSLA	**DRIVEWEALTH, LLC**	**178387**	**178387**
TSLA	De Minimis Firms	2482347	2880
TSLA	G1 EXECUTION SERVICES, LLC	11010635	359128
TSLA	HRT EXECUTION SERVICES LLC	164911	3561
TSLA	**INTERACTIVE BROKERS LLC**	**2933**	**2933**
TSLA	JANE STREET CAPITAL, LLC	3100546	73213
TSLA	LEK SECURITIES CORPORATION	505349	12013
TSLA	**NATIONAL FINANCIAL SERVICES LLC**	**39977**	**39951**
TSLA	**ROBINHOOD SECURITIES, LLC**	**447271**	**447263**
TSLA	STOCKPILE INVESTMENTS, INC.	7874	5844
TSLA	TWO SIGMA SECURITIES, LLC	3410229	165039
TSLA	UBS SECURITIES LLC	5175864	70291
TSLA	VIRTU AMERICAS LLC	32782852	517421
TSLA	WOLVERINE SECURITIES, LLC	59534	8200

Appendix C

Sample Construction Process

Table C.1: Sample Construction Process

Sample Construction	**Filing Observations**
Raw 8-K filings excluding 8-K/A	403,096 8-K filings (907,782 filing-items)
Excluding Item 9.01, which is a supplement	394,630 8-K filings (594,383 filing-items)
Keeping single item filing	257,115 8-K filings
Removing 8-K filings that share a filing date or event date with another 8-K filing by the same firm	234,564 8-K filings
Merging with WRDS linking tables and Compustat/CSRP Merged dataset; applying CRSP share codes 10 and 11	144,737 8-K filing-PERMNO pairs
Keeping reporting gap up to four business days	143,097 8-K filing-PERMNO pairs
Keeping reporting gap at least one business days; Removing 2019 and 2020 events and events with absolute filing-period returns smaller than 2%; Removing events with another 8-K event in the 10-day window	10,576 8-K filing-PERMNO pairs
Keeping positive events	5,187 8-K filing-PERMNO pairs

Appendix D

An Investment Model with Coordination

Fang et al. (2022) extend the canonical model of investment beautify contest (Angeletos and Pavan, 2004) by incorporating the influence of social media platforms. They set up a three-period model that features a social media leader strategically revealing the investment position and a continuum of followers. The model mirrors the coordination mechanism observed on social media platforms and focuses on the role of strategic information disclosure in the coordination game. The simplified model in this section adapts from Fang et al. (2022) to derive a static trading equilibrium for both informed traders and tiny traders with a specific focus on understanding the factors influencing the price runup following positive 8-K filings. I use this model to provide empirical predictions for the cross-sectional analyses.

D.1 Model Setup

This model is based on the model setup in Fang et al. (2022) to examine the trading incentives of informed traders and how they might potentially take advantage of unsophisticated tiny investors, who are heavily influenced by social media platforms such as Reddit WallStreetBets. Furthermore, it aims to derive insights on how the dynamic interplay between informed traders and tiny investors influences the degree of market

mispricing. I set up a static model which features an informed trader (I) and a continuum of tiny (uninformed) traders (U), indexed by i and uniformly distributed over $[0, \delta]$, where δ measures the size of tiny traders.

Suppose that all traders are risk-neutral. The informed trader's payoff is determined by her investment amount m, and the stock price P to be determined in the future. The payoff function is given by:

$$u_I = Pm - \frac{m^2}{2}.$$

The quadratic cost component in the payoff function is similar to the variance term in the mean-variance framework. Similarly, the tiny trader's payoff is given by:

$$u_i = Pk_i - \frac{k_i^2}{2},$$

where k_i represents the amount of investment by trader i.

The stock price P is realized in the future as it represents the future return, and traders do not observe it at the time of investing. I introduce the strategic complementarity by assuming that P is increasing in the total investment of all traders:

$$P = \lambda(K + m) + (1 - \lambda)\,\theta,$$

where the state variable $\theta \sim N\left(\bar{\theta}, \frac{1}{\phi}\right)$, represents the underlying fundamentals (or future cash flows) of the firm, m represents the investment by the informed investor, and $K \equiv \int_0^\delta k_i di$ represents the total investment by the tiny traders. The stock price P is a linear combination of the total investment and the state variable. The weight $\lambda \in (0, 1)$ implies that the price increases with the total investment of both informed and tiny traders. Traders have stronger incentives to invest either when there is a favorable shock to the fundamental (higher θ) or when other traders also make larger investments (higher K). The parameter λ thus captures the magnitude of the coordination incentive or the level of investment externality. This price function provides a parsimonious reduced-form representation of the beauty-contest feature (or strategic complementarity).

The state variable θ is not known at the time when investment decisions are made. In the case of 8-K filings with early- and late-informed traders, the state variable is perceived as short-lived information for sophisticated institutional investors and is revealed to late-informed investors after the disclosure event. There is a strong demand

for immediacy as highlighted in Hirshleifer et al. (1994) and Brunnermeier (2005) and previous empirical literature finds general empirical support (Ben-Rephael et al., 2022; Callen et al., 2022).

However, in the setting with an influx of tiny traders, who are "on the lowest end of the sophistication spectrum" (Blankespoor et al., 2019), the textual contents in 8-K filings are difficult to process and could be interpreted as a form of long-lived private information (Blankespoor et al., 2020), where tiny trades could be seen as uninformed (or at least not fully informed) even post-filing. To incorporate this feature into the model, I allow both the informed trader and tiny traders to be endowed with additional private signals about θ separately. But given the setup of the final payoff, the tiny trader's private signal will be averaged out, and therefore she trades heavily on the common signal, exhibiting a sense of unsophistication. For simplicity, I consider the case of improper prior with $\phi = 0$. In other words, there is little prior knowledge about θ.

The model has two dates, $t \in \{0, 1\}$. The figure below summarizes the timeline of the model.

At $t = 0$, the informed trader I and each tiny trader i are endowed with a common signal (z) and different private signals (x_I and x_i) about the state θ respectively:

$$x_I = \theta + \varepsilon_I; z = \theta + \varepsilon_z; x_i = \theta + \varepsilon_i,$$

where $\varepsilon_I \sim N\left(0, \frac{1}{\alpha}\right)$, $\varepsilon_i \sim N\left(0, \frac{1}{\gamma}\right)$ and $\varepsilon_z \sim N\left(0, \frac{1}{\beta}\right)$. The noise terms ε_I, ε_i and ε_z are independent of each other and of θ. Given her private information x_I and public information z, the informed trader chooses her investment amount m. Given x_i and z, each trader i chooses the investment amount k_i. This setup is different from Fang et al. (2022) where the sophisticated lead player is the early decision maker and the unsophisticated trader is the later decision maker. The model in this paper simplifies

the dynamics of interaction between social media leaders and their followers. Notably, the model does not include strategic disclosures by the leader to influence the trading decisions of their followers, in contrast to the emphasis placed on this aspect in Fang et al. (2022). Fang et al. (2022) focus on the role of strategic disclosure in coordination games and explore the trade-offs involved in a leader's decision-making regarding the precision of their social media disclosures, an aspect not addressed in this simplified model.

At $t = 1$, the state variable θ is realized and the price P is determined by the aggregate investment K and the true state θ.

The following table provides a list of notations that will be used in the model.

Notation	**Note**	**Notation**	**Note**
u_L	informed trader's payoff	u_i	tiny trader i's payoff
m	informed trader's investment	k_i	tiny trader i's investment
θ	state variable	K	tiny traders' total investment
λ	coordination motive	P	stock price
x_I	informed trader's private signal of θ	z	public signal of θ
x_i	tiny trader i's private signal of θ	ε_i	noise of x_i
ε_I	noise of x_I	ε_z	noise of z
$\bar{\theta}$	mean of θ	ϕ	precision of θ
α	precision of ε_I	β	precision of ε_z
δ	the size of tiny traders	γ	precision of ε_i

D.2 Model Analysis

To solve the model, I start from the tiny trader's investment k_i. At $t = 0$, each tiny trader i observes $\{x_i, z\}$. The trader thus maximizes her conditional expected utility

$$\mathbb{E}_i[u_i] \equiv \mathbb{E}\left[u_i | x_i, z\right] = \mathbb{E}\left[P | x_i, z\right] k_i - \frac{k_i^2}{2}.$$

After taking the first-order condition, the tiny trader's investment k_i is given by:

$$k_i^* = \mathbb{E}_i\left[P\right] = \lambda \mathbb{E}_i\left[K\right] + \lambda \mathbb{E}_i\left[m\right] + (1-\lambda)\mathbb{E}_i\left[\theta\right]. \tag{D.1}$$

The tiny trader conjectures the informed trader's and the other tiny investors' linear

equilibrium investment schedule as:

$$m^*(x_I, z) = a_I x_I + b_I z; k^*(z) = a_U x_i + b_U z.$$

Rewrite the first component of equation (D.1), $\mathbb{E}_i[K]$, as

$$\mathbb{E}_i[K] = \mathbb{E}[\int_0^\delta (a_U x_i + b_U z) di | x_i, z] = \delta (a_U \mathbb{E}_i[\theta] + b_U z)$$

Rewrite the second component of equation (D.1), $\mathbb{E}_i[m]$, as

$$\mathbb{E}_i[m] = \mathbb{E}[a_I x_I + b_I z | x_i, z] = a_I \mathbb{E}_i[\theta] + b_I z,$$

because $\mathbb{E}[\varepsilon_I | x_i, z] = 0$ due to independence between ε_I and x_i and between ε_I and z.

Following Bayesian updating, the third component of (D.1),$\mathbb{E}_i[\theta]$, the posterior expectation about θ of trader i is the weighted average of the public signal and private signal, which is given by

$$\mathbb{E}_i[\theta] = \frac{\gamma}{\gamma + \beta} x_I + \frac{\beta}{\gamma + \beta} z$$

Therefore, rewrite equation (D.1) as

$$\begin{aligned} k_i &= (\lambda\delta a_U + \lambda a_I + 1 - \lambda)\, \mathbb{E}_i[\theta] + (\lambda\delta b_U + \lambda b_I) z \\ &= (\lambda\delta a_U + \lambda a_I + 1 - \lambda) \frac{\gamma}{\gamma + \beta} x_i + \left((\lambda\delta a_U + \lambda a_I + 1 - \lambda) \frac{\beta}{\gamma + \beta} + \lambda\delta b_U + \lambda b_I \right) z \end{aligned}$$

By matching with the coefficients, it follows that

$$\begin{aligned} a_U &= (\lambda\delta a_U + \lambda a_I + 1 - \lambda) \frac{\gamma}{\gamma + \beta} \\ b_U &= (\lambda\delta a_U + \lambda a_I + 1 - \lambda) \frac{\beta}{\gamma + \beta} + \lambda\delta b_U + \lambda b_I \end{aligned} \tag{D.2}$$

For the informed trader, at $t = 0$, she maximizes the utility given her private information x_I and public information z:

$$\mathbb{E}_I[u_I] \equiv \mathbb{E}[u_I | x_I, z, m] = \mathbb{E}[P | x_I, z, m]\, m - \frac{m^2}{2}.$$

Taking the first-order condition gives that:

$$m = \mathbb{E}[P | x_I, z, m] + \frac{\partial \mathbb{E}[P | x_I, z, m]}{\partial m} m. \tag{D.3}$$

$$\begin{aligned}\mathbb{E}_I[P] &= \mathbb{E}[\lambda(K+m) + (1-\lambda)\theta | x_I, z, m] \\ &= \lambda \mathbb{E}_I[K] + \lambda m + (1-\lambda)\mathbb{E}_I[\theta]\end{aligned} \tag{D.4}$$

Rewrite the first component of equation (D.4), $\mathbb{E}_I[K]$, as

$$\mathbb{E}_I[K] = \mathbb{E}[\int_0^{\delta} (a_U x_i + b_U z) di | x_I, z] = \delta \left(a_U \mathbb{E}_I[\theta] + b_U z\right)$$

Following Bayesian updating, the third component of (D.4), $\mathbb{E}_I[\theta]$, the posterior expectation about θ of trader I is the weighted average of the public signal and private signal, which is given by

$$\mathbb{E}_I[\theta] = \frac{\alpha}{\alpha+\beta} x_I + \frac{\beta}{\alpha+\beta} z.$$

Therefore, rewrite equation (D.3) as

$$m = \frac{(1-\lambda+\lambda\delta a_U)\alpha}{(1-2\lambda)(\alpha+\beta)} x_I + \left(\frac{(1-\lambda+\lambda\delta a_U)\beta}{(1-2\lambda)(\alpha+\beta)} + \frac{\lambda\delta b_U}{1-2\lambda} \right) z$$

By matching with the coefficients, it follows that

$$\begin{aligned} a_I &= \frac{(1-\lambda+\lambda\delta a_U)\alpha}{(1-2\lambda)(\alpha+\beta)} \\ b_I &= \frac{(1-\lambda+\lambda\delta a_U)\beta}{(1-2\lambda)(\alpha+\beta)} + \frac{\lambda\delta b_U}{1-2\lambda} \end{aligned} \tag{D.5}$$

Therefore, the set of coefficients $\{a_I, b_I, a_U, b_U\}$ which satisfies the simultaneous equations (D.2) and (D.5), characterizes the equilibrium investment amount of the informed trader and the tiny trader in the model. Matching coefficients solve the investment equilibrium, which is characterized in **Theorem D.1**.

Theorem D.1 *The informed trader I and the tiny trader i take the following linear equilibrium investment schedule:*

$$m^*(x_I, z) = a_I x_I + b_I z; k^*(z) = a_U x_i + b_U z,$$

where

$$\begin{aligned} a_I &= \frac{(1-\lambda)\alpha}{(1-2\lambda)(\alpha+\beta)} \\ b_I &= \frac{(1-\lambda)\left[\delta(1-\lambda)\lambda\alpha+(1-2\lambda)\beta\right]}{(1-2\lambda)[(1-\delta\lambda)(1-\lambda)-\lambda](\alpha+\beta)} \\ a_U &= 0 \\ b_U &= \frac{(1-\lambda)^2}{(1-\delta\lambda)(1-\lambda)-\lambda}. \end{aligned}$$

Note that $a_I, b_I, b_U > 0$ if and only if $(1-\delta\lambda)(1-\lambda) > \lambda$, which requires that:

Assumption D.1:

$$\delta < \frac{1-2\lambda}{(1-\lambda)\lambda} \text{ and } \lambda < \frac{1}{2}.$$

I impose **Assumption D.1** for all of the remaining analyses.

b_U is independent of γ and β. Given signal z, the tiny trader will invest more only when there is a stronger coordination incentive λ or a larger trader size δ. It is easy to see that $\frac{\partial b_U}{\partial \lambda} > 0$ and $\frac{\partial b_U}{\partial \delta} > 0$. At the same time, the informed trader has a stronger incentive to trade on public signal than on private signal. To see this, the relative weight of the response coefficients b_I and a_I is greater than the relative weight of the precision of the signals:

$$\frac{b_I}{a_I} - \frac{\beta}{\alpha} = \frac{\delta(1-\lambda)\lambda(\alpha+\beta)}{[(1-\delta\lambda)(1-\lambda)-\lambda]\alpha} > 0.$$

D.3 Comparative Statics and Testable Predictions

Given the realization of θ and signals x_I and z, the final stock price is

$$\begin{aligned} P^* &= \lambda(\delta k^* + m^*) + (1-\lambda)\theta \\ &= \lambda[(\delta b_U^* + b_I^*)z + a_I^* x_I] + (1-\lambda)\theta. \end{aligned}$$

The unconditional expected price is given by

$$\begin{aligned} \mathbb{E}[P^*] &= \left[\lambda\delta(b_U^*) + \lambda a_I^* + \lambda b_I^* + (1-\lambda)\right]\bar{\theta} \\ &= \frac{(1-\lambda)^2}{(1-\delta\lambda)(1-\lambda)-\lambda}\bar{\theta}. \end{aligned}$$

The unconditional expected positive mispricing due to coordination is given by

$$\mathbb{E}\left[P^*\right] - \bar{\theta} = \lambda \frac{1-(1-\lambda)(1-\delta)}{(1-\delta\lambda)(1-\lambda)-\lambda}\bar{\theta}.$$

The overvaluation $\mathbb{E}\left[P^*\right] - \bar{\theta}$ is determined by the magnitude of the state variable $\bar{\theta}$, the size of traders (or the impact of social media) δ, and the coordination incentive λ. It is easy to see that $\mathbb{E}\left[P^*\right] - \bar{\theta}$ is increasing in $\bar{\theta}$. $\mathbb{E}\left[P^*\right] - \bar{\theta}$ is increasing in the size of tiny traders δ. To see this,

$$\frac{\partial(\mathbb{E}\left[P^*\right] - \bar{\theta})}{\partial\delta} = \frac{\lambda(1-\lambda)^3}{\left((1-\delta\lambda)(1-\lambda)-\lambda\right)^2}\bar{\theta} > 0.$$

$\mathbb{E}\left[P^*\right] - \bar{\theta}$ is increasing in the coordination incentive λ. To see this,

$$\frac{\partial(\mathbb{E}\left[P^*\right] - \bar{\theta})}{\partial\lambda} = \frac{(1-\lambda)(\delta(1-\lambda)+2\lambda)}{\left((1-\delta\lambda)(1-\lambda)-\lambda\right)^2}\bar{\theta} > 0.$$

Then, I study how the informed trader's private information precision α and public information precision β affect the response coefficient on the public signal b_I. b_I is decreasing in α while increasing in β. To see this,

$$\frac{\partial b_I}{\partial\alpha} = -\frac{\beta(1-\lambda)}{(1-2\lambda)(\alpha+\beta)^2} < 0,$$

$$\frac{\partial b_I}{\partial\beta} = \frac{\alpha(1-\lambda)}{(1-2\lambda)(\alpha+\beta)^2} > 0.$$

Intuitively, if the informed trader is endowed with a more precise private signal, she puts less weight on the public signal and therefore trades less aggressively.

And given the positive bias in the public signal,

$$\frac{\partial P^*}{\partial\alpha} \sim \frac{\partial b_I}{\partial\alpha} < 0,$$

$$\frac{\partial P^*}{\partial\beta} \sim \frac{\partial b_I}{\partial\beta} > 0.$$

Therefore, the magnitude of the mispricing is increasing in the magnitude of the state variable $\bar{\theta}$, the size of tiny traders δ, the coordination incentive λ, and the exposure to public (or common) signal β. The magnitude of the mispricing is decreasing in the informed trader's private information precision α. Institutional shorting volume is higher when the mispricing is more positive.

Empirically, for the set of high-FT stocks in the post-FT period, I expect that they experience a higher short interest ratio around the price peak when the magnitude of the state variable is higher, the size of tiny traders is higher, the coordination incentive is higher, the exposure to public (or common) signal is higher, and the informed trader's private information precision is lower. To motivate the cross-sectional analyses, I focus on the magnitude of the state variable and the exposure to the common signal. It is difficult to find an empirical measure for the coordination incentive and informed trader's private information precision because they are unobservable. In addition, the *High FT* dummy is highly correlated with the size of tiny traders. Therefore, I focus on testing whether the interaction term *High FT*$\times$*Post FT* is more significant if the state variable is stronger and the exposure to the common signal is stronger.

I measure $\bar{\theta}$ using filing-period return and measure β using the total number of social media mentions during the price run-up period. Goldstein et al. (2013) suggest the number of social media discussions indicates the extent to which traders are exposed to the common signal. I expect the institutional shorting volume around the price peak for high-FT stocks in the post-FT period to be higher when the filing-period return is higher and when the total number of social media mentions is higher.

Appendix E

Detecting Fractional Trades

Most retail brokers who offer direct fractional trading services execute fractional share trades on a principal basis. These trades are reported as one-share trades as per the "rounding-up rule" to a FINRA TRF and not easily distinguishable from one-whole-share trades executed on an agency basis. Bartlett et al. (2022b) introduce a novel approach to differentiate between these two types of trades. They find that the reporting for the fractional share trades executed by Robinhood and Drivewealth, which are observed in the TAQ data, display distinct broker-specific characteristics. Notably, these trades would be reported to one of three FINRA TRFs and exhibit noticeably longer trade reporting. Bartlett et al. (2022b) specifically focus on Robinhood and Drivewealth because these two brokers are the largest in terms of executing fractional trades, accounting for approximately 80 percent of the reported volume in FINRA's OTC Transparency initiative. While the majority of the market experiences reporting latencies of less than 20 milliseconds, Robinhood and Drivewealth have a reporting latency exceeding 20 milliseconds. I follow their methodology to detect fractional trades reported by Robinhood and Drivewealth.

Specifically, I start with all the one-share trades marked with exchange code "D" in TAQ. In the next step, I classify an off-exchange one-share trade as a Robinhood fractional share trade if the trade is tagged with the Nasdaq TRF (`TR_RF` in TAQ) and has a reporting latency (`TIME_M` – `PART_TIME`) of between 135 and 300 milliseconds during trading hours or of more than 1 second at the opening of the trading day from March 1, 2021 to December 31, 2022. In contrast, I classify an off-exchange one-share

trade as a Drivewealth fractional share trade if the trade is tagged with the NYSE TRF and has a reporting latency of more than 20 milliseconds during trading hours from November 1, 2021 to October 6, 2022. I also classify an off-exchange one-share trade as a Drivewealth fractional share trade if the trade is tagged with the Nasdaq TRF and has a reporting latency of more than 20 milliseconds during trading hours from October 7, 2022 to December 31, 2022. This detecting algorithm is applicable to Robinhood from March 2021 and to Drivewealth from November 2021 when both brokers began to make real-time trade reports to a FINRA TRF.

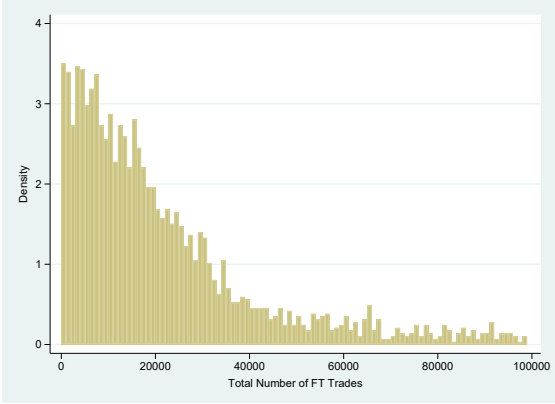
Panel A of Figure E.1 shows the distribution of the total number of fractional trades detected by Bartlett et al. (2022b). Consistent with the trades recorded in OTC Transparency platform, these detected fractional share trades on Robinhood and Drivewealth display a right-skewed distribution. As indicated by Figure E.1 Panel B, the top 100 stocks alone account for more than 60% of all estimated fractional share trades in TAQ, and this dominance extends further with the top 300 stocks capturing more than 75% of all trades. Additionally, focusing on just slightly less than half of the sample stocks would nevertheless capture almost 95% of all estimated fractional share trades. While retail trades detected by Boehmer et al. (2021) also exhibit a skewed distribution towards the top-ranked stocks, fractional share trades stand out for their heightened concentration among just a fraction of all stocks.

I further checked the robustness of return patterns around positive 8-K events for the high- and low-FT stocks before and after the introduction of fractional trading. For Figure E.2, the high-FT stocks comprise the top decile stocks in terms of the total number of fractional trades detected by Bartlett et al. (2022b) in the post-FT period within the sample stock universe. The overshoot and reversal pattern for positive 8-K events post-filing as suggested by Panel A of Figure E.2 is consistent with the pattern shown in Figure 3 Panel A. Overall, these return patterns are robust to using both OTC Transparency Dataset and Bartlett et al. (2022b) measure.

Figure E.1: Distribution of Total Number of Fractional Trades (BMO Measure)

Panel A plots the distribution of the total number of fractional trades detected by Bartlett et al. (2022b) during the sample period from March 2021 to December 2022 for each stock. X-axis indicates the intervals for the number of trades and Y-axis indicates the number of firms included in each interval. Panel B plots the cumulative density function of the distribution of fractional trades in blue line and general retail trades in red line. X-axis indicates the rank of the total number of fractional trades and Y-axis indicates the cumulative density.

Panel A: Distribution by Number of Trades



Panel B: Cumulative Density Function by Rank

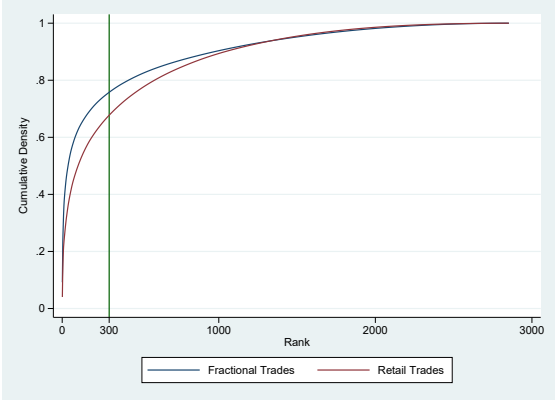
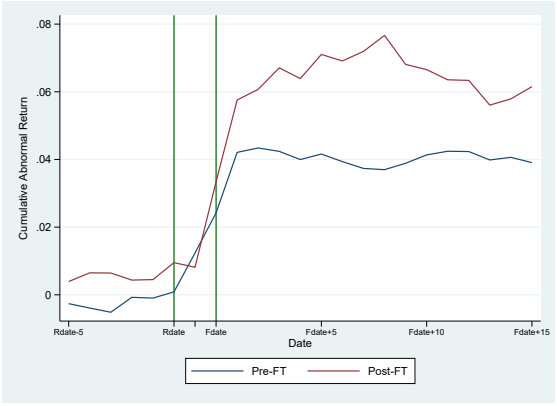


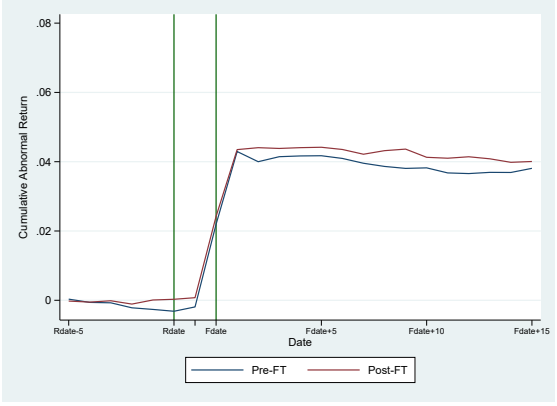
Figure E.2: Cumulative Abnormal Return around 8-K Events (BMO Measure)

This figure plots the cumulative abnormal return around positive 8-K events for the high-FT stocks in Panel A and low-FT stocks in Panel B. For each 8-K event, we set the event period to start from 5 trading days before the event date (labeled *Rdate*) and end 15 trading days after the filing date (labeled *Fdate*). For each day t on the x-axis, the cumulative abnormal return (CAR) is calculated as the daily abnormal return compounded over the window [*Rdate-5*, t], with daily abnormal return being the difference between the stock's raw return and the corresponding return on the CRSP value-weighted index. The blue line represents the average CAR across events in the pre-FT period (2017-2019) and the red line represents the average CAR across events in the post-FT period (2021-2022). The two green vertical lines indicate the event date and filing date, and the point in-between indicates CAR averaged over [*Rdate+1*, *Fdate-1*].

Panel A: High–FT Stocks



Panel B: Low–FT Stocks



Appendix F

Collecting Reddit WallStreetBets Mentions

I follow Bryzgalova et al. (2023) to construct the measure of daily ticker mentions on WallStreetBets. First, I download all the submissions and comments on Reddit WallStreetBets for the period between January 2017 and December 2022 using the Pushshift API. Then I extract submissions that have a "Daily Discussion" thread in the title. These particular posts on Reddit are important for members to engage in discussions about the stock market. Within these threads, users commonly express their thoughts and expectations as comments in response to the original posts. For each submission, I collect its unique ID, timestamp, title, main text. Second, I utilize the unique ID of each submission to retrieve all associated comments. For each comment, I gather essential information such as its unique ID, timestamp, main text, and parent ID indicating the submission to which it refers.

To count ticker mentions in the comment, I obtain all the CRSP symbols from WRDS CRSP Stock Header Information. Then I exclude tickers whose names coincide with commonly used words in the WallStreetBets forum or carry special meanings: NEW, USA, GDP, EOD, ONE, TWO, WANT, BUY, HOLD, SELL, GO, CPI, EPS, FREE, ALL, DD, RH, AI, ATH, API, BEAT, BTC, CEO, CDC, COLD, DATA, DCF, DD, DM, GDP, GF, GOOD, GOV, EOD, ETH, EV, HF, IP, IPO, IQ, IRS, IV, JAN, LIFE, LTD, PSA, PE, NYC, MRNA, PS, RH, ROI, SF, TA, TV, UI, UK, USA, WIN,

WOW, WSB, YOLO, AND, TO, THE, IS, YOU, MOON, THIS, ON, TD, IT, FOR, CNBC, ARE, GET, IN, LINE, HAS, A, UP, WE, F, FOMO, PM, BE, DO, AM, U, V, R, JUST, SO, DIP, NOW, PLUG, ME, R, H, OR, TIME, L, C, T, CAN, BY, BIG, E, O, M, G, D, SEE, ANY, NEXT, VS, S, RIDE, NET, TLT, DASH, OPEN, WOOF, PUMP, VERY, JD, AN, EVEN, Z, H, K, MUST, CFO, YEAR, SOS.

I count the number of times a particular ticker is mentioned in the comments on a daily basis. I search only for capitalized tickers, given the common practice among Reddit users to use capitalized tickers. Specifically, using regular expressions, I extract all capitalized words from the full text of each comment. Each matching word is counted as one mention if it aligns with any CRSP tickers. Consequently, I compile a stock-day panel indicating the daily count of ticker mentions. This dataset is then merged with the CRSP Daily file to get the number of ticker mentions on each trading day for each stock.

Appendix G

An Illustrative Example

AMAZON (symbol: AMZN) filed a Form 8-K on July 2, 2021, which triggered social media discussions and tiny trades following the filing.

Filing Date: 2021-07-02

Accepted: 2021-07-02 16:07:53

Period of Report: 2021-06-28

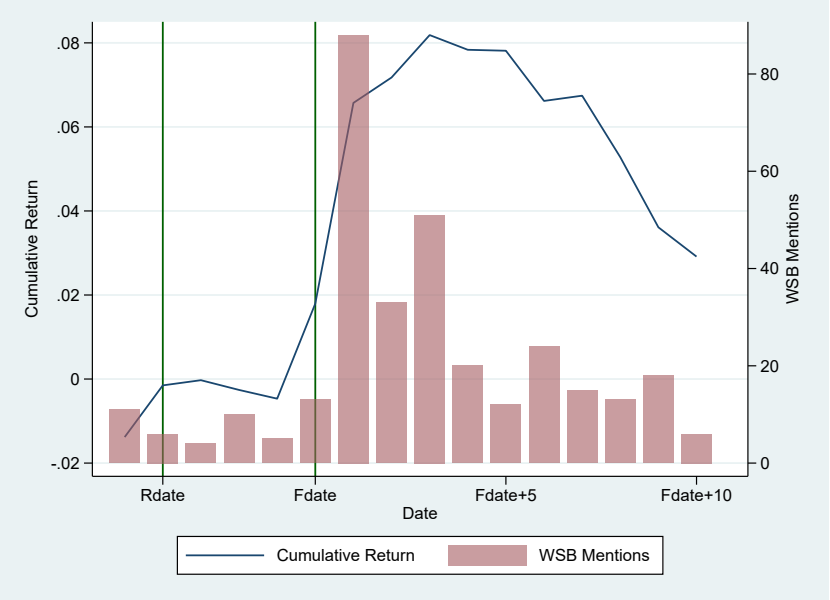
Item 5.02: Departure of Directors or Certain Officers; Election of Directors; Appointment of Certain Officers: Compensatory Arrangements of Certain Officers

In connection with Andrew R. Jassy's promotion to President and Chief Executive Officer of Amazon.com, Inc. (the "Company"), which will occur on July 5, 2021, the Board of Directors elected Mr. Jassy as a director of the Company effective as of the date he becomes President and Chief Executive Officer. In connection with Mr. Jassy's promotion, the Company approved a restricted stock unit award under the Company's 1997 Stock Incentive Plan with respect to 61,000 shares of common stock of the Company, which will be granted as of the date Mr. Jassy becomes President and Chief Executive Officer and vest over ten years, and approved providing Mr. Jassy with appropriate security arrangements. Mr. Jassy also is entering into an indemnification agreement with the Company in the same form as its other directors have entered, which is filed as an exhibit to Amendment No. 1, filed April 21, 1997, to the Company's Registration Statement on Form S-1 (Registration No. 333-23795). Mr. Jassy joined the Company in 1997 and has held numerous leadership roles across the Company. He has led Amazon Web Services since its inception as Senior Vice President from April

2006 until April 2016 and as its CEO since April 2016.

Figure G.1 plots the cumulative return and the number of daily Reddit discussions of Amazon from June 25, 2021 (one day before the 8-K Event Day) to July 19, 2021 (ten days after the 8-K Filing Day). On July 2, 2021, Amazon filed a Form 8-K under Item 5.02, which involved changes in management that occurred on June 28, 2021 (the Event Day). In particular, Andy Jassy was elected as a director of the Company effective as of the date he became President and Chief Executive Officer. There is no significant increase in Reddit discussions before July 2, 2021 (the Filing Day). The stock price increased by 1.5% on June 28 and 2% on July 2. Retail attention and social media discussions spiked on the following trading day, which was the first trading day after the after-market filing. The price further increased by 5% and kept drifting upwards for another 2%, which suggests that coordinated retail trading induced short-run price pressure. After a few days, both the stock price and the discussions on social media returned to the pre-filing levels. Some of the Reddit discussions during the two-day filing period are listed below. These social media posts are relevant to the 8-K event and exhibit a pronounced positive bias.

Figure G.1: Amazon Case



Examples of Reddit Discussions:

"Andy Jassy will grow Amazon to the biggest business on a planet earth."

"Andy Jassy what a guy."

"Never fear, Andy Jassy is here."

"Oh daddy Jassy."

"I should have just bought AMZN."

"AMZN yolo."

"AMZN looks bullish to me."

Appendix H

Additional Tables and Figures

Table H.1: Filing Gaps and Disclosure Complexity of 8-K Filings

This table reports the ordinary least squares (OLS) regression results on differences in high- and low-FT firms' filing gaps and disclosure complexity of positive 8-K events before and after the availability of fractional trading. Column (1) reports the results of filing gap, the number of business days between the calendar event day and the calendar filing day, stated in the 8-K filing. Column (2) reports the results for *Smog Index*. Column (3) reports the results for *Fog Index*. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the interaction term between the two. Controls include the log of market cap on the previous trading day ($ln(Market\ Cap)_{t-1}$), book-to-market of prior year ($Book\ to\ Market_{y-1}$), ROA of prior year ($Return\ on\ Asset_{y-1}$), institutional ownership of prior quarter ($Institutional\ Ownership_{q-1}$), stock price volatility of past month ($Past\ Month\ Volatility_t$), the stock's maximum daily return of past month ($Past\ Month\ Max\ Return_t$), and the stock's cumulative return of past month and year ($Past\ Month\ Return_t$ and $Past\ Year\ Return_t$) as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Filing Gap	*Smog Index*	*Fog Index*
	(1)	(2)	(3)
High FT × *Post FT*	0.024	-0.236	-0.365
	(0.20)	(-1.02)	(-0.96)
Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes
Item Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Filing Gap Fixed Effects	No	Yes	Yes
Observations	4,402	4,402	4,402
Adjusted R^2	0.191	0.333	0.329

Table H.2: Intraday Volatility

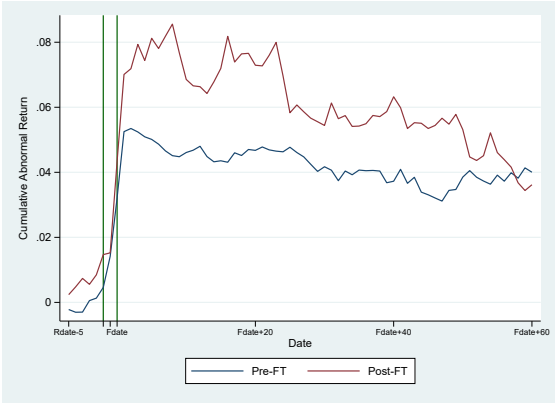
This table reports the OLS regression results on differences in high- and low-FT firms' intraday volatility around positive 8-K events before and after the availability of fractional trading. Column (1) reports the results for the pre-filing period. Column (2) reports the results for the filing period. *Post FT* indicates whether the 8-K event is in the post-FT period. *High FT* indicates whether the firm is in the high-FT group. The key independent variable is the interaction term between the two. Controls include the log of market cap on the previous trading day ($ln(Market\ Cap)_{t-1}$), book-to-market of prior year ($Book\ to\ Market_{y-1}$), ROA of prior year ($Return\ on\ Asset_{y-1}$), institutional ownership of prior quarter ($Institutional\ Ownership_{q-1}$), stock price volatility of past month ($Past\ Month\ Volatility_t$), the stock's maximum daily return of past month ($Past\ Month\ Max\ Return_t$), and the stock's cumulative return of past month and year ($Past\ Month\ Return_t$ and $Past\ Year\ Return_t$) as well as year, month, day-of-week, item, firm and filing gap fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm. All continuous variables are winsorized at the top and bottom 1%. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Intraday Volatility	
	(1)	(2)
	Pre-Filing Period	*Filing Period*
High FT × *Post FT*	0.205	0.306*
	(1.30)	(1.88)
Controls	Yes	Yes
Year Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes
Item Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Filing Gap Fixed Effects	No	Yes
Observations	4,402	4,402
Adjusted R^2	0.854	0.854

Figure H.1: Cumulative Abnormal Return around 8-K Events (Long Horizon)

This figure plots the cumulative abnormal return around positive 8-K events for the high-FT stocks in Panel A and low-FT stocks in Panel B. For each 8-K event, we set the event period to start from 5 trading days before the event date (labeled *Rdate*) and end 60 trading days after the filing date (labeled *Fdate*). For each day t on the x-axis, the cumulative abnormal return (CAR) is calculated as the daily abnormal return compounded over the window [*Rdate-5*, t], with daily abnormal return being the difference between the stock's raw return and the corresponding return on the CRSP value-weighted index. The blue line represents the average CAR across events in the pre-FT period (2017-2019) and the red line represents the average CAR across events in the post-FT period (2021-2022). The two green vertical lines indicate the event date and filing date, and the point in-between indicates CAR averaged over [*Rdate+1*, *Fdate-1*].

Panel A: High–FT Stocks



Panel B: Low–FT Stocks

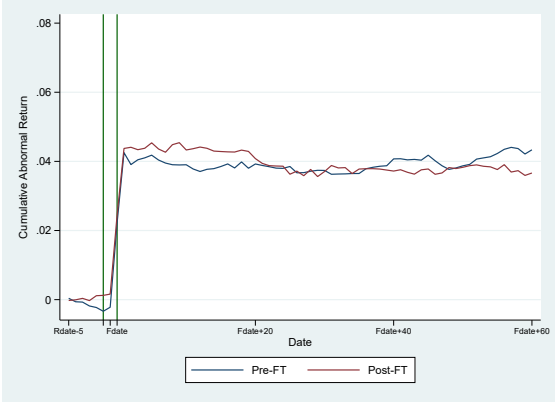
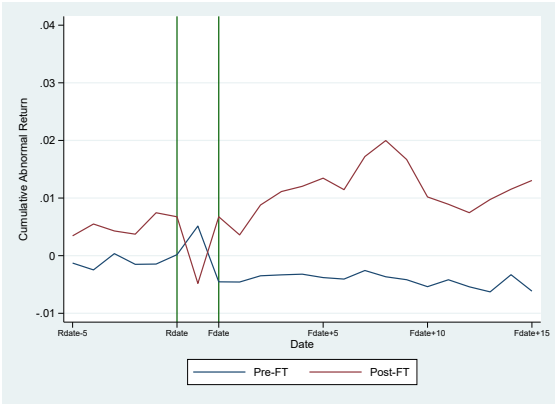


Figure H.2: Cumulative Abnormal Return around 8-K Events (Textual Sentiment)

This figure plots the cumulative abnormal return around positive 8-K events for the high-FT stocks in Panel A and low-FT stocks in Panel B. The classification of positive events is based on the textual sentiment of 8-K filings. For each 8-K event, we set the event period to start from 5 trading days before the event date (labeled *Rdate*) and end 15 trading days after the filing date (labeled *Fdate*). For each day t on the x-axis, the cumulative abnormal return (CAR) is calculated as the daily abnormal return compounded over the window [*Rdate-5*, t], with daily abnormal return being the difference between the stock's raw return and the corresponding return on the CRSP value-weighted index. The blue line represents the average CAR across events in the pre-FT period (2017-2019) and the red line represents the average CAR across events in the post-FT period (2021-2022). The two green vertical lines indicate the event date and filing date, and the point in-between indicates CAR averaged over [*Rdate+1*, *Fdate-1*].

Panel A: High–FT Stocks



Panel B: Low–FT Stocks