Fractional Trading *

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Abstract

Fractional trading (FT)—the ability to trade less than a whole share—removes barriers to high-priced stocks and facilitates entry by capital-constrained retail investors. We observe a surge of tiny trades, measured using off-exchange one-share trades, among high-priced stocks compared to low-priced stocks after FT is introduced to the U.S. equity markets. These tiny trades, when coordinated during attention-grabbing events, are forceful enough to exert large price pressure on high-priced stocks. Further evidence suggests that FT can even fuel meme stock-like trading frenzies and bubbles in high-priced stocks, for which feedback effect likely plays an important role.

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1 Introduction

The U.S. equity markets have witnessed a sharp increase of retail trading in recent years. At its peak, retail volume accounted for more than 30% of the total trading volume (Reuters (2021)). The rise of retail army is likely driven by a confluence of factors tied to advances in trading technology and policy responses to the COVID-19 pandemic. For example, the advent of mobile-friendly trading platforms like Robinhood eased access to stock markets for tech savvy millennial and Generation (Gen) Z investors (Barber et al. (2022); Welch (2022)); the race to zero-commission fees between Fintech trading platforms and traditional brokerage firms slashed trading costs (Eaton et al. (2022)); and the COVID-19 pandemic further fueled retail trading as the stay-at-home restrictions and distribution of unemployment benefits and stimulus left people with more time and spare cash to spend on trading (Ozik et al. (2021)).

Despite these researched factors, the fact remains that most retail investors have limited capital—indeed, the average account size for a Robinhood investor was approximately $3,500 in 2021 (Forbes Advisor (2021)) and the median account balance was only $240 (SEC (2021)). Yet, the impact of retail trading on the U.S. equity markets appears to be far-reaching. Take Berkshire Hathaway's Class A Stock (BRK.A) as an example. With a single share trading well above a quarter million dollars, the stock is commonly considered as out of reach for most retail investors. However, as Figure 1 shows, the stock has evidenced a sharp increase in Robinhood ownership since 2019. The fact that Robinhood investors are able to access high-priced stocks like BRK.A suggests that alternative factors capable of relaxing capital constraints likely also contribute to the rise of retail activity. In this paper, we study such a factor—fractional trading (henceforth FT)—or the ability to trade less than a whole share, with a focus on how FT may impact retail activity and return patterns of high-priced stocks.

FT is not exactly a new concept. In the past, retail investors may own a small amount of fractional shares through either dividend reinvestment plans or special corporate events (e.g., stock splits or mergers and acquisitions), both of which would require a long position in a stock to begin with. Recently, as an attempt to attract retail clientele, several brokers transformed their FT services to allow stock purchase by the slice with as little as a penny. Interactive Brokers was the first major U.S. broker to announce FT 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. Although Charles Schwab restricts its FT services to S&P 500 stocks, FT offerings at the other three brokers are comprehensive, covering nearly all stocks. Direct FT offerings eliminate barriers to high-priced stocks. Indeed, retail investors with low capital reportedly take advantage of FT to trade prominent stocks like FANG and Tesla, which tend to have a steep price tag (Washington Post (2020)).

FT encourages entry to high-priced stocks by investors with binding capital constraints. To see this, consider a marginal investor with \$180 to potentially invest in a firm's stock trading at \$100 per share. With FT, the investor can buy roughly 1.8 shares of the stock. Without FT, s/he can afford to buy only one share and so may turn to lower-priced alternatives all together. Therefore, we expect the introduction of FT to induce a larger increase of tiny trades in high-priced stocks than low-priced stocks as it not only makes fractional ownership possible for marginal investors (a direct effect) but also arguably increases their general willingness to enter and trade high-priced stocks (an indirect effect). The indirect effect may be amplified if fractional ownership further fosters familiarity bias and/or endowment effect.[1] This hypothesis is not without tension. Retail investors are commonly believed to favor lower-priced stocks because they suffer from the nominal price illusion that such stocks are more likely to appreciate (e.g., Kumar (2009); Birru and Wang (2016)) and they are predisposed to think more in terms of share than dollar (Shue and Townsend (2021)).[2] Given these two documented biases, to what extent FT introduction leads retail investors to enter and trade high-priced stocks remains an empirical question.

[1]Prior literature shows that retail investors are susceptible to familiarity bias (see Lewis (1999); Karolyi and Stulz (2003)) and endowment effect (see Kahneman et al. (1990)), which lead them to value equity that they are familiar with or already own more than alternatives.

[2]This bias may be mitigated by the introduction of FT, as investors have the option to place fractional trades in dollar amount. Indeed, Scott Ignall, head of Fidelity's retail brokerage business, commented that post-FT, "retail investors will be thinking 100% in dollars, not in shares," as they "no longer need to use a calculator to figure out how many shares of stock they want to buy." (Wall Street Journal (2020))

We rely on the off-exchange one-share trades to capture FT-induced trading by capital-constrained marginal investors (i.e., FT investors). This measure builds on the institutional knowledge detailed in Bartlett et al. (2022b). As Bartlett et al. (2022b) explain, at most FT offering brokers, the whole share portion of a fractional trade order (i.e., one share in the earlier example) would be executed on an agency basis and then reported to a Financial Industry Regulatory Authority (FINRA) trade reporting facility (TRF) as it is. The fractional share portion of the order (0.8 share in the example), however, would be executed on a principal basis and then reported to a FINRA TRF as a one-share trade as per the "rounding-up rule." Therefore, our measure reflects an increase in fractional trades through the direct effect as well as an increase in small whole-share trades through the indirect effect.[3]

A difference-in-differences (DiD) test shows that compared to low-priced stocks (primarily defined as those with a share price below $100 at the end of November 2019), high-priced stocks have experienced a larger increase of 14.7% in the daily number of off-exchange one-share trades after FT was first available through a major U.S. broker (Interactive Brokers) on November 25, 2019 and a further increase of 148.1% after FT became widely available in the markets through the largest U.S. broker (Fidelity) on January 29, 2020. We obtain this result after matching the two groups on industry and pre-FT characteristics (book-to-market, stock popularity, institutional ownership, and growth in daily one-share trades) and controlling for size, book-to-market, earnings announcement, past stock returns and volatility as well as firm and date fixed effects. Consistent with FT investors driving the surge of tiny trades, the result is concentrated in the subsample of stocks with lower institutional ownership. It is also robust to using either a lower price cutoff of $75 (77 percentile) or a higher price cutoff of $150 (92 percentile).

The sequential introduction of FT covering all stocks, rather than a staggered intro-

[3]Because we cannot separately observe the two portions due to limitations of the current reporting rule, restricting the measure to include only one-share trades is most effective at capturing activity by FT investors. Charles Schwab reports that an average buy order through its FT service is $300, which translates to three shares for a stock trading at $100. Consistently, we show that results are similar if we define the measure to include two- or three-share trades but become weaker if we define it to include five-share trades.

duction that affects different sets of stocks at different times, helps with identification since our DiD test is less likely to yield biased estimates as discussed in Baker et al. (2022). We conduct four additional analyses to further establish a causal effect of FT introduction on tiny trades in high-price stocks. First, we show that the effect is not explained by zero-commission trading (henceforth ZCT) as it kicks in only after November 2019 while ZCT has been available through all major brokers since October 2019. Second, we show that the effect cannot be attributed to COVID-19 alone as it starts to show well before the pandemic. However, the effect may be amplified by the disruption and policy responses brought about by the pandemic, as the increase of off-exchange one-share trades in high-priced stocks relative to low-priced stocks has become more significant after March 2020. Third, we exploit Robinhood's stock-level ownership data, which is emblematic of tiny trades but available only through August 2020. We find the broker's FT introduction induced a larger increase in its user trading intensity among high-priced stocks than low-priced stocks. Finally, exploiting Charles Schwab's partial FT offerings as a shock, we show that high-priced S&P 500 stocks experience a larger increase in off-exchange one-share trades than low-priced S&P 500 stocks or high-priced non-S&P 500 stocks in the seven trading days following the FT introduction date (June 9, 2020) compared to the seven trading days before. Overall, our analyses suggest that the BRK.A example represents the norm rather than the exception. That is, FT eases access to high-priced stocks for retail investors with capital constraints, encourages their entry, and facilitates their trading.

Having established that FT introduction has induced a significant increase of tiny trades in high-priced stocks, we turn to examining its impact on asset price. A null finding is possible because trades by FT investors may be too small to exert any economic impact. Even if an impact is measurable, the theoretical prediction is unclear ex ante. On the one hand, an increase in these tiny trades, which mostly resemble noise, may encourage informed investors to trade more aggressively and therefore accelerate price discovery (e.g., Kyle (1985)). On the other hand, a surge of tiny noise trades could lead to price fluctuations even among the high-priced stocks if they are coordinated during attention-grabbing events to generate large price pressure (Collin-Dufresne and Fos (2016); Fang et al. (2021)). Since retail investors rarely short, their collective attention to a firm's stock leads to net purchase on average, which often translates to a positive but temporary price increase that is subsequently reverted (Barber and Odean (2008); Da et al. (2011)). FT may even give rise to trading frenzies and price bubble if social media serves as a coordination device that leads speculators in the market to trade in the same direction and the resulting price fluctuations affect capital providers' decisions (see Goldstein et al. (2011) and Goldstein et al. (2013) for models of the role of feedback effect in trading decisions).

We first assess the impact of attention-coordinated tiny trades on asset price. This analysis is inspired by Barber et al. (2022) and Kumar et al. (2021). Barber et al. (2022) show that retail attention to Robinhood's "Top Mover" list, which features 20 stocks with extreme price movements, leads to collective buying and positive price pressure, and that these stocks subsequently experience lower returns. Kumar et al. (2021) show that a broader sample of stocks with large daily price movements experience lower returns in the subsequent month. Building on these two studies, we first identify a daily list of 25 stocks with the most positive price movements ("Top Winners") and 25 stocks with the most negative price movements ("Top Losers"). To further capture retail attention, we identify another daily list of 25 stocks with the largest increase in Google abnormal search volume index (i.e., "ASVI" as defined in Da et al. (2011)) relative to the stock's average ASVI in the past 90 days ("Top ASVIs"). We then combine these two lists to create a super set of stocks experiencing retail attention spikes. We find that, after FT introduction, high-priced stocks in the super set experience a larger increase in off-exchange one-share trades than low-priced stocks in the set and start to exhibit price overshot and reversals. During a five-trading day window starting two trading days after a super set is created, high-priced stocks in the set experience a lower return of seven basis points than low-priced ones. This result suggests that attention-coordinated tiny trades are forceful enough to exert price pressure on high-priced stocks.

We then study the extent to which FT contributes to meme stock-like trading frenzies and fuels price bubbles. Using GameStop as a leading example of meme stock, we show that the number of tiny trades (as a percentage of total trades) closely tracks stock price during its legendary trading frenzy episode at the end of January 2021. In regression analysis, we find that the likelihood of a high-priced stock experiencing a bubble is 27% higher than a low-priced stock after FT introduction compared to before. We define bubble occurrence as when the peak price of a firm's stock in the next three months equals or exceeds 150% of the current price but the trough price in the three months following peak drops at least 40% from peak. This finding is more pronounced in the subsample of stocks with lower institutional ownership and robust to using alternative price cutoffs. We also show that the increase in tiny trades as a percentage of total trades is positively related to price pressure, confirming that the price patterns observed for GameStop extend to a larger sample of stocks.

Goldstein et al. (2013) model a feedback mechanism for bubble formation. When speculators like FT traders pour into a meme stock like GameStop, its price increases. Capital providers may interpret the price increase as a positive signal of firm fundamentals and become more willing to offer capital. The enhanced access to financing improves firm valuation, prompting more speculation. As such, this mechanism creates a reinforcing loop of frenetic buying and price rising. We find supporting evidence for such a mechanism in cross-sectional analyses. First, we find that a FT-induced bubble is more likely to occur in a high-priced stock if the stock is prominently discussed via the Reddit forum r/wallstreetbets (WSB), consistent with speculators trading in a coordinated fashion based on common signals. Second, we find that a FT-induced bubble is more likely to occur in a high-priced stock if a firm faces more binding financial constraints (proxied using a lower credit rating), consistent with the firm's valuation benefiting more from improved access to financing. Third, we find that a FT-induced bubble is more likely to occur in retail and consumer industries where capital providers are more likely to learn information about a firm from the aggregate price, precisely when the feedback effect is predicted to play a bigger role.

FT, which represents the most important trading innovation that relaxes retail investors' capital constraints since odd lot trading (see O'Hara et al. (2014) and Chan and Xie (2020)), warrants a study of its own. To our best knowledge, there are three concurrent papers on FT. Gempesaw et al. (2022) focus on Robinhood and find that its users' ownership of high-priced stocks has increased significantly after the broker introduced FT. Bartlett et al. (2022a) use BRK.A as a prominent example to illustrate how the current reporting rule for fractional trades leads to inflated trading volume of the stock on tape, impairing its trading quality. Bartlett et al. (2022b) provide more detailed institutional knowledge about the execution and reporting rule of fractional trades, introduce a method instrumental to identify fractional trades, and then link them to general market outcomes. Our study complements Bartlett et al. (2022b) but also differs from it as our goal is not to identify fractional trades but to evaluate how the ability to invest through fractional shares affects investors' willingness to enter and trade high-priced stocks and how an increase in coordinated tiny trades by FT investors affects the return patterns of these stocks.

Our paper also contributes to the literature on retail trading. A stream of this literature examines how retail trading relates to price efficiency. Evidence, coming from different samples and measures, is mixed (see Barber and Odean (2000); Barber and Odean (2008); Kaniel et al. (2008); Barber et al. (2009); Kaniel et al. (2012); Kelley and Tetlock (2013); Fong et al. (2014); and Barrot et al. (2016) among others). Recently, Boehmer et al. (2021) develop a new methodology to identify retail trades and find that retail order imbalance predicts future returns. Bartlett et al. (2022b) add to this evidence and find that fractional trades predict future liquidity and volatility. A separate stream of this literature studies the rise of retail trading using data from Robinhood (see Ozik et al. (2021); Barber et al. (2022); Eaton et al. (2022); Fedyk (2022); and Welch (2022) among others). By comparing return patterns of high- and low-priced stocks surrounding the introduction of FT, we add new evidence to this literature. Specifically, we show that tiny trardes by FT investors, when coordinated by attention, can cause significant price fluctuations in high-priced stocks.

Finally, our paper speaks to the literature on feedback effect. Financial economists have long noted that the stock market is not just a sideshow and stock prices in the secondary financial markets serve an important informational role (see Bond et al. (2012) and Goldstein (2023) for excellent surveys of this literature). The crux of the arguments for feedback effect is that stock price provides aggregate information about firm value and real decision makers (e.g., managers and capital providers) learn from this information and use it to guide their decisions. Recently, several theories extend the idea to study how feedback effect alters other market participants' trading decisions (e.g., Angeletos et al. (2010), Goldstein et al. (2011), and Goldstein et al. (2013)). In particular, Goldstein et al. (2013) model feedback-induced trading frenzies and make several testable predictions with respect to social media influence, financial constraints, and the likelihood of market participants learning from stock price. Our findings, which exploit the introduction of FT as a setting, provide broad support for these predictions. FT investors, who are mostly capital-constrained millennials and Gen Z, are prone to social media influence. The fact that their collective trading through FT can give rise to meme stock-like trading frenzies and fuel bubbles is worthy of attention.

2 Data and Variable Measurement

This section describes variables and the sample used in the baseline analyses linking FT introduction to tiny trades. Variables and samples used in additional analyses are described along with the results in later sections for ease of composition. Detailed definitions of all variables are provided in Appendix A.

2.1 FT Introduction and Retail Activity by FT Investors

Based on when FT is introduced in the U.S. markets, we define two indicators to use in the baseline analyses. The first indicator, labeled $Post\ IB\text{–}FID_t$, denotes whether trading day t falls between November 25, 2019 and January 28, 2020, thus capturing when FT is available through the two smaller brokers (first Interactive Brokers and then Robinhood shortly after) but not yet through the largest broker (Fidelity). The second indicator, labeled $Post\ FID_t$, denotes whether day t falls on or after January 29, 2020, thus capturing when FT becomes more widely available in the market. For further identification, we also define two indicators to use in Robinhood- and Charles Schwab-specific analyses, respectively. The first indicator, labeled $Post\ RH_t$, denotes whether day t falls on or after December 12, 2019 and captures when FT becomes available through Robinhood. The second one, labeled $Post\ CS_t$, denotes whether day t falls on or after June 9, 2020 and captures when FT of S&P 500 stocks becomes available through Charles Schwab, the second largest broker in the U.S.[4]

We expect FT introduction to induce an increase in tiny trades by capital-constrained retail investors (i.e., FT investors). To capture such activity, we lean on Bartlett et al. (2022b) who offer a wealth of knowledge about fractional trades. As they explain, fractional trades executed merely as accounting entries on books of a broker cannot be identified under the current reporting rule but those executed by a broker on a principal basis may be identifiable as they are reported to a FINRA TRF. The second approach is applied by most brokers that offer direct FT services, including those covered in our analyses. However, identifying fractional trades under this approach is complicated by the fact that they are reported as one-share trades as per the "rounding-up rule" and thus cannot be easily distinguishable from one-whole-share trades executed on an agency basis. Bartlett et al. (2022b) introduce a novel method to distinguish the two based on the observation that the reporting latency for fractional trades reported as one-share trades appears to be longer than that for one-whole-share trades for the two brokers covered in their experiment (i.e., Robinhood and Drivewealth). This method is, however, only applicable to Robinhood from March 2021 when the broker's fractional trades became available in the Trades and Quotes (TAQ) database and to Drivewealth from November 2021 when the broker introduced FT.

[4]According to brokerage-review.com and Wikipedia, as of 2021, Interactive Brokers serves nearly 1 million client accounts with over \$200 billion in customer equity; Robinhood serves 31 million accounts with \$20 billion in customer equity; Fidelity serves 37 million accounts with \$10.4 trillion in customer equity; and Charles Schwab serves 32.1 million accounts with \$7.4 trillion in customer equity.

Unlike Bartlett et al. (2022b), our goal is not to identify fractional trades but to measure changes in FT investors' willingness to enter and trade high-priced stocks surrounding FT introduction, so we use the daily number of off-exchange one-share trades for a firm's stock recorded in the TAQ database, labeled *# of One-Share Trades*, as our primary measure of tiny trades. This measure, which includes only one-whole-share trades pre-FT but both fractional trades (reported as one-share trades) and one-whole-share trades post-FT, helps capture FT-induced changes in tiny trades. Although we cannot use the measure of Bartlett et al. (2022b) in the DiD analysis (because it is not available before March 2021 and fractional trades would be zero pre-FT for both high- and low-priced stocks), we show that our measure has an average Pearson correlation coefficient of 98.5% with Bartlett et al.'s (2022b) measure after March 2021 when their measure is available, which adds credence that our measure indeed captures trading activity by FT investors. In robustness checks, we expand the measure to include larger whole-share trades (i.e., two-, three-, and five-share trades), understanding that the larger the trades, the less likely they are from FT investors.[5]

2.2 Control Variables

We include a long list of controls in all 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 quarter ($Book\ to\ Market_{q-1}$), an indicator to denote whether day t falls within a three-day window centered on a quarterly earnings announcement day ($Earnings\ Announcement_t$), the standard deviation of the stock's daily returns over the past 30 days in percentage points ($Past\ Month\ Volatility_t$), the stock's maximum daily return over the past 30 days ($Past\ Month\ Max\ Return_t$), and the stock's cumulative return of the past week, month, and year (labeled $Past\ Week\ Return_t$, $Past\ Month\ Return_t$, and $Past\ Year\ Return_t$, respectively).

[5]Indeed, Table IA1 of the Internet Appendix shows that results are similar if we define the measure to include two- or three-share trades but predictably weaken when we define it to include five-share trades presumably because the latter picks up retail activity by non-FT investors.

2.3 Summary Statistics

To build the sample, we start with the universe of common stocks (share code 10 or 11) in the CRSP/Compustat Merged database with no missing daily returns between January 2, 2019 and December 31, 2020. We remove five trading days during our sample period on which markets closed early due to observed holidays to make sure that the total number of one-share trades are comparable across trading days. As is standard in the asset pricing literature, we exclude penny stocks (i.e., those with closing price of $5 or less as of the end of November 2019) to alleviate the impact of market microstructure noise on return analysis; our results are robust to using a lower price filter of $1. We also exclude stocks with splits or reverse splits from the sample to make sure that the level of nominal share price is not mechanically affected by these events.

The sample used in the baseline analyses linking FT to tiny trades, which merges the daily measure of off-exchange one-share trades, the two primary indicators related to the timing of FT introduction, and controls, consists of 1,218,500 firm-trading day observations by 2,437 unique firms between January 2019 and December 2020. Table 1 Panel A reports descriptive statistics for the sample. The average daily number of off-exchange one-share trades for a firm's stock ($\#$ *of One-Share Trades*$_t$) is 149 and the median is 42.

3 Empirical Results

3.1 FT and Tiny Trades: Baseline Analyses

Our hypothesis for the baseline analyses follows that the introduction of FT induces a larger increase of tiny trades in high-priced stocks than low-priced stocks as it not only makes fractional ownership possible for marginal investors (a direct effect) but also arguably increases their general willingness to enter and trade high-priced stocks (an indirect effect). However, retail investors tend to suffer from nominal price illusion (e.g., Kumar (2009); Birru and Wang (2016)) and think more in terms of share than dollar (Shue and Townsend (2021)) so they may continue to favor low-priced stocks even if capital constraints are relaxed.

We conduct a DiD analysis to estimate the impact of FT introduction on tiny trades. We build the sample used in this analysis in three steps. First, we sort all unique firm-years (to which the daily observations belong) in an initial sample into a high-priced group if the firm's nominal share price equals or exceeds $100 at the end of November 2019 or a low-priced group otherwise. Second, we estimate a Probit model. The dependent variable equals one for the high-priced group and zero for the low-priced group. The regressors include indicators for the Fama-French 12 industries, book-to-market measured at the end of prior fiscal year, stock popularity measured as the number of Robinhood users holding the stock at the end of November 2019, institutional ownership measured at the end of November 2019, and growth in the number of off-exchange one-share trades (our primary measure of tiny trades) as the cumulative daily values over the five-month period of June-October 2019 minus the cumulative daily values over the five-month period of January-May 2019. Including the growth variable in matching helps ensure that the matched sample satisfies the parallel trends assumption pre-FT. Third, we conduct propensity score matching (PSM) by using the predicted probabilities from the Probit model to perform nearest-neighbor matching without replacement. We use the matched firm-years to retrieve daily observations from the initial sample, and the resulting sample thus consists of pairs of one-to-one matched firm-day observations from both two groups. Consistent with the parallel trends assumption, Table 1 Panel B shows that there are no systematic differences in observable firm characteristics between the two groups post-PSM.[6]

Using the sample, we first perform a visual inspection of how the number of tiny trades evolves for the high- and low-priced groups surrounding the introduction of FT. As Figure 2

[6]Admittedly, PSM can only match high- and low-priced stock groups on observable characteristics and there may be lingering concerns about omitted variables related to retail popularity. In the Internet Appendix, we show that our main results are consistent if we exclude 11 FANG-like stocks including AAPL, AMZN, BABA, BIDU, FB, GOOG, GOOGL, MSFT, NFLX, NVDA, and TSLA (in Table IA2) or if we exclude top 50 popular stocks based on Robinhood ownership at the end of November 2019 (in Table IA3).

shows, the two lines representing the number of off-exchange one-share trades for the high- and low-priced groups trended closely in parallel pre-FT. After FT was gradually introduced to the market in November 2019 and January 2020, the two lines started to trend up and diverge, indicating an increase in tiny trades for both groups and a larger increase for the high-priced group. In Figure IA1 of the Internet Appendix, we redo this analysis dividing the sample into six groups based on the level of nominal share price at the end of November 2019. The figure shows that the impact of FT introduction on tiny trades is nearly increasing in the price level monotonically, as the increase in the number of off-exchange one-share trades is noticeably larger for the two top groups (with price between \$100 and \$200 and price exceeding \$200, respectively) than for the two bottom groups (with price between \$25 and \$50 and price between \$50 and \$75, respectively). This pattern adds to the evidence that FT relaxes capital constraints more for high-priced stocks than for low-priced stocks.

Next, we examine this graphical evidence in a multivariate DiD analysis. To do so, we estimate the following ordinary least squares (OLS) model to study how the sequential introduction of FT first by the two relatively small brokers (Interactive Brokers and Robinhood) and then by the largest broker (Fidelity) respectively affected the number of tiny trades in high-priced stocks relative to low-priced stocks:

$$\begin{aligned} \#\ \textit{of One-Share Trades}_t = \alpha + \beta_1 \textit{High Price} \times \textit{Post IB–FID}_t \\ + \beta_2 \textit{High Price} \times \textit{Post FID}_t + \gamma \textit{Controls}_t + \epsilon_t. \end{aligned} \tag{1}$$

The sample is at the firm-trading day level, with subscript t indexing day and the subscript for firm omitted for brevity. The dependent variable is the number of off-exchange one-share trades defined in Section 2.1. The key regressors are the two DiD estimators: the first one interacts the indicator of *High Price* with *Post IB–FID*$_t$, an indicator for whether trading day t falls in the period when FT was available through either Interactive Brokers or Robinhood but not yet through Fidelity, and the second one interacts *High Price* with *Post FID*$_t$, an indicator for whether trading day t falls in the period after FT became available through all three brokers. $Controls_t$ includes those discussed in Section 2.2, firm fixed effects to control for firm-level heterogeneity, and date fixed effects to control for intertemporal variation in retail activity due to common shocks (e.g., market conditions). With the inclusion of these fixed effects, the three standalone indicators —*High Price*, *Post IB–FID*$_t$, and *Post FID*$_t$— drop out from the regression outputs. We cluster standard errors by firm and date.

Column (1) of Table 2 reports the regression results of estimating equation (1). The coefficient estimate on the first DiD estimator, *High Price*$\times$*Post IB–FID*$_t$, is positive and significant at the 1% level. Its magnitude suggests that although the increase in the daily number of off-exchange one-share trades is greater for high-priced stocks than for low-priced stocks after the two small brokers began FT compared to before, the difference (19 trades, or 14.7%) is modest. The coefficient estimate on the second DiD estimator, *High Price*$\times$*Post FID*$_t$, is also positive and significant at the 1% level. Its magnitude suggests that the relative increase in the daily number of off-exchange one-share trades between the high- and low-priced stocks becomes much larger after Fidelity began FT (191, or 148.1%), presumably because Fidelity is the largest U.S. broker so its FT introduction is more market-moving. Among the controls, we find that the number of off-exchange one-share trades increases surrounding earnings announcements and is positively associated with the firm's market size, price volatility of prior month, and cumulative return of prior year.

If it is true that the introduction of FT facilitates trading activity by capital-constrained retail investors in high-priced stocks, then we would expect the baseline finding in column (1) to be more pronounced for firms with lower institutional ownership (IO). Columns (2)–(3) of Table 2 reestimate equation (1) using the low- and high-IO subsamples, respectively. Since nominal stock price and IO are positively correlated, we first cut the high- and low-priced groups separately based on the within-group median at the end of November 2019 and then combine the two low-IO subgroups into the low-IO subsample used in column (2) and the two high-IO subgroups into the high-IO subsample used in column (3), respectively. The two DiD estimators of interest are statistically significant only in column (2) and statistically insignificant in column (3). Within the low-IO subsample, high-priced stocks experience a larger increase of 57 (or 31.7%) in the number of off-exchange one-share trades than low-priced stocks after the two small brokers began FT and a further relative increase of 361 (or 200.6%) after Fidelity began FT. In further analyses, we check the robustness of the baseline finding to using alternative price cutoffs. As columns (4)–(5) of Table 2 show, the two DiD estimators of interest remain significantly positive if we use a lower price cutoff of $75 or a higher price cutoff of $150. Overall, results from the baseline analyses are consistent with FT spurring tiny trades in high-priced stocks by easing access to these stocks for capital-constrained retail investors, encouraging their entry, and facilitating their trading. Thus, the BRK.A example highlighted earlier likely represents the norm rather than the exception.

3.2 FT and Tiny Trades: Additional Analyses

In this section, we conduct four additional analyses to further establish a causal effect of FT introduction on tiny trades in high-price stocks. The first analysis addresses the possible confounding effect of ZCT. Unlike FT, ZCT has been available through Robinhood since 2013, but the small broker remained an outlier in the industry until Interactive Brokers rolled out a platform to allow ZCT for all U.S.-exchange listed stocks and exchange-traded funds (ETFs) on September 26, 2019. The announcement of this platform pressured rival brokerage firms to join the race to ZCT. Charles Schwab kicked off the race on October 1, 2019, Fidelity followed suit on October 10, 2019, and most other U.S. brokers began ZCT by the end of October 2019. Since the introduction of ZCT was rather swift compared to the introduction of FT, we code a single indicator ($Post\ ZCT–FT_t$) to denote whether a trading day t falls between October 1, 2019 when major brokers rushed to offer ZCT and November 24, 2019, the day before Interactive Brokers introduced FT. We then repeat the baseline analyses in Table 2 including an additional DiD estimator interacting *High Price* with $Post\ ZCT–FT_t$. Table 3 Panel A reports the results. Interestingly, the coefficient estimates on the added DiD estimator are either insignificant or significantly negative in all columns while the coefficient estimates on the two FT-related DiD estimators are barely affected. This result suggests that the mere availability of ZCT actually induced a greater increase in the number of off-exchange one-share trades for low-priced stocks than for high-priced stocks before FT was introduced, which may not be surprising since removing a fixed commission per trade should decrease the trading cost of low-priced stocks by a greater percentage.

The second analysis addresses the possible confounding effect of the COVID-19 pandemic. The pandemic brought a flush of small investors into the stock market, as the steep sell-off at the start of the pandemic was seen as an opportunity to play its comeback and the policy responses such as stay-at-home restrictions and distribution of unemployment benefits and stimulus payments gave regular people more time and spare cash to trade (CNBC (2021)). We first code an indicator to capture the period when FT was widely available but the pandemic effect has not kicked in. This indicator, labeled $\textit{Post FID–COVID}_t$, denotes whether a trading day t falls between January 29, 2020 when Fidelity began FT and February 29, 2020 when Washington declared a state of emergency related to the pandemic.[7] We then code an indicator, labeled $\textit{Post COVID}_t$, to denote whether day t falls on or after March 1, 2020 to capture the post-pandemic effect. Table 3 Panel B repeats the baseline analyses replacing $\textit{High Price}\times\textit{Post FID}_t$ with *High Price* interacted with the two COVID-related indicators, respectively. In all columns, the coefficient estimates on the first DiD estimator, $\textit{High Price}\times\textit{Post FID–COVID}_t$, are consistent with those reported in Table 2. This result suggests that the effect of FT on tiny trades in high-priced stocks started to show well before the pandemic shook the market. The coefficient estimates on the second DiD estimator, $\textit{High Price}\times\textit{Post COVID}_t$, are also consistent and of greater magnitude. This result suggests that COVID-19 likely amplified the effect of FT by bringing more small retail investors into the market who take advantage of FT to enter and trade aggressively in high-priced stocks.

The third analysis is exchange-specific, which takes advantage of Robinhood's stock-

[7]Washington was the first state to declare emergency, but the declaration date, February 29, 2020, fell on a non-trading Saturday. Thus, we group it with other states that declared emergency in March 2020. In addition, 43 states issued either complete or partial stay-at-home orders in March and April 2020.

level ownership data to construct an alternative measure of tiny trades. Because Robinhood hosts the greatest number of small retail accounts, measures based on its user activity should be capable of picking up trading activity by FT investors. Robinhood provided aggregate intraday data on its users holding a stock from May 2, 2018 to August 13, 2020. Robintrack, an independent website, downloaded the data on an hourly basis while it was available.[8] For each stock, Robintrack provides the trading symbol, time of the download, and number of Robinhood user accounts holding the stock. Based on the data, we calculate changes in the number of Robinhood users holding a stock between downloads during trading day t, take the absolute value of these changes, and then sum them up. The resulting variable, labeled $\textit{RH Trading Intensity}_t$, captures how actively Robinhood users trade a stock during the day. In Table 4 Panel A, we estimate a model analogous to equation (1) regressing $\textit{RH Trading Intensity}_t$ on a DiD estimator interacting *High Price* with $\textit{Post RH}_t$, an indicator denoting when Robinhood began FT, and controls. The magnitude of the coefficient estimate on the DiD estimator suggests that Robinhood's FT introduction induced a larger increase of 18.8% in its user trading intensity for high-priced stocks than for low-priced stocks, particularly among those with lower institutional ownership to begin with. The results are again robust to using alternative price cutoffs. In Table IA4 of the Internet Appendix, we show that the results are also consistent if we instead measure $\textit{RH Trading Intensity}_t$ as the standard deviation of hourly changes in the number of Robinhood users holding a stock.

The final analysis makes use of Charles Schwab's partial FT offerings. On June 9, 2020, the broker offered FT services but only for S&P 500 stocks. Although FT of S&P 500 stocks was already available through Fidelity at the time, this event could still result in a measurable change in tiny trades of high-priced S&P 500 stocks by easing access to these stocks for Charles Schwab's own retail clients, especially since it is the second largest U.S. broker. Table 4 Panel B reports the results regressing $\textit{\# of One-Share Trades}_t$ on a DiD

[8] Robinhood discontinued the data on August 13, 2020 saying that " 'other people' are using it in ways they can't monitor/control and potentially at the expense of their users" (Bloomberg (2020)). The data misses 11 trading days in our sample period, but this small omission (<2.7%) is unlikely to affect results.

estimator interacting $High\ Price_{cs}$, an indicator denoting whether a firm's nominal share price equals or exceeds \$100 on June 8, 2020 (the day before Charles Schwab began FT for S&P 500 stocks), with $Post\ CS_t$, an indicator denoting when the broker began FT, and controls. Columns (1)–(4) report on the subsamples of S&P 500 stocks, non-S&P 500 stocks, high-priced stocks, and low-priced stocks, respectively. To sharpen identification, we focus this analysis on a 14-trading day window centered on June 9, 2020. As shown, the DiD estimator exhibits a significantly positive coefficient estimate in columns (1) and (3), which suggests that high-priced S&P 500 stocks experienced a larger increase in the number of off-exchange one-share trades than low-priced S&P 500 stocks and high-priced non-S&P 500 stocks in the seven trading days after Charles Schwab began FT compared to the seven trading days before. Interestingly, the DiD estimator exhibits a significantly negative coefficient estimate in column (2). This result points to a substitution effect, as Charles Schwab's own retail investors may have switched from buying whole shares of high-priced non-S&P 500 stocks to buying fractional shares of high-priced S&P 500 stocks immediately following the broker's FT introduction. The DiD estimator is insignificant in column (4), which suggests that there is no measurable change in the number of off-exchange one-share trades between low-priced S&P 500 and non-S&P 500 stocks after the broker began FT.[9]

In summary, results in this section suggest that the introduction of ZCT and COVID-19 pandemic alone cannot explain away the greater increase in tiny trades observed for high-priced stocks than for low-priced stocks since the trend did not surface until FT was introduced but already started showing before the pandemic. Results from exchange-specific analyses further confirm the role of FT, rather than other market trends, in inducing a greater increase of tiny trades in high-priced stocks.

[9]Given the short time-series, we do not cluster standard errors by date in this analysis. If we do, the coefficient estimate on the DiD estimator is still significant at the 10% level in columns (1) and (3). The coefficient estimates on the DiD estimators in columns (2) and (4) become insignificant.

3.3 FT, Coordinated Attention, and Price Pressure

Results thus far show that the sequential introduction of FT leads to an increase of tiny trades in high-priced stocks. Prior research suggests that such an increase is often associated with greater stock price fluctuations. Because retail investors rarely short, their collective attention to a firm's stock leads to net purchase on average, which tends to result in a positive but temporary price increase that is subsequently reverted (e.g., Barber and Odean (2008); Da et al. (2011)). Might FT-enabled tiny trades, when coordinated during attention-grabbing events, work collectively to generate large price pressure even among high-priced stocks? We study the question in this section.

Recently, Barber et al. (2022) study a retail herding event on Robinhood and find strong evidence for attention-induced price overshot and reversals. Robinhood maintains a "Top Mover" list that prominently features 20 stocks with the most extreme up or down price movements relative to the previous market close price. Barber et al. (2022) show that retail attention to this list leads to collective buying and thus positive price pressure on featured top movers. Consequently, these stocks suffer significantly lower future returns. In a similar vein, Kumar et al. (2021) find that daily winners and losers, defined as the top and bottom 80 stocks in terms of daily returns, are associated with significantly lower returns in the subsequent month.

We extend these two studies to examine the role that FT may have played in inducing retail herding. We conjecture that high-priced stocks are more likely to experience attention-induced price pressure after FT introduction. To test this conjecture, we first build a daily list of stocks with large price movements, which consists of 25 stocks with the most positive returns on trading day t ("Top Winners") and 25 stocks with the most negative returns on day t ("Top Losers"). We then build a second daily list to further capture spikes in retail attention, which consists of 25 stocks with the largest increase in ASVI relative to the stock's average ASVI over the past 90 days ("Top ASVIs"). The final sample used in this analysis is a super set that combines "Top Winners," "Top Losers," and "Top ASVIs." We find similar results if we limit the set to include just top 50 or 100 winners and losers. Table IA5 of the Internet Appendix reports results of these robustness checks.

We conduct two analyses using this super set. In the first analysis, we check whether high-priced stocks are more likely to experience a surge of tiny trades than low-priced stocks during attention-grabbing events after the introduction of FT. Specifically, we estimate the following OLS model analogous to equation (1):

$$\# \textit{ of One-Share Trades}_{t+1} = \alpha + \beta_1 \textit{High Price}_t \times \textit{Post FT}_{t+1} + \gamma \textit{Controls}_t + \epsilon_t, \qquad (2)$$

where t denotes the trading day on which the super set is created. The dependent variable represents the number of off-exchange one-share trades on trading day t+1, which is measured one day forward to allow adequate time for attention-induced retail herding to take place. $\textit{High Price}_t$ is an indicator denoting whether a stock's closing price on day t equals or exceeds \$100, $\textit{Post FT}_{t+1}$ is an indicator denoting whether day $t+1$ falls on or after November 25, 2019 when Interactive Brokers introduced FT, and the DiD estimator is the interaction of the two. Controls are defined the same as in Table 2. Because $\textit{High Price}_t$ is now time-variant, it does not drop out from the regression outputs with the inclusion of firm fixed effects. Again, we cluster standard errors by firm and date in this analysis.

Column (1) of Table 5 reports the results of estimating equation (2). As shown, the coefficient estimate on the DiD estimator is positive and significant at the 1% level, which corroborates the baseline result. Importantly, the magnitude of the coefficient estimate more than doubles the corresponding number in column (1) of Table 2 (422 vs. 210 (19+191) trades). This contrast indicates that FT introduction induces a greater increase in tiny trades for high-priced stocks than for low-priced stocks, particularly when such trades are coordinated during attention-grabbing events. We then reestimate equation (2) using the subsamples of stocks with below- and above-median institutional ownership, respectively. The coefficient estimate on the DiD estimator is economically sizable in column (2) of Table

5 for the low-IO subsample, as its magnitude is nearly seven times the corresponding number in column (3) of Table 5 (1,010 vs. 150 trades) and more than doubles the corresponding number in column (2) of Table 2 (1,010 vs. 418 (57+361) trades). This result again confirms that retail investors are driving the surge of tiny trades in high-priced stocks during attention-grabbing events. Columns (4) and (5) of Table 5 report consistent results using alternative price cutoffs of \$75 and \$150.

Second, we conduct an analysis similar to the main specification in Barber et al. (2022) to assess whether high-priced stocks are more likely to experience attention-induced price overshot and reversals by estimating the following OLS model:

$$BHAR_{[+2,+6]} = \alpha + \beta_1 High\ Price_t \times Post\ FT_{t+1} + \gamma Controls_t + \epsilon_t. \tag{3}$$

Again, t denotes the trading day on which the super set is created. The dependent variable, $BHAR_{[+2,+6]}$, measures a stock's five-day buy-and-hold abnormal return as the stock's raw daily return compounded over day $t+2$ to $t+6$ minus the corresponding market return compounded over the same period, i.e., $\prod_{\tau=t+2}^{\tau=t+6}(1+r_\tau) - \prod_{\tau=t+2}^{\tau=t+6}(1+r_{m\tau})$. The regressors are as described above and we continue to cluster standard errors by firm and date.

Table 6 reports the results of estimating equation (3). As shown in column (1), the coefficient estimate on the standalone indicator of $High\ Price_t$ is statistically insignificant, which suggests that high-priced stocks in the super set are not more exposed to price overshot and reversals than low-priced ones pre-FT. However, the coefficient estimate on the DiD estimator is significant at the 1% level, which indicates that high-priced stocks tend to experience strong price overshot and reversals relative to low-priced stocks after FT becomes widely available compared to before. The magnitude of the coefficient estimate suggests that, post-FT, high-priced stocks in a super set created on day t experience a lower return of seven basis points (bps) than low-priced stocks in the set over the five-trading day window of $[t+2, t+6]$. Columns (2) and (3) repeat the analysis using the subsamples of stocks with below-and above-median IO, respectively, and show that the result in column (1) is likely driven by stocks with lower IO. Within the low-IO subsample, high-priced stocks in a super set created on day t experience a lower return of 15 bps than low-priced stocks over the five-trading day window of $[t+2, t+6]$. As before, the result is also robust to using alternative price cutoffs, as shown in columns (4) and (5).

In summary, results in this section suggest that retail herding during attention-grabbing events is more likely to occur in high-priced stocks than low-priced stocks after the introduction of FT. Put differently, the ability to trade fractional shares invites retail investors into high-priced stocks and exposes such stocks to attention-induced price pressure.

3.4 FT, Trading Frenzy, and Price Bubble

In this section, we study whether FT investors' collective trading in high-priced stocks can even give rise to meme stock-like trading frenzies and fuel stock price bubbles, particularly when feedback effect is at play as modeled by Goldstein et al. (2013).

We lead with GameStop as an anecdote. GameStop is widely regarded as the first meme stock, and its price rose as much as 100 times over several months in 2021. We focus on its most prominent trading frenzy episode that occurred in late January 2021. Figure 3 plots the stock's daily closing price along with the daily number of off-exchange one-share trades (as a percentage of the total number of trades) during January 2021. As shown, GameStop's stock price soared from \$77 on January 25 to \$348 on January 27, rising over four times in two days. More importantly, the two lines representing daily stock price and tiny trades closely tracked each other once the meme movement picked up and the pattern persisted even when price crossed \$300, while the median account balance of a Robinhood user then was reportedly around \$240 (SEC (2021)). This anecdotal evidence sheds light on the role FT plays in enabling meme stock movements because the rapidly rising price can no longer serve as a natural barrier that prevents entry by capital-constrained retail investors. As such, these investors, many of whom are millennials and Gen Z active on social media, can orchestra their trading via platforms like the Reddit WSB forum. Thus, we conjecture that high-priced stocks are more prone to meme stock-like trading frenzies and price bubbles after FT becomes widely available.

We perform three sets of analyses to formally test this conjecture. In the first set of analyses, we estimate the following Probit model using a similar DiD framework:

$$\begin{aligned} \mathit{Prob(Bubble{=}1)}_m = \alpha + \beta_1 \mathit{High\ Price}_m + \beta_2 \mathit{Post\ FT}_m \\ + \beta_3 \mathit{High\ Price}_m \times \mathit{Post\ FT}_m + \gamma \mathit{Controls}_m + \epsilon_m. \end{aligned} \tag{4}$$

The dependent variable, $\mathit{Prob(Bubble{=}1)}_m$, is an indicator that denotes whether the stock experiences a price bubble over a maximum period of six months. Specifically, we define bubble occurrence as when the stock's peak price during the first three months (i.e., $m+1$ to $m+n$ with $1 \leq n \leq 3$) is more than 150% of its price at the end of month m but the stock's subsequent trough price during the following three months (i.e., $m+n$ to $m+n+3$) drops at least 40% from the peak price. We set the pre-FT period to be from July 2017 to June 2019 and post-FT period to be from January 2020 to December 2021, thus leaving six months in-between to avoid overlapping.[10] Our method of identifying a price bubble is similar to that of Greenwood et al. (2019) except that we define peak and trough prices over a shorter horizon, given the relatively short post-FT period. We verify that our results are qualitatively similar if we use alternative return cutoffs to define the peak price (+120%, +100%, +80%) or the trough price (-50% or -70%).

Among the regressors, $\mathit{High\ Price}_m$ is an indicator denoting whether the nominal stock price equals or exceeds \$100 at the end of month m, $\mathit{Post\ FT}_m$ is an indicator denoting whether month m falls after January 2020 when FT becomes widely available, and the DiD estimator is the interaction of the two. Controls, defined at the monthly frequency to be consistent with the dependent variable, include the log of market capitalization at the end of

[10]This definition of pre- and post-FT periods also skips the period from November 2019 to January 2020 when FT was only available through two smaller brokers.

month m (*ln(Market Cap)*$_m$), book-to-market at the end of past quarter (*Book to Market*$_{q-1}$), an indicator denoting whether month m has a quarterly earnings announcement (*Earnings Announcement*$_m$), the standard deviation of monthly returns of the past year (*Past Year Volatility*$_m$), the maximum monthly return of the past year (*Past Year Max Return*$_m$), and the cumulative return of the past month and past year (*Past Month Return*$_m$ and *Past Year Return*$_m$, respectively). We cluster standard errors by firm and year-month in this analysis.

Table 7 reports the results of estimating equation (4). Starting with column (1), the coefficient estimate on *High Price*$_m$ is significantly negative, which suggests that high-priced stocks are less likely to experience a bubble than low-priced stocks pre-FT. The coefficient estimate on *Post FT*$_m$ is significantly positive, which is consistent with bubbles occurring more often for all stocks post-FT presumably due to the rise of retail trading in general. In support of our conjecture, the coefficient estimate on the DiD estimator is positive and significant at the 1% level, and the marginal effect suggests that the likelihood of a high-priced stock experiencing a bubble is 27% higher than a low-priced stock after FT introduction compared to before. In fact, this coefficient estimate completely offsets that on *High Price*$_m$, suggesting that high- and low-priced stocks are equally likely to experience bubbles post-FT, exactly what we would expect after FT makes the nominal price per share less relevant.

Columns (2) and (3) of Table 7 repeat the analysis using the subsamples of stocks with below- and above-median institutional ownership. As before, the coefficient estimate on the DiD estimator is significantly higher in column (2) for low-IO stocks than that in column (3) for high-IO stocks; the two are statistically different at the 1% level. This result suggests that high-priced stocks are even more likely to experience bubbles post-FT if they have a higher retail ownership to begin with. Columns (4) and (5) confirm that the result in column (1) is robust to using alternative cutoffs to define high-priced stocks. In column (6), we define an alternative pre-FT period to be from July 1997 to June 1999, which intends to cover the dot-com period, and find similar results. This finding highlights the importance of FT as a requisite for bubble formation among high-priced stocks. Even though this alternative pre-FT period is known to have seen trading frenzies and bubbles of many stocks listed on the NASDAQ exchange, our results indicate that high-priced stocks were still less likely to be exposed than low-priced stocks until FT is introduced.

In the second set of analyses, we conduct an event study to examine whether patterns observed for the illustrative example in Figure 3 extend to a broad sample of stocks. We limit the event study to post-FT and estimate the following OLS regression:

$$Ret_t = \alpha + \beta_1 \% Tiny\ Trades_t + \beta_2 High\ Price_m \times \% Tiny\ Trades_t + \gamma Controls_t + \epsilon_t. \tag{5}$$

The sample consists of 241 unique bubble events that occurred post-FT (i.e., after January 31, 2020). For each event, the event window runs from five trading days before the peak day to five trading days after, and day t denotes the trading day. Ret_t is the daily return of the stock, $Tiny\ Trades_t$ represents the daily number of tiny trades as a percentage of total number of trades, and $High\ Price_m$ is as defined in equation (4). The controls are the same as in Table 2, and we cluster by firm and date. The standalone indicator $High\ Price_m$ drops out from regression outputs due to the inclusion of fixed effects.

Table 8 reports the results of estimating equation (5). In column (1), we measure tiny trades using the off-exchange one-share trades and label the variable *# of One-Share Trades* $\%_t$. It carries a statistically insignificant coefficient estimate, suggesting that the percentage of tiny trades does not track daily price for low-priced stocks during bubble events. The coefficient estimate on the interaction between $High\ Price_m$ and *# of One-Share Trades* $\%_t$ is, however, positive and significant at the 5% level, suggesting that the percentage of tiny trades closely track price for high-priced stocks during bubble events, consistent with the patterns shown in Figure 3. In column (2), we measure tiny trades using the number of fractional trades detected by Bartlett et al. (2022b) and label the variable *# of Fractional Trades* $\%_t$. As explained in Section 2.1, although this measure more accurately captures fractional trades (albeit still rounded up to one shares in reporting), it is limited to trades executed by two brokerage firms and available only from March 2021 for Robinhood and November 2021 for Drivewealth, which explains a 83% drop of sample size in column (2). Despite a much smaller sample, we find similar patterns: a significantly positive coefficient estimate on the interaction between $High\ Price_m$ and $\#\ of\ Fractional\ Trades\ \%_t$ suggests that the percentage of fractional trades tracks price only among high-priced stocks post-FT.

In the final set of analyses, we study the role that feedback plays in inducing trading frenzies and price bubbles among high-priced stocks post-FT. Goldstein et al. (2013) illustrate how the feedback effect gives rise to a reinforcing loop of frenetic buying and price rising: when speculators like FT traders pour into a meme stock like GameStop, its price increases. Capital providers, who observe the price increase but do not know the exact reason for the increase, may interpret it as a positive signal of firm fundamentals and become more willing to provide financing. The enhanced access to capital further improves firm valuation, prompting more speculation. We examine three empirical predictions of Goldstein et al. (2013) in the analyses below.

The first prediction posits that the feedback effect is stronger when speculators put larger weights on common signals and trade in a coordinated fashion. Goldstein et al. (2013) suggest testing this prediction by examining "the extent to which speculators exchange information about a stock over the Internet as indication for the extent to which they are exposed to common information" (Goldstein et al. (2013), p.568). This suggestion becomes particularly pertinent in recent years with the emergence of social media platforms like the Reddit WSB forum and increased participation by retail investors who actively communicate their trading strategies via these platforms. We manually collect the number of times that a stock was discussed via the Reddit WSB forum from January 1, 2020 to December 31, 2021, cut the sample based on median, and create an indicator denoting the two subsamples (labeled *Subsample Indicator*). We augment equation (4) with this indicator, its respective interactions with $High\ Price_m$ and $Post\ FT_m$ (both previously defined), and the triple interaction. Column (1) of Table 9 reports the results. The highly positive coefficient estimate on the triple interaction term provides strong support for Goldstein et al.'s (2013) prediction.

The second prediction posits that the feedback effect is stronger for financially constrained firms as their valuation is more sensitive to capital providers' decisions. We consider a firm financially constrained if it carries a credit rating of BB+ or lower and create a indicator, also labeled *Subsample Indicator*, to separate the sample into two subsamples. Column (2) of Table 9 reports results with this new indicator. The significantly positive coefficient estimate on the triple interaction again supports Goldstein et al.'s (2013) prediction.

The third prediction posits that the feedback effect is stronger in industries where capital providers are more likely to learn information about a firm from the aggregate stock price, as their decisions rely more heavily on common price signals. As Luo (2005) and Goldstein et al. (2013) suggest, the market likely has greater informational advantage in consumer-oriented industries where the uncertainty centers on product demand (see also the discussion in footnote 2 of Chen et al. (2007), p.620). We proxy for such industries using "Retail" and "Consumer Nondurables" based on the Fama-French 12 industry definition as these two sectors are most likely to involve day-to-day consumer products. We again create a *Subsample Indicator* to denote whether a firm belongs to these two sectors. Column (3) of Table 9 reports results with this industry indicator. The triple interaction again exhibits a significantly positive coefficient estimate, which supports Goldstein et al.'s (2013) prediction.

Overall, results in this section suggest that tiny trades by FT investors can fuel meme stock-like trading frenzies and bubbles in high-priced stocks, particularly in situations where feedback effect plays an important role.

4 Conclusion

FT, a trading innovation introduced to the U.S. equity markets in late 2019, is considered a game changer. Brokers that offer FT intend to use the service to attract retail clientele, particularly the Gen Z investors who tend to be young and capital constrained (Washington Post (2020)). According to a recent survey by CreditDonkey, the Gen Z investors, on average, begin investing at a younger age than previous generations and they are more used to acquiring financial information through social media platforms.[11] Apex Clearing Corporation, a broker-dealer that provides services to other broker-dealers, indicated that among the six million accounts it opened in 2020, which represent a 137% year-to-year increase, approximately one million belong to investors with an average age of 19 (SEC (2021)).

Consistent with the industry's expectation, our baseline finding shows that FT encourages these capital-constrained retail investors to enter and trade high-priced stocks. Specifically, we exploit the sequential introduction of FT and find that high-priced stocks, particularly the ones that have lower institutional ownership, have evidenced a sharp increase in off-exchange one-share trades since FT introduction in late 2019. In further analyses, we show that the effects of FT on tiny trades in high-priced stocks cannot be attributed to ZCT or COVID-19 alone although the effects could very well be amplified by such factors.

Although it is clear that FT triggered an increase in tiny trades among high-priced stocks, its impact on market quality is more nuanced. On the one hand, by inviting an influx of small retail investors into high-priced stocks who are particularly prone to social media influence, FT subjects these stocks to greater price fluctuations. Our results suggest tiny trades by FT traders, when coordinated during attention-grabbing events, can exert large price pressure on high-priced stocks. With the feedback effect at play, such trades may even give rise to meme stock-like trading frenzies and bubbles in high-priced stocks, exactly as predicted by Goldstein et al. (2013).

On the other hand, by opening access to high-priced stocks of quality firms (like BRK.A) for low-capital retail investors, FT reduces fragmentation in the market by broadening investor base in its high-priced section. As such, FT arguably helps democratize financial markets, increase general market participation, and improve portfolio diversification for less wealthy investors. In the past, retail investors are believed to favor penny stocks because

[11] The survey finds that 57% of the surveyed Gen Z adults began investing between age 18 and 24. This compares to 14% of the surveyed millennials and 8% of the surveyed baby boomers.

they suffer from the nominal price illusion (e.g., Kumar (2009); Birru and Wang (2016)) even though penny stocks often provide poorer long-term returns (Bradley et al. (2006)). However, our results suggest that capital constraints also played a big role in retail investors' preference for penny stocks as they are increasingly shifting to high-priced stocks after FT eases access to these stocks. Prior research also finds that retail investors have a tendency to fixate on nominal share price (see Shue and Townsend (2021) for a study of the U.S. markets and Balasubramaniam et al. (2023) for a study of the Indian markets). The introduction of FT may also help retail investors overcome this bias.

The U.S. markets evidenced a huge surge of retail participation during the COVID-19 pandemic and surprisingly, the retail army's grip on the markets has become even tighter post-pandemic (Bloomberg (2023)). With a growing number of young and inexperienced retail traders entering the stock market, our study provides an interesting analysis of how these individually small market participants may exert their collective influence on the market using new trading innovations like FT. Since the adoption of FT is still relatively fresh with most brokers, more research in this area is warranted.

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Appendix A: Variable Definitions

This appendix describes the calculation of variables used in the main analyses. Underlined variables refer to variable names within Compustat or CRSP. t indexes trading day, m indexes month, q indexes quarter, and y indexes year, respectively.

Variable	**Definition**
Variables Used in Baseline Analyses	
Post IB–FID$_t$	An indicator that equals one if day t falls between November 25, 2019 when Interactive Brokers introduced FT and January 28, 2020, the day before Fidelity introduced FT, and zero otherwise. This indicator captures when FT was available through either Interactive Brokers or Robinhood.
Post FID$_t$	An indicator that equals one if day t falls on or after January 29, 2020 when Fidelity introduced FT. This indicator captures when FT was available through all three brokers.
High Price	An indicator that equals one if the stock price as the end of November 2019, when Interactive Brokers first introduced FT, equals or exceeds $100 (alternatively, $75 or $150 in robustness checks) and zero otherwise.
# of One-Share Trades$_t$	The total number of off-exchange one-share trades detected from TAQ on day t in thousands.
ln(Market Cap)$_{t-1}$	Natural logarithm of market capitalization (<u>PRC</u> × <u>SHROUT</u>) on trading day $t-1$.
Book to Market$_{q-1}$	Book value of assets (<u>ATQ</u>) divided by market value of assets (<u>PRCCQ</u> × <u>CSHOQ</u> + <u>LTQ</u>) at the end of quarter $q-1$.
Earnings Announcement$_t$	An indicator that equals one if day t falls within a three-day window centered on a quarterly earnings announcement and zero otherwise.
Past Volatility$_t$	The standard deviation of the stock's daily returns over the past 30 calendar days in percentage points.
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).
Past Week Return$_t$	The stock's cumulative return of the past week by compounding the stock's daily returns over the past seven calendar days.
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.
Additional Variables Used in Identification Analyses	
Post ZCT–FT$_t$	An indicator that equals one if day t falls between October 1, 2019 when Charles Schwab introduced ZCT and November 24, 2019, the day before Interactive Brokers introduced FT, and zero otherwise. This indicator captures the period when ZCT was available but FT was not.
Post FID–COVID$_t$	An indicator that equals one if day t falls between January 29, 2020 when Fidelity introduced FT and February 29, 2020 when Washington declared the state of emergency, and zero otherwise. This indicator captures the period after FT became widely available but before COVID-19 lockdowns.
Post COVID$_t$	An indicator that equals one if day t falls on or after March 1, 2020, the first day of the month when all states declared emergency, and zero otherwise.
Post RH$_t$	An indicator, used only in Robinhood-specific analyses, that equals one if day t falls on or after December 12, 2019 when the broker introduced FT and zero otherwise.

Variable	Definition
Post CS_t	An indicator, used only in Charles Schwab-specific analyses, that equals one if day t falls on or after June 9, 2020 when the broker began FT for the S&P 500 firms and zero otherwise.
High $Price_{CS}$	An indicator that equals one if the stock price as of June 8, 2020, the day before Charles Schwab began FT for the S&P 500 firms, equals or exceeds $100 and zero otherwise.
S&P 500	An indicator that equals one if the firm is included in the S&P 500 index and zero otherwise.
RH Trading $Intensity_t$	The sum of the absolute value of intraday hourly changes in the number of Robinhood users holding the stock on trading day t scaled by the number of Robinhood users holding the stock at the end of the previous trading day.
Additional Variables Used in Price Pressure Analyses	
Post FT_{t+1}	An indicator that equals one if day $t+1$ falls on and after November 25, 2019 when Interactive Brokers introduced FT and zero otherwise. This indicator captures when FT was introduced to the market.
High $Price_t$	An indicator that equals one if the stock price as the end of trading day t equals or exceeds $100 (alternatively, $75 or $150 in robustness checks) and zero otherwise.
# of One-Share $Trades_{t+1}$	The total number of off-exchange one-share trades detected from TAQ on day $t+1$ in thousands.
$BHAR_{[+2,+6]}$	Buy and hold abnormal return over the next 5 trading days. It is computed as the firm's raw daily return compounded from day $t+2$ to day $t+6$ minus the corresponding daily return on the CRSP value-weighted index compounded over the same window, $\prod_{\tau=t+2}^{\tau=t+6}(1+r_\tau) - \prod_{\tau=t+2}^{\tau=t+6}(1+r_{m\tau})$.
Additional Variables Used in Stock Bubble Analyses	
Prob(Bubble=1)	An indicator that equals one if the stock experiences a bubble in the next six months and zero otherwise. we define bubble occurrence as when the stock's peak price during the first three months (i.e., $m+1$ to $m+n$ with 0 $\leq$n$\leq$ 3) is more than 150% of its price at the end of month m but the stock's subsequent trough price during the following three months (i.e., $m+n$ to $m+n+3$) drops at least 40% from the peak price.
Ret_t	The stock's daily raw return on trading day t.
Post FT_m	An indicator that equals one if month m falls in or after February 2020. This indicator captures the period when FT is widely available in the market.
High $Price_m$	An indicator that equals one if the stock price at the end of month m equals or exceeds $100 (alternatively, $75 or $150 in robustness checks) and zero otherwise.
Subsample Indicator	An indicator that equals one if the firm's total number of times being discussed on the Reddit WSB forum from January 2020 to December 2021 equals or exceeds the sample median and zero otherwise in Table 9 column (1). An indicator that equals one if the firm carries a credit rating of BB+ or lower and zero otherwise in Table 9 column (2). An indicator that equals one if the firm belongs to "Retail" and "Consumer Nondurables" sectors based on Fama-French 12 industry classification and zero otherwise in Table 9 column (3).
# of One-Share Trades $\%_t$	The daily number of off-exchange one-share trades as a percentage of total number of trades on trading day t.
# of Fractional Trades $\%_t$	The daily number of fractional trades detected by Bartlett et al. (2022b) as a percentage of total number of trades on trading day t.

Variable	Definition
ln(Market Cap)$_m$	Natural logarithm of market capitalization (PRC $\times$ SHROUT) at the end of month m.
Book to Market$_{q-1}$	Book value of assets (AT) divided by market value of assets (PRCC_F $\times$ CSHO + LT) at the end of quarter $q-1$.
Earnings Announcement$_m$	An indicator that equals one if month m has a quarterly earnings announcement and zero otherwise.
Past Year Volatility$_m$	The standard deviation of the stock's monthly returns over the past 12 months in percentage points.
Past Year Max Return$_m$	The stock's maximum monthly return over the past 12 months.
Past Month Return$_m$	The stock's cumulative return of past month by compounding the stock's daily returns during the month.
Past Year Return$_m$	The stock's cumulative return of past year by compounding the stock's monthly returns over the past 12 months.

Figure 1: Number of Robinhood Users Holding BRK.A

This figure plots the daily number of Robinhood users holding BRK.A during the sample period from January 16, 2020 to August 13, 2020. BRK.A has the highest nominal share price among the listed stocks.

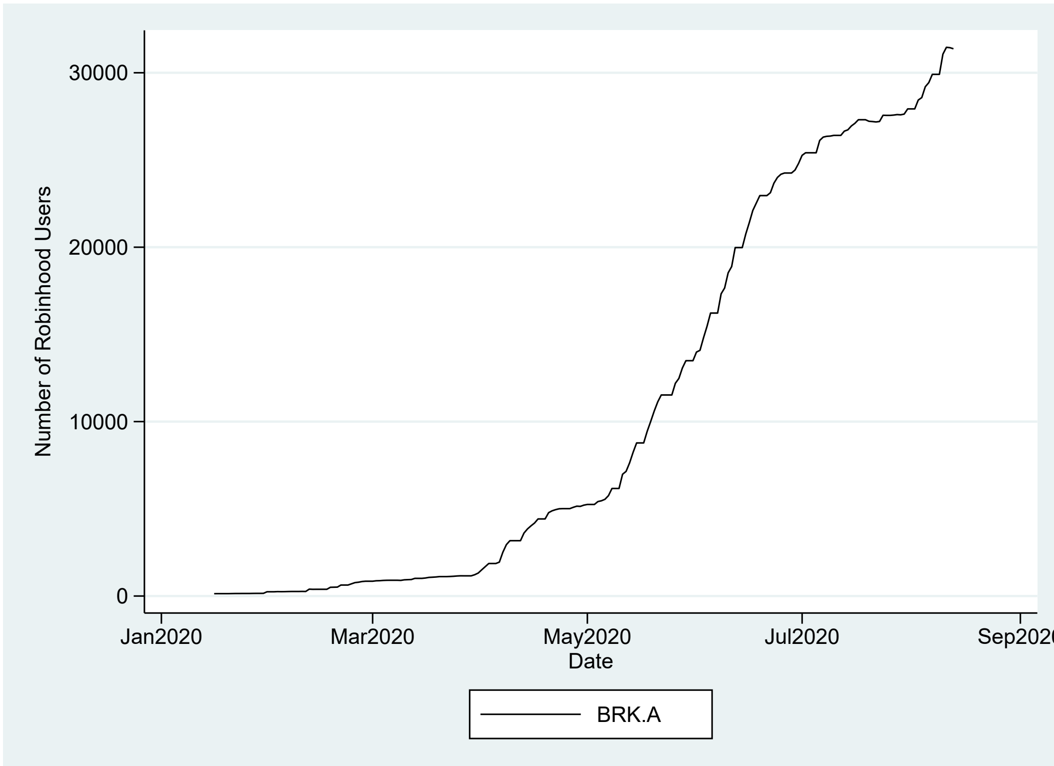

Figure 2: Number of Off-Exchange One-Share Trades for High- vs. Low-Priced Groups

This figure plots the number of off-exchange one-share trades for high- vs. low-priced groups. The sample period is from January 2, 2019 to December 31, 2020. The solid line indicates the high-priced group (i.e., stocks with nominal share price of $100 or above at the end of November 2019) and the dotted line indicates the low-priced group (i.e., stocks with nominal share price below $100 at the end of November 2019), respectively. The two vertical lines denote November 25, 2019 (the day Interactive Brokers introduced FT) and January 29, 2020 (the day Fidelity introduced FT), respectively.

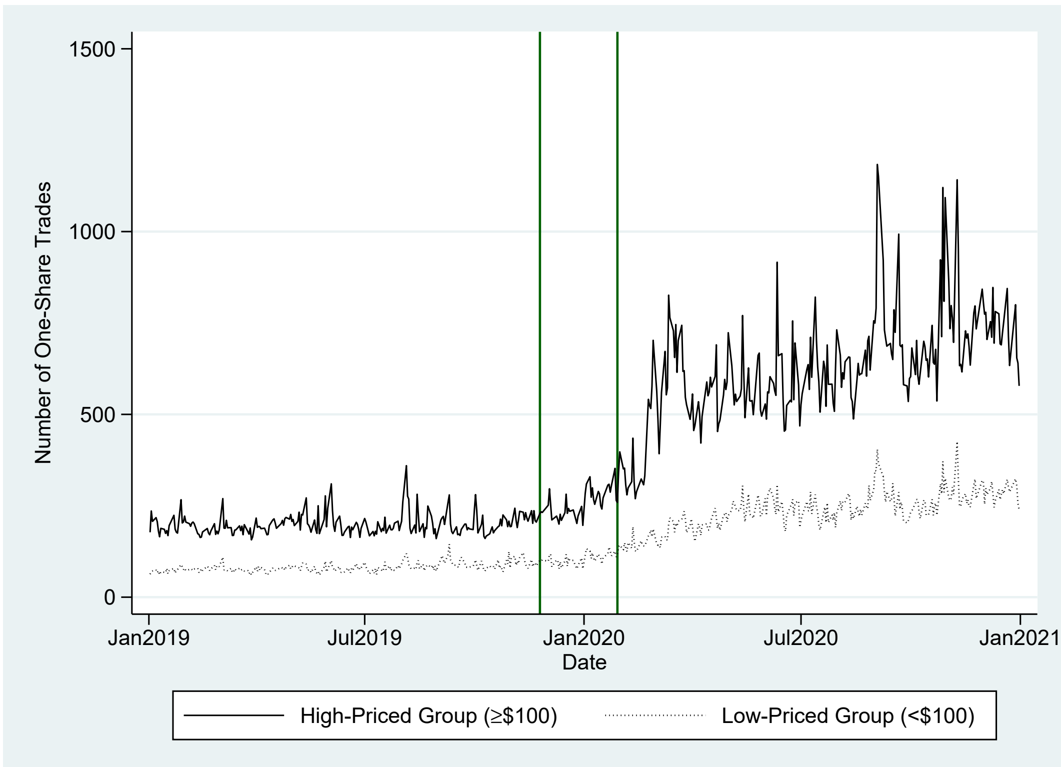

Figure 3: Stock Bubbles and Percentage of Off-Exchange One-Share Trades

This figure plots GameStop's daily closing price along with the daily number of off-exchange one-share trades (as a percentage of the total number of trades) during January 2021. The solid line indicates the daily closing price and the dotted line indicates the daily number of off-exchange one-share trades as a percentage of total number of trades.

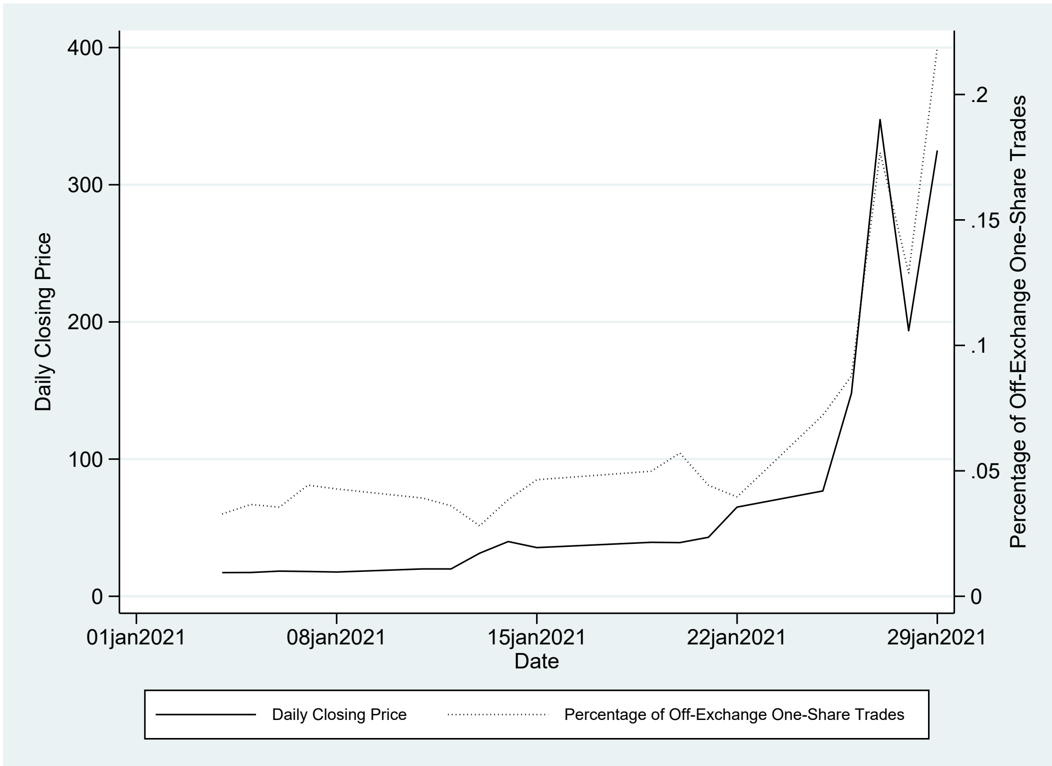

Table 1: Summary Statistics

Panel A: Pre-Match Sample

This table reports summary statistics of the continuous variables used in the baseline analyses linking FT introduction to small retail activity for the pre-match sample. *# of One-Share Trades*$_t$ is the number of off-exchange one-share trades on day t in thousands. *ln(Market Cap)*$_{t-1}$ is the log of market capitalization on the previous trading day. *Book to Market*$_{q-1}$ is the book-to-market of prior quarter. *Past Month Volatility*$_t$ is the standard deviation of the stock's daily returns over the past month in percentage points. *Past Month Max Return*$_t$ is the stock's maximum daily return over the past month. *Past Week Return*$_t$, *Past Month Return*$_t$, and *Past Year Return*$_t$ are the stock's cumulative return of the past week, month, and year, respectively. Detailed variable definitions are in Appendix A. All variables are winsorized at the top and bottom 1% by trading days.

Variable	Obs	Mean	SD	P25	P50	P75
# of One-Share Trades$_t$	1,218,500	0.149	0.399	0.011	0.042	0.122
ln(Market Cap)$_{t-1}$	1,218,500	14.288	1.880	12.898	14.231	15.496
Book to Market$_{q-1}$	1,218,500	0.685	0.327	0.404	0.710	0.968
Past Month Volatility$_t$	1,218,500	2.933	2.081	1.578	2.319	3.595
Past Month Max Return$_t$	1,218,500	0.063	0.054	0.029	0.046	0.077
Past Week Return$_t$	1,218,500	0.004	0.072	-0.026	0.003	0.034
Past Month Return$_t$	1,218,500	0.020	0.149	-0.049	0.017	0.087
Past Year Return$_t$	1,218,500	0.023	0.417	-0.231	-0.032	0.192

Table 1: Summary Statistics - Cont'd

Panel B: Post-Match Sample

This table reports summary statistics of the high- and low-priced groups and the differences between the two within the three pooled samples, the subsample of low-IO stocks, and the subsample of high-IO stocks after PSM. The high- (low-) priced group includes firm-day observations with nominal share price of \$100, \$75, and \$150 or above (below \$100, \$75, and \$150) at the end of November 2019. The high- and low-IO subsamples are divided within high- and low-priced groups based on whether the percentage of stock's institutional ownership equals or falls below sample median of each group at the end of November 2019. *Book to Market*$_{y-1}$ is the book-to-market of prior year. *Popularity* is the number of Robinhood users holding a given stock at the end of November 2019. *Institutional Ownership* is the percentage of institutional investors holding a given stock at the end of November 2019. The growth measure for *# of One-Share Trades*$_t$ variable is calculated as the cumulative daily values over the five-month period of June-October 2019 minus the cumulative daily values over the five-month period of January-May 2019. Detailed variable definitions are in Appendix A. The last column of each panel reports the p-value of the two-tailed t-test.

	Obs	Low	High	P-value
Pooled (\$100) Sample				
Book to Market$_{y-1}$	622	0.505	0.500	0.80
Popularity	622	4379.585	3332.270	0.52
Institutional Ownership	622	0.828	0.816	0.41
Growth of # of One-Share Trades$_t$	622	1.179	0.918	0.62
Low-IO Subsample				
Book to Market$_{y-1}$	192	0.599	0.603	0.92
Popularity	192	4706.594	7060.917	0.51
Institutional Ownership	192	0.639	0.651	0.67
Growth of # of One-Share Trades$_t$	192	1.813	1.991	0.85
High-IO Subsample				
Book to Market$_{y-1}$	284	0.480	0.481	0.99
Popularity	284	1317.296	1271.373	0.92
Institutional Ownership	284	0.932	0.936	0.60
Growth of # of One-Share Trades$_t$	284	0.913	0.842	0.84
Pooled (\$75) Sample				
Book to Market$_{y-1}$	858	0.541	0.546	0.78
Popularity	858	2632.403	2849.333	0.82
Institutional Ownership	858	0.810	0.815	0.70
Growth of # of One-Share Trades$_t$	858	1.114	0.737	0.36
Pooled (\$150) Sample				
Book to Market$_{y-1}$	342	0.434	0.427	0.83
Popularity	342	5728.544	3536.193	0.36
Institutional Ownership	342	0.809	0.803	0.77
Growth of # of One-Share Trades$_t$	342	1.047	1.445	0.51

Table 2: FT and Retail Trading: Baseline Analyses

This table reports the ordinary least squares (OLS) regression results on differences in high- and low-priced firms' number of off-exchange one-share trades surrounding the introduction of FT. A firm-day observation is classified into the high-priced group if the firm's nominal stock price equals or exceeds $100 for columns (1)–(3) ($75 for column (4) and $150 for column (5)) at the end of November 2019 and into the low-priced group otherwise. The pooled sample, from January 2, 2019 to December 31, 2020, includes observations pulled from both groups that are matched on Fama-French industry, book-to-market, stock popularity, institutional ownership, and growth in the daily number of off-exchange one-share trades pre-FT. The two subsamples in columns (2) and (3) are divided within high- and low-priced groups based on whether the percentage of stock's institutional ownership equals or falls below sample median of each group at the end of November 2019 and then matched applying the same PSM procedure. Column (1) uses the pooled sample, column (2) uses the subsample of low–IO stocks, and column (3) uses the subsample of high–IO stocks, and columns (4) and (5) use different price cutoffs for high-priced groups, respectively. *# of One-Share Trades$_t$* measures the daily number of off-exchange one-share trades. *High Price* indicates whether the firm is in the high-priced group. *Post IB–FID$_t$* indicates whether trading day t falls in the period when FT was available through either Interactive Brokers or Robinhood but not yet through Fidelity. *Post FID$_t$* indicates whether trading day t falls in the period after FT became available through all three brokers. The DiD estimators are *High Price*×*Post IB–FID$_t$* and *High Price*×*Post FID$_t$*. Controls include the log of market cap on the previous trading day (*ln(Market Cap)$_{t-1}$*), book-to-market of prior quarter (*Book to Market$_{q-1}$*), an indicator for quarterly earnings announcement (*Earnings Announcement$_t$*), stock price volatility of past month (*Past Month Volatility$_t$*), the stock's maximum daily return of past month (*Past Month Max Return$_t$*), and the stock's cumulative return of past week, month, and year (*Past Week Return$_t$*, *Past Month Return$_t$*, and *Past Year Return$_t$*) as well as firm and date fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm and date. All continuous variables are winsorized at the top and bottom 1% by trading days. t statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	# of One-Share Trades$_t$				
	(1)	(2)	(3)	(4)	(5)
	Pooled ($100)	Low–IO	High–IO	$75	$150
High Price × Post IB–FID$_t$	0.019***	0.057**	-0.010	0.013**	0.031**
	(2.78)	(2.35)	(-1.34)	(2.20)	(2.40)
High Price× Post FID$_t$	0.191***	0.361***	0.017	0.169***	0.158**
	(4.84)	(2.72)	(0.57)	(5.37)	(2.18)
ln(Market Cap)$_{t-1}$	0.099**	0.089	0.188***	0.025	0.144
	(2.19)	(0.97)	(3.34)	(0.55)	(1.31)
Book to Market$_{q-1}$	-0.008	-0.011	0.125	-0.056	0.163
	(-0.08)	(-0.03)	(1.19)	(-0.53)	(0.66)
Earnings Announcement$_t$	0.085***	0.103***	0.064***	0.064***	0.124***
	(10.56)	(5.74)	(9.85)	(11.88)	(8.58)
Past Month Volatility$_t$	0.023***	-0.016	0.034***	0.027***	0.035***
	(3.76)	(-1.09)	(4.64)	(4.06)	(2.86)
Past Month Max Return$_t$	-0.165	0.441	-0.174	-0.046	-0.277
	(-1.48)	(1.65)	(-1.31)	(-0.38)	(-1.48)
Past Week Return$_t$	0.021	0.074	-0.042***	0.028	0.015
	(0.86)	(1.10)	(-2.68)	(1.38)	(0.47)
Past Month Return$_t$	-0.046	-0.112*	-0.102**	-0.027	-0.097
	(-1.36)	(-1.76)	(-2.14)	(-0.81)	(-1.60)
Past Year Return$_t$	0.094**	0.041	0.070**	0.086***	0.099*
	(2.31)	(0.70)	(2.14)	(2.76)	(1.76)
Observations	311,000	96,000	142,000	429,000	171,000
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.657	0.627	0.567	0.631	0.622

Table 3: FT and Retail Trading: Additional Analyses

Panel A reports the OLS regression results on differences in high- and low-priced firms' number of off-exchange one-share trades surrounding the introduction of ZCT and FT. Panel B reports the OLS regression results on differences in high- and low-priced firms' number of off-exchange one-share trades surrounding the introduction of FT and COVID-19 pandemic. Column (1) uses the pooled sample, column (2) uses the subsample of low–IO stocks, and column (3) uses the subsample of high–IO stocks, and columns (4) and (5) use \$75 and \$150 as price cutoffs for high- and low-priced groups, respectively. Samples are defined the same as in Table 2. *# of One-Share Trades*$_t$ measures the daily number of off-exchange one-share trades. *High Price* indicates whether the firm is in the high-priced group. In Panel A, *Post ZCT–FT*$_t$ indicates whether trading day t falls in the period when ZCT was available but FT was not. *Post IB–FID*$_t$ indicates whether trading day t falls in the period when FT was available through either Interactive Brokers or Robinhood but not yet through Fidelity. *Post FID*$_t$ indicates whether trading day t falls in the period after FT became available through all three brokers. The DiD estimators are *High Price*×*Post ZCT–FT*$_t$, *High Price*×*Post IB–FID*$_t$, and *High Price*×*Post FID*$_t$. In Panel B, *Post FID–COVID*$_t$ indicates whether trading day t falls in the period after FT was widely available but before the pandemic started. *Post COVID*$_t$ indicates whether trading day t falls in the period after the pandemic started. The DiD estimators are *High Price*×*Post IB–FID*$_t$, *High Price*×*Post FID–COVID*$_t$, and *High Price*×*Post COVID*$_t$. Controls and fixed effects are as in Table 2. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm and date. All continuous variables are winsorized at the top and bottom 1% by trading days. t statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Effect of ZCT

	# of One-Share Trades$_t$				
	(1)	(2)	(3)	(4)	(5)
	Pooled (\$100)	Low–IO	High–IO	\$75	\$150
High Price × *Post ZCT–FT*$_t$	-0.013***	0.008	-0.025***	-0.012**	-0.006
	(-3.12)	(0.91)	(-3.36)	(-2.45)	(-0.80)
High Price × *Post IB–FID*$_t$	0.017**	0.058**	-0.015*	0.011*	0.030**
	(2.30)	(2.26)	(-1.67)	(1.68)	(2.14)
High Price × *Post FID*$_t$	0.189***	0.362***	0.013	0.167***	0.157**
	(4.77)	(2.70)	(0.41)	(5.27)	(2.15)
Observations	311,000	96,000	142,000	429,000	171,000
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.657	0.627	0.567	0.631	0.622

Panel B: Effect of the COVID-19 Pandemic

	# of One-Share Trades$_t$				
	(1)	(2)	(3)	(4)	(5)
	Pooled (\$100)	Low–IO	High–IO	\$75	\$150
High Price × *Post IB–FID*$_t$	0.019***	0.057**	-0.010	0.013**	0.031**
	(2.79)	(2.35)	(-1.34)	(2.19)	(2.39)
High Price × *Post FID–COVID*$_t$	0.072***	0.175**	0.004	0.064***	0.089***
	(3.26)	(2.24)	(0.28)	(3.59)	(2.61)
High Price × *Post COVID*$_t$	0.204***	0.381***	0.019	0.180***	0.166**
	(4.84)	(2.73)	(0.58)	(5.34)	(2.14)
Observations	311,000	96,000	142,000	429,000	171,000
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.658	0.628	0.567	0.631	0.622

Table 4: FT and Retail Trading: Exchange-Specific Analyses

Panel A reports the OLS regression results on differences in high- and low-priced firms' Robinhood trading intensity surrounding the broker's introduction of FT. Panel B reports the OLS regression results on differences in off-exchange one-share trades between high- and low-priced S&P 500 firms, high- and low-priced non-S&P 500 firms, high-priced S&P 500 and non-S&P 500 firms, and low-priced S&P 500 and non-S&P 500 firms surrounding Charles Schwab's FT introduction. In Panel A, the classification of firm-day observation into the high- vs. low-priced groups and the construction of the low–IO and high–IO subsamples are both as described in Table 2. The pooled sample, from January 2, 2019 to August 13, 2020, includes observations pulled from both groups that are matched on Fama-French industry, book-to-market, stock popularity, and growth in the daily intraday Robinhood retail trading pre-FT. Column (1) uses the pooled sample, column (2) uses the subsample of low–IO stocks, and column (3) uses the subsample of high–IO stocks, and columns (4) and (5) use \$75 and \$150 as price cutoffs, respectively. *RH Trading Intensity*$_t$ measures Robinhood users' trading intensity of a stock during trading day t. *High Price* indicates whether the firm is in the high-priced group. *Post RH*$_t$ indicates whether trading day t falls in the period after Robinhood began FT. The DiD estimator is *High Price*$\times$*Post RH*$_t$. In Panel B, a firm-day observation is classified into the high-priced group if the firm's nominal stock price as of June 8, 2020, the day before Charles Schwab began FT for the S&P 500 firms, equals or exceeds \$100, and into the low-priced group otherwise. The sample period is from May 29, 2020 (seven trading days before Charles Schwab introduced FT) to June 17, 2020 (seven trading days after Charles Schwab introduced FT). *# of One-Share Trades*$_t$ measures the number of one-share trades on trading day t. *High Price*$_{CS}$ indicates whether the firm is in the high-priced group. *S&P 500* indicates whether the firm is in the S&P 500 index. *Post CS*$_t$ indicates whether trading day t falls in the period when FT was available for S&P 500 stocks through Charles Schwab. The DiD estimators are *Post CS*$_t$ $\times$ *High Price*$_{CS}$ and *S&P 500* $\times$ *Post CS*$_t$. In both panels, controls and fixed effects are as in Table 2. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm and date in Panel A but not clustered in Panel B due to short time-series. All continuous variables are winsorized at the top and bottom 1% by trading days. t statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Evidence from Robinhood

	RH Trading Intensity$_t$				
	(1)	(2)	(3)	(4)	(5)
	Pooled (\$100)	Low–IO	High–IO	\$75	\$150
High Price $\times$ *Post RH*$_t$	0.003***	0.002***	0.001	0.002***	0.003***
	(5.26)	(2.75)	(1.10)	(4.78)	(3.67)
Observations	263,608	92,898	128,628	370,004	132,598
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.259	0.225	0.239	0.243	0.265

Panel B: Evidence from Charles Schwab

	# of One-Share Trades$_t$			
	(1)	(2)	(3)	(4)
	S&P 500 Firms	Non-S&P 500 Firms	High-Priced Firms	Low-Priced Firms
High Price$_{CS}$ $\times$ *Post CS*$_t$	0.167***	-0.015***		
	(4.92)	(-4.35)		
S&P 500 $\times$ *Post CS*$_t$			0.220***	-0.002
			(7.31)	(-0.39)
Observations	6,230	27,216	5,236	28,210
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.895	0.856	0.910	0.914

Table 5: FT and Price Pressure: Retail Herding

This table reports the OLS regression results on differences in high- and low-priced firms' number of off-exchange one-share trades around attention-grabbing events surrounding the introduction of FT. A firm-day observation is classified into the high-priced group if the firm's nominal stock closing price on trading day t equals or exceeds \$100 for columns (1)–(3) (\$75 for column (4) and \$150 for column (5)) and into the low-priced group otherwise. The two subsamples in columns (2) and (3) are divided within high- and low-priced groups based on whether the percentage of stock's institutional ownership equals or falls below sample median on trading day t. The sample period is from January 2018 to December 2021. $\#$ *of One-Share Trades*$_{t+1}$ is the total number of off-exchange one-share trades on day $t+1$ in thousands. *High Price*$_t$ indicates whether the firm is in the high-priced group. *Post FT*$_{t+1}$ indicates whether trading day $t+1$ falls in the period after FT first became available in the market. The DiD estimator is *High Price*$_t$ $\times$ *Post FT*$_{t+1}$. Controls are as in Table 2. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm and date. 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.

	# *of One-Share Trades*$_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
	Pooled (\$100)	Low–IO	High–IO	\$75	\$150
High Price$_t$	-0.001	0.078	-0.047	-0.043	0.078
	(-0.01)	(0.22)	(-1.56)	(-0.65)	(0.59)
High Price$_t$ $\times$ *Post FT*$_{t+1}$	0.422***	1.010***	0.150***	0.354***	0.531***
	(5.24)	(3.81)	(4.21)	(5.43)	(4.23)
ln(Market Cap)$_{t-1}$	0.227***	0.278***	0.113***	0.227***	0.233***
	(5.25)	(3.96)	(4.31)	(5.24)	(5.43)
Book to Market$_{q-1}$	0.103	0.187	0.038	0.101	0.107
	(1.00)	(1.30)	(0.57)	(0.98)	(1.04)
Earnings Announcement$_t$	0.066***	0.077***	0.063***	0.066***	0.067***
	(5.48)	(3.03)	(8.10)	(5.47)	(5.55)
Past Month Volatility$_t$	0.056***	0.050***	0.040***	0.057***	0.056***
	(6.73)	(3.92)	(7.73)	(6.76)	(6.73)
Past Month Max Return$_t$	-0.928***	-1.086***	-0.426***	-0.932***	-0.929***
	(-4.59)	(-3.38)	(-3.93)	(-4.63)	(-4.60)
Past Week Return$_t$	0.345***	0.529***	0.014	0.347***	0.344***
	(6.54)	(6.26)	(0.44)	(6.56)	(6.53)
Past Month Return$_t$	0.016	0.035	0.032	0.016	0.016
	(0.42)	(0.61)	(1.29)	(0.42)	(0.41)
Past Year Return$_t$	0.042**	0.044*	0.008	0.042**	0.041**
	(2.15)	(1.87)	(0.88)	(2.14)	(2.13)
Observations	73,966	36,867	36,943	73,966	73,966
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.639	0.657	0.585	0.638	0.639

Table 6: FT and Price Pressure: Price Reversals

This table reports the OLS regression results on differences in high- and low-priced firms' five-day buy-and-hold abnormal returns (BHAR) around attention-grabbing events surrounding the introduction of FT. A firm-day observation is classified into the high-priced group if the firm's nominal closing price on trading day t equals or exceeds \$100 for columns (1)–(3) (\$75 for column (4) and \$150 for column (5)) and into the low-priced group otherwise. The two subsamples in columns (2) and (3) are divided based on whether the percentage of stock's institutional ownership equals or falls below sample median on trading day t. The sample period is from January 2018 to December 2021. $BHAR_{[+2,+6]}$ is the stock's raw return compounded over $[t+2,\ t+6]$ minus the corresponding market return compounded over the same window. $High\ Price_t$ indicates whether the firm is in the high-priced group on trading day t. $Post\ FT_{t+1}$ indicates whether trading day $t+1$ falls in the period after FT first became available in the market. The DiD estimator is $High\ Price_t \times Post\ FT_{t+1}$. Controls are as in Table 2. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm and date. 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.

	$BHAR_{[+2,+6]}$				
	(1)	(2)	(3)	(4)	(5)
	Pooled (\$100)	Low–IO	High–IO	\$75	\$150
$High\ Price_t$	0.003	0.007	0.006*	0.003	-0.007
	(0.96)	(0.86)	(1.80)	(1.01)	(-1.58)
$High\ Price_t \times Post\ FT_{t+1}$	-0.007***	-0.015***	-0.004	-0.007***	-0.006*
	(-2.58)	(-3.23)	(-1.13)	(-2.73)	(-1.67)
$ln(Market\ Cap)_{t-1}$	-0.018***	-0.018***	-0.021***	-0.018***	-0.018***
	(-8.02)	(-4.61)	(-8.79)	(-7.95)	(-8.04)
$Book\ to\ Market_{q-1}$	0.005	0.002	0.005	0.005	0.005
	(0.75)	(0.16)	(0.78)	(0.75)	(0.74)
$Earnings\ Announcement_t$	0.001	0.001	0.002	0.001	0.001
	(0.74)	(0.39)	(1.10)	(0.74)	(0.71)
$Past\ Month\ Volatility_t$	-0.002***	-0.002***	-0.002	-0.002***	-0.002***
	(-2.96)	(-2.98)	(-1.58)	(-2.96)	(-2.96)
$Past\ Month\ Max\ Return_t$	0.043**	0.051**	0.056*	0.043**	0.043**
	(2.56)	(2.55)	(1.89)	(2.56)	(2.57)
$Past\ Week\ Return_t$	-0.025***	-0.026***	-0.017	-0.025***	-0.025***
	(-3.68)	(-3.57)	(-1.56)	(-3.68)	(-3.67)
$Past\ Month\ Return_t$	-0.009**	-0.005	-0.019***	-0.009**	-0.009**
	(-2.09)	(-1.05)	(-2.64)	(-2.09)	(-2.09)
$Past\ Year\ Return_t$	0.001	-0.000	0.002**	0.001	0.001
	(0.81)	(-0.34)	(2.03)	(0.80)	(0.82)
Observations	73,966	36,867	36,943	73,966	73,966
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.081	0.081	0.094	0.081	0.081

Table 7: FT and Stock Bubbles

This table reports the Probit regression results on differences in high- and low-priced firms' likelihood of experiencing a price bubble surrounding the introduction of FT. Columns (1) – (5) use firm-month observations from July 2017 to June 2019 as pre-FT period and column (6) uses firm-month observations from July 1997 to June 1999 as pre-FT period (the dot-com period). The post-FT period is from January 2020 to December 2021. A firm-month observation is classified into the high-priced group if the firm's nominal stock price during month m equals or exceeds \$100 for columns (1)–(3) and (6) (\$75 for column (4) and \$150 for column (5)) and into the low-priced group otherwise. Columns (1), (4), (5) and (6) use the pooled sample, column (2) uses the subsample of low-IO stocks, and column (3) uses the subsample of high-IO stocks, respectively. The two subsamples in columns (2) and (3) are divided based on whether the percentage of stock's institutional ownership equals or falls below sample median at month m. $Prob(Bubble{=}1)_m$ equals one for a firm that experiences a bubble event and zero otherwise. $High\ Price_m$ whether the firm is in the high-priced group at the end of month m. $Post\ FT_m$ indicates whether month m falls in the post-FT period. The DiD variable is $High\ Price_m \times Post\ FT_m$. Controls include the log of market cap of given month ($ln(Market\ Cap)_m$), book-to-market of prior quarter ($Book\ to\ Market_{q-1}$), an indicator for quarterly earnings announcement ($Earnings\ Announcement_m$), monthly stock price volatility of past year ($Past\ Year\ Volatility_m$), the stock's maximum monthly return of past year ($Past\ Year\ Max\ Return_m$), and the stock's cumulative return of past month and year ($Past\ Month\ Return_m$ and $Past\ Year\ Return_m$). Detailed variable definitions are in Appendix A. Standard errors are clustered by firm and year-month. All continuous variables are winsorized at the top and bottom 1% by year-month. z statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	$Prob(Bubble{=}1)_m$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled (\$100)	Low–IO	High–IO	\$75	\$150	Alternative Pre
$High\ Price_m$	-2.517***	-2.661***	-1.782***	-2.831***	-2.469***	-2.677***
	(-28.64)	(-25.98)	(-7.21)	(-31.98)	(-28.43)	(-13.94)
$Post\ FT_m$	0.492***	0.466***	0.817***	0.489***	0.497***	0.368***
	(4.53)	(4.05)	(2.96)	(4.49)	(4.65)	(2.84)
$High\ Price_m \times Post\ FT_m$	2.594***	2.703***	1.907***	2.811***	2.588***	2.711***
	(14.97)	(12.88)	(5.79)	(18.16)	(12.08)	(11.36)
$ln(Market\ Cap)_m$	-0.210***	-0.173***	-0.234***	-0.205***	-0.210***	-0.163***
	(-8.88)	(-6.95)	(-2.71)	(-8.46)	(-9.37)	(-9.10)
$Book\ to\ Market_{q-1}$	-0.435***	-0.490***	-0.204	-0.438***	-0.435***	-0.431***
	(-4.06)	(-3.98)	(-0.85)	(-4.08)	(-4.09)	(-5.23)
$Earnings\ Announcement_m$	-0.000	-0.011	0.041	-0.000	-0.001	-0.014
	(-0.00)	(-0.08)	(0.36)	(-0.00)	(-0.01)	(-0.10)
$Past\ Year\ Volatility_m$	0.016**	0.011*	0.058***	0.015**	0.016**	0.030***
	(2.32)	(1.92)	(4.17)	(2.24)	(2.36)	(4.47)
$Past\ Year\ Max\ Return_m$	0.005	0.038	-1.602***	0.015	0.002	-0.293
	(0.02)	(0.21)	(-3.08)	(0.07)	(0.01)	(-1.42)
$Past\ Month\ Return_m$	0.521***	0.439***	0.695***	0.522***	0.521***	0.383***
	(3.28)	(2.85)	(3.83)	(3.29)	(3.29)	(2.80)
$Past\ Year\ Return_m$	-0.020	-0.022	0.081	-0.020	-0.019	-0.040*
	(-0.78)	(-0.98)	(1.07)	(-0.77)	(-0.77)	(-1.71)
Observations	135,722	67,860	67,862	135,722	135,722	181,731
Pseudo R^2	0.182	0.154	0.176	0.183	0.182	0.144

Table 8: FT and Stock Bubbles: Percentage of Tiny Trades

This table reports the OLS regression results on differences in high- and low-priced firms' relation between the daily return and the percentage of the number of tiny trades around bubble events. Column (1) uses the number of off-exchange one-share trades to measure tiny trades and the bubble events are measured from January 2020 to December 2021. Column (2) uses the number of fractional trades detected by Bartlett et al. (2022b) to measure tiny trades and the bubble events are measured from March 2021 to December 2021 due to data limitations. A firm-month bubble event is classified into the high-priced group if the firm's nominal stock price at month m equals or exceeds \$100. For each bubble event, we include five trading days before and after the peak day in the regression analysis. Ret_t is the raw return of trading day t. *# of One-Share Trades* $\%_t$ is the daily number of off-exchange one-share trades as a percentage of total trades on trading day t. *# of Fractional Trades* $\%_t$ is the daily number of fractional trades as a percentage of total trades on trading day t. $High\ Price_m$ denotes whether the firm is in the high-priced group at the end of month m. Controls include the log of market cap on the previous trading day ($ln(Market\ Cap)_{t-1}$), book-to-market of prior quarter ($Book\ to\ Market_{q-1}$), an indicator for quarterly earnings announcement ($Earnings\ Announcement_t$), 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 week, month, and year ($Past\ Week\ Return_t$, $Past\ Month\ Return_t$, and $Past\ Year\ Return_t$) as well as firm and date fixed effects. Detailed variable definitions are in Appendix A. Standard errors are clustered by firm and date. 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.

	Ret_t	
	(1)	(2)
# of One-Share Trades $\%_t$	-0.505	
	(-1.60)	
$High\ Price_m$ × *# of One-Share Trades* $\%_t$	2.705**	
	(2.33)	
# of Fractional Trades $\%_t$		-3.648**
		(-2.03)
$High\ Price_m$ × *# of Fractional Trades* $\%_t$		24.545**
		(2.52)
$ln(Market\ Cap)_{t-1}$	-0.036	-0.055
	(-1.58)	(-0.61)
$Book\ to\ Market_{q-1}$	0.398**	0.566***
	(2.29)	(10.27)
$Earnings\ Announcement_t$	0.018	0.039
	(0.82)	(0.83)
$Past\ Month\ Volatility_t$	-0.014***	-0.005
	(-4.64)	(-0.50)
$Past\ Month\ Max\ Return_t$	0.276***	0.071
	(3.52)	(0.36)
$Past\ Week\ Return_t$	-0.046***	-0.052
	(-4.19)	(-1.18)
$Past\ Month\ Return_t$	-0.032***	-0.009
	(-3.32)	(-0.36)
$Past\ Year\ Return_t$	-0.002	-0.022**
	(-1.50)	(-2.29)
Observations	2,521	441
Firm Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	Yes
Adjusted R^2	0.203	0.217

Table 9: FT and Stock Bubbles: Feedback Effect

This table reports cross-sectional analyses of the Probit regression results on differences in high- and low-priced firms' likelihood of experiencing a price bubble surrounding the introduction of FT. The pre-FT period is from July 2017 to June 2019 and the post-FT period is from January 2020 to December 2021. Column (1) uses the pooled sample in Table 7 merged with a list of popular stocks on the Reddit WSB platform. *Subsample Indicator* in column (1) indicates whether the total number of times being discussed on the forum from January 2020 to December 2021 equals or exceeds the sample median. Column (2) uses the pooled sample in Table 7 with credit rating data. *Subsample Indicator* in column (2) indicates whether the credit rating is of BB+ or lower. Column (3) uses the pooled sample in Table 7. *Subsample Indicator* in column (3) indicates whether the firm belongs to "Retail" and "Consumer Nondurables" sectors based on Fama-French 12 industry classification. $Prob(Bubble{=}1)_m$ equals one for a firm that experiences a bubble event and zero otherwise. $High\ Price_m$ denotes whether the firm is in the high-priced group at the end of month m. $Post\ FT_m$ indicates whether month m falls in the post-FT period. The key DiD variable is the three-way interaction of $High\ Price_m$, $Post\ FT_m$, and *Subsample Indicator*. Controls include the log of market cap of the given month ($ln(Market\ Cap)_m$), book-to-market of prior quarter ($Book\ to\ Market_{q-1}$), an indicator for quarterly earnings announcement ($Earnings\ Announcement_m$), monthly stock price volatility of past year ($Past\ Year\ Volatility_m$), the stock's maximum monthly return of past year ($Past\ Year\ Max\ Return_m$), and the stock's cumulative return of past month and year ($Past\ Month\ Return_m$ and $Past\ Year\ Return_m$). Detailed variable definitions are in Appendix A. Standard errors are clustered by firm and year-month. All continuous variables are winsorized at the top and bottom 1% by year-month. z statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	$Prob(Bubble{=}1)_m$		
	(1)	(2)	(3)
	WSB Posts	Credit Rating	Industry Cut
$High\ Price_m$	-2.514***	-2.647***	-2.434***
	(-10.03)	(-9.08)	(-24.79)
$Post\ FT_m$	0.659**	-0.050	0.540***
	(2.27)	(-0.18)	(4.70)
Subsample Indicator	-0.261	-1.122**	0.233
	(-0.67)	(-2.44)	(1.48)
$High\ Price_m \times Post\ FT_m$	-0.615**	0.015	2.428***
	(-2.05)	(0.04)	(14.02)
$High\ Price_m \times Subsample\ Indicator$	0.254	0.713*	-0.244
	(0.57)	(1.70)	(-1.37)
$Post\ FT_m \times Subsample\ Indicator$	0.850**	0.461	-0.392**
	(2.06)	(1.03)	(-2.16)
$High\ Price_m \times Post\ FT_m \times Subsample\ Indicator$	3.024***	2.673***	0.677*
	(6.00)	(6.52)	(1.76)
$ln(Market\ Cap)_m$	-0.215***	-0.293**	-0.209***
	(-8.01)	(-2.54)	(-8.88)
$Book\ to\ Market_{q-1}$	-0.104	0.239	-0.426***
	(-0.64)	(1.05)	(-4.01)
$Earnings\ Announcement_m$	0.030	-0.060	-0.001
	(0.19)	(-0.70)	(-0.01)
$Past\ Year\ Volatility_m$	0.004	0.047*	0.016**
	(0.80)	(1.87)	(2.39)
$Past\ Year\ Max\ Return_m$	-0.106	-0.364	-0.007
	(-0.63)	(-0.41)	(-0.03)
$Past\ Month\ Return_m$	0.306**	0.659**	0.527***
	(2.54)	(2.10)	(3.33)
$Past\ Year\ Return_m$	-0.007	0.026	-0.019
	(-0.49)	(0.33)	(-0.75)
Observations	9,298	46,160	135,722
Pseudo R^2	0.201	0.322	0.184