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Fractional Trading

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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 the feedback effect likely plays a role. (*JEL* G10, G12, G14, G18, G32, G41)

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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 the 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 millennial and Generation (Gen) Z investors (Barber et al. 2022; Welch 2022); the reduction of trading costs at zero-commission brokers gained significant retail popularity (Jain et al. 2023); and the COVID-19 pandemic further fueled

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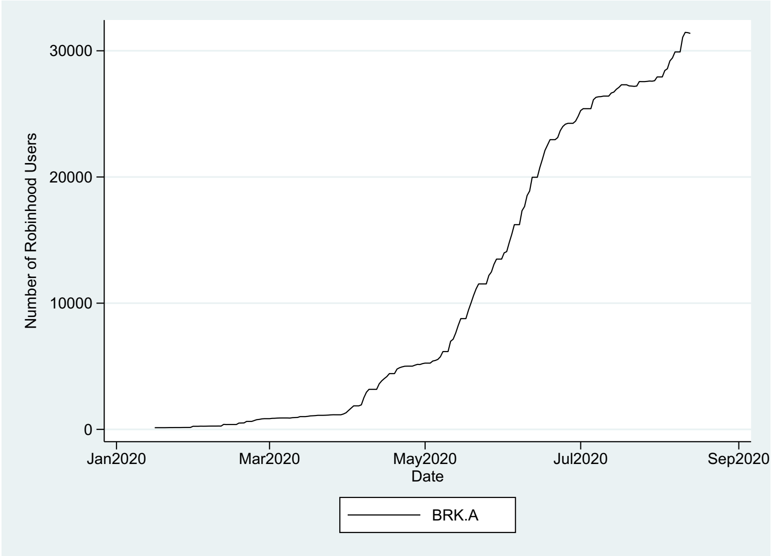

Figure 1
Number of Robinhood users holding BRK.A
This figure plots the daily number of Robinhood users holding BRK.A during the sample period from January 16, 2020, to August 13, 2020. BRK.A has the highest nominal share price among the listed stocks.

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, Sadka, and Shen 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 affect 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 facilitate 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.

We rely on the off-exchange one-share trades to capture FT-facilitated trading by capital-constrained marginal investors (i.e., FT investors). This measure builds on the institutional knowledge detailed in Bartlett, McCrary, and O'Hara (2023b). As Bartlett, McCrary, and O'Hara (2023b) 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

[1] Prior literature has shown that retail investors are susceptible to familiarity bias (see Lewis 1999; Karolyi and Stulz 2003) and endowment effect (see Kahneman, Knetsch, and Thaler 1990), leading them to value equity that they are familiar with and equity they already own more than alternatives, respectively.

[2] The latter 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).

(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 14.1% in the daily number of off-exchange one-share trades after FT first became available through a major U.S. broker (Interactive Brokers) on November 25, 2019, and a further increase of 138.7% 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 (77th percentile) or a higher price cutoff of $150 (92nd percentile).

The sequential introduction of FT covering all stocks, rather than a staggered introduction 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, Larcker, and Wang (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 facilitated 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

[3] We cannot separately observe the two portions due to limitations of the current reporting rule. Thus, restricting the measure to include only one-share trades is likely 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.

S&P 500 stocks or high-priced non-S&P 500 stocks in the 7 trading days following the FT introduction date (June 9, 2020) compared to the 7 trading days before. Overall, our analyses suggest that the BRK.A example is representative rather than an 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 facilitated a significant increase of tiny trades in high-priced stocks, we turn to examining its impact on asset prices. 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 (e.g., Collin-Dufresne and Fos 2016), particularly if these trades are coordinated during attention-grabbing events to generate large price pressure (Fang, Madsen, and Shao 2023). 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, Engelberg, and Gao 2011). FT may even give rise to trading frenzies and price bubbles if social media serves as a coordination device that leads speculators in the market to trade in the same direction and the resultant price fluctuations affect capital providers' decisions (see Goldstein, Ozdenoren, and Yuan [2011] and Goldstein, Ozdenoren, and Yuan [2013] for models of feedback effect in trading).

We first assess the impact of attention-coordinated tiny trades on asset prices. This analysis is inspired by Barber et al. (2022) and Kumar, Ruenzi, and Ungeheuer (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, Ruenzi, and Ungeheuer (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, Engelberg, and Gao 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, social media discussions, and price pressure than their low-priced counterparts.

During a 5-trading-day window starting 2 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 increase in the likelihood of experiencing a bubble from the pre-FT period to the post-FT period is 21% higher for a high-priced stock than a low-priced stock. We define bubble occurrence as when the peak price of a firm's stock in the next 3 months equals or exceeds 150% of the current price but the trough price in the 3 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 contemporaneous price change, confirming that the price patterns observed for GameStop extend to a larger sample of stocks.

Goldstein, Ozdenoren, and Yuan (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-facilitated 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-facilitated 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-facilitated bubble is more likely to occur in firms whose capital providers are more sensitive to recent price movements, precisely when the feedback effect is predicted to play a bigger role. Given a relatively short post-FT period, we interpret these results as suggestive evidence for the feedback mechanism.

FT, which represents the most important trading innovation that relaxes retail investors' capital constraints since odd lot trading (see O'Hara, Yao, and Ye 2014; Chan and Xie 2020), warrants a study of its own. To our best knowledge, there are three concurrent papers on FT. Gempesaw, Henry, and Velthuis (2022) focus on Robinhood and find that its users' ownership of high-priced stocks has increased significantly after the broker introduced FT.

Bartlett, McCrary, and O'Hara (2023a) use BRK.A as a prominent example to illustrate how the current reporting rule for fractional trades leads to inflated trading volume on tape. However, the fact that the share premium of BRK.A (relative to BRK.B) actually increases with fractional trading is in line with our finding that tiny trades can collectively exert price pressure on even the highest priced stocks. Bartlett, McCrary, and O'Hara (2023b) 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, McCrary, and O'Hara (2023b) 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, Saar, and Titman 2008; Barber, Odean, and Zhu 2009; Kaniel et al. 2012; Kelley and Tetlock 2013; Fong, Gallagher, and Lee 2014; Barrot, Kaniel, and Sraer 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, McCrary, and O'Hara (2023b) 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, Sadka, and Shen 2021; Barber et al. 2022; Eaton et al. 2022; Fedyk 2022; 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 trades 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 (for excellent surveys of this literature, see Bond, Edmans, and Goldstein 2012; Goldstein 2023). 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. Focusing on trading, several theories model how feedback effect alters market participants' decisions (Angeletos, Lorenzoni, and Pavan 2010; Goldstein, Ozdenoren, and Yuan 2011, 2013). In particular, Goldstein, Ozdenoren, and Yuan (2013) model feedback-facilitated 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 support for these predictions. FT investors, predominantly capital-constrained Millennials and Gen Z, are susceptible 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.

1. 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.

1.1 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 $Post\text{–}IB\text{–}FID_t$, 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 $Post\text{–}FID_t$, 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 $Post\text{–}RH_t$, denotes whether day t falls on or after December 12, 2019, and captures when FT becomes available through Robinhood. The second one, labeled $Post\text{–}CS_t$, 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 United States.[4]

We expect FT introduction to facilitate an increase in tiny trades by capital-constrained retail investors (i.e., FT investors). To capture such activity, we lean on Bartlett, McCrary, and O'Hara (2023b), who offer a wealth of knowledge about fractional trades. As they explain, fractional trades executed merely as accounting entries on books of a broker (such as Apex Clearing) cannot be identified because they result in no public reporting but those executed on a principal basis by a broker (such as Robinhood and Drivewealth) may be identifiable because 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

[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.

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, McCrary, and O'Hara (2023b) introduce a novel method to distinguish between 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).

Unlike Bartlett, McCrary, and O'Hara (2023b), 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. Therefore, we define our primary measure of tiny trades as the daily number of off-exchange one-share trades for a firm's stock recorded in the TAQ database, labeled *# of one-share 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-facilitated changes in tiny trades. Although we cannot use the measure of Bartlett, McCrary, and O'Hara (2023b) 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 the mean (median) Pearson correlation coefficient between our measure and Bartlett, McCrary, and O'Hara (2023b) measure is 77% (80%) after March 2021 when their measure is available, adding credence that our measure indeed captures trading activity by FT investors. It is, however, noteworthy that both measures underestimate tiny trades in early months, as Robinhood only started reporting round-up fractional trades from February 16, 2021 and Drivewealth from October 6, 2021. In robustness checks, we expand our 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]

1.2 Control variables

We include a long list of controls in the regression analyses. These controls are the log of market capitalization at the end of previous trading day $t-1$ ($ln(Market\ cap)_{t-1}$), book-to-market at the end of previous quarter ($Book\ to\ market_{q-1}$), an indicator to denote whether day t falls within a 3-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 IA2 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.

Table 1
Summary statistics

A. Prematch sample

Variable	Obs	Mean	SD	P25	P50	P75
Price	2,385	57.587	70.265	16.570	34.360	70.240
# of one-share trades$_t$	1,192,500	0.153	0.408	0.012	0.044	0.125
ln(Market cap)$_{t-1}$	1,192,500	14.351	1.843	12.980	14.276	15.531
Book to market$_{q-1}$	1,192,500	0.679	0.326	0.398	0.700	0.963
Past month volatility$_t$	1,192,500	2.934	2.082	1.580	2.318	3.591
Past month max return$_t$	1,192,500	0.063	0.054	0.029	0.046	0.077
Past week return$_t$	1,192,500	0.004	0.073	−0.027	0.003	0.034
Past month return$_t$	1,192,500	0.020	0.150	−0.050	0.017	0.087
Past year return$_t$	1,192,500	0.024	0.420	−0.232	−0.032	0.195

This panel reports summary statistics of the continuous variables used in the baseline analyses linking FT introduction to small retail activity for the pre-match sample and the stock price. The sample period is from January 2, 2019, to December 31, 2020. *Price* is the firm's nominal stock price at the end of November 2019. *# 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. All variables are winsorized at the top and bottom 1% by trading days.

1.3 Summary statistics

To build the sample, we start with the universe of common stocks (share code 10 or 11) traded on major exchanges (exchange code 1, 2, or 3) in the CRSP/Compustat Merged database with no missing daily returns between January 2, 2019, and December 31, 2020. We remove 5 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); 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 1,192,500 firm-trading day observations by 2,385 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 153 and the median is 44.

2. Empirical Results

2.1 FT and tiny trades: Baseline analyses

Our hypothesis for the baseline analyses follows that the introduction of FT facilitates 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

Table 1
(Continued)

B. Postmatch firm characteristics

	Obs	Low-priced	High-priced	p-value
Pooled ($100) sample				
Book to market$_{y-1}$	708	0.446	0.460	.48
Popularity	708	5,451.404	3,729.749	.29
Institutional ownership	708	0.822	0.828	.61
Growth of # of one-share trades$_t$	708	1.072	1.044	.96
Low-IO subsample				
Book to market$_{y-1}$	282	0.526	0.544	.60
Popularity	282	5,354.142	7,045.355	.55
Institutional ownership	282	0.686	0.703	.30
Growth of # of one-share trades$_t$	282	0.883	1.511	.46
High-IO subsample				
Book to market$_{y-1}$	342	0.423	0.434	.67
Popularity	342	1,512.374	1,277.678	.60
Institutional ownership	342	0.936	0.937	.83
Growth of # of one-share trades$_t$	342	1.083	1.206	.69
Pooled ($75) sample				
Book to market$_{y-1}$	850	0.555	0.541	.47
Popularity	850	2,868.012	2,999.72	.90
Institutional ownership	850	0.829	0.823	.56
Growth of # of one-share trades$_t$	850	0.990	1.029	.92
Pooled ($150) sample				
Book to market$_{y-1}$	360	0.408	0.400	.77
Popularity	360	5,144.211	4,196.578	.68
Institutional ownership	360	0.824	0.820	.82
Growth of # of one-share trades$_t$	360	1.799	1.549	.73

This panel reports summary statistics of the high- and low-priced groups and the differences between the two groups within the three pooled samples (based on different price cutoffs) as well as the two subsamples of low- and high-IO stocks (based on the first price cutoff) after PSM. 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 high- (low-) priced group includes firm-year observations with nominal share price of $100, $75, and $150 or above (below $100, $75, and $150) at the end of November 2019. The high- and low-IO subsamples are divided within high- and low-priced groups based on how a stock's institutional ownership compares to the group median at the end of November 2019. The first column of each subpanel reports the number of firms for the subsample after PSM. The second and third columns of each subpanel report the mean of variables in low and high-priced groups, respectively. The last column of each subpanel reports the p-value of the two-tailed t-test. *Book to market*$_{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 5-month period of June-October 2019 minus the cumulative daily values over the 5-month period of January-May 2019. Detailed variable definitions are in Appendix.

(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

Table 1
(Continued)

C. Postmatch sample

Variable	Obs	Mean	SD	P25	P50	P75
Price	708	129.652	172.967	39.445	98.875	150.930
# of one-share trades$_t$	354,000	0.274	0.633	0.039	0.098	0.237
ln(Market cap)$_{t-1}$	354,000	15.463	1.718	14.256	15.430	16.624
Book to market$_{q-1}$	354,000	0.462	0.275	0.239	0.399	0.638
Past month volatility$_t$	354,000	2.634	1.812	1.466	2.107	3.174
Past month max return$_t$	354,000	0.056	0.047	0.027	0.041	0.068
Past week return$_t$	354,000	0.006	0.065	−0.023	0.005	0.033
Past month return$_t$	354,000	0.024	0.135	−0.040	0.023	0.087
Past year return$_t$	354,000	0.122	0.423	−0.135	0.068	0.299

This panel reports summary statistics of the continuous variables used in the baseline analyses linking FT introduction to small retail activity and the stock price for the pooled sample after PSM. 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 high- (low-) priced group includes firm-day observations with nominal share price of $100 or above (below $100) at the end of November 2019. Variables are as in Table 1, panel A. Detailed variable definitions are in Appendix. All variables are winsorized at the top and bottom 1% by trading days.

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.[6] 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 5-month period of June-October 2019 minus the cumulative daily values over the 5-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 resultant sample thus consists of pairs of one-to-one matched firm-day observations from the two groups. Table IA1, column 1, shows that high-priced stocks have lower book-to-market, higher institutional ownership, and higher stock popularity pre-PSM. Consistent with the parallel trends assumption, Table 1, panel B, and Table IA1, column 2, show that there are no systematic differences in observable firm characteristics between the two groups

6 We use a static price cutoff (as of November 2019) in DiD analyses to facilitate propensity score matching but a timelier cutoff based on more recent stock prices in subsequent event-based analyses.

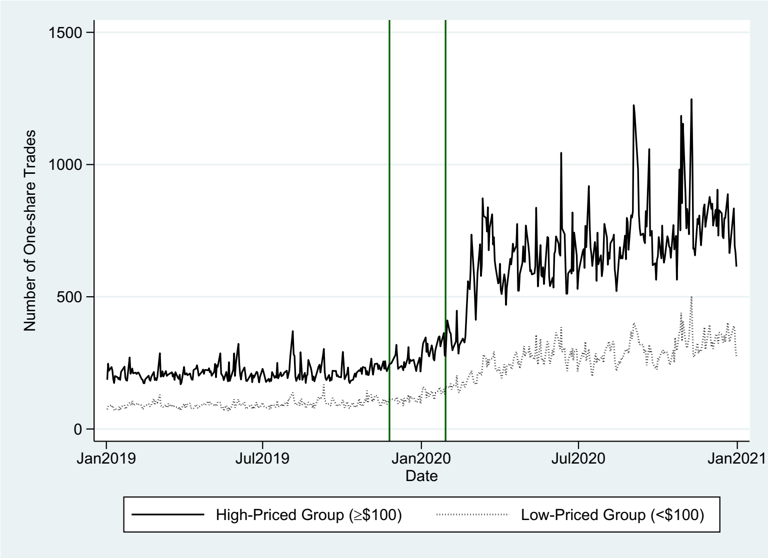

Figure 2
Number of off-exchange one-share trades for high- versus low-priced groups
This figure plots the number of off-exchange one-share trades for high- versus low-priced groups. The sample period is from January 2, 2019, to December 31, 2020. The solid line indicates the high-priced group (i.e.,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

post-PSM.[7] Panel C repeats panel A for the post-match sample using a $100 cutoff to define high- and low-priced stocks. As expected, the post-match sample has a median price close to $100. The average daily number of off-exchange one-share trades increases to 274 and the median increases to 98.

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 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

[7] We acknowledge the lingering concerns about omitted variables related to retail popularity, since PSM matches high- and low-priced stock groups only on observable characteristics. In the Internet Appendix, we show that results in Sections 2.1 and 2.2 are consistent if we exclude 11 FANG-like stocks including AAPL, AMZN, BABA, BIDU, FB, GOOG, GOOGL, MSFT, NFLX, NVDA, and TSLA (in Table IA3) or if we exclude top-50 popular stocks based on Robinhood ownership at the end of November 2019 (in Table IA4).

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 top-two 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 1.1. The key regressors are the two DiD estimators: the first one interacts the indicator of *High price* with $\textit{Post–IB–FID}_t$, 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 $\textit{Post–FID}_t$, an indicator for whether trading day t falls in the period after FT became available through all three brokers. $\textit{Controls}_t$ includes those discussed in Section 1.2, 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 stand-alone indicators —*High price*, $\textit{Post–IB–FID}_t$, and $\textit{Post–FID}_t$—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).[8] The coefficient estimate on the first DiD estimator, $\textit{High price} \times \textit{Post–IB–FID}_t$, is positive and significant at the 5% 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 (20 trades, or 14.1%) is modest. The coefficient estimate on the second DiD estimator, $\textit{High price} \times \textit{Post–FID}_t$, is positive and significant at the 1% level. Its magnitude

[8] To alleviate concerns that stocks with extremely large $\textit{\# of one-share trades}_t$ are driving our results, we also tried winsorizing the variable at the top and bottom 5% by trading days, using $ln(1+\textit{\# of one-share trades})_t$, or scaling $\textit{\# of one-share trades}_t$ by the daily total number of trades as the dependent variable. Our results remain qualitatively similar.

Table 2
FT and retail trading: Baseline analyses

	# of one-share trades$_t$				
	(1) Pooled ($100)	(2) Low–IO	(3) High–IO	(4) $75	(5) $150
High price × Post–IB–FID$_t$	0.020**	0.050**	−0.006	0.013**	0.034**
	(2.39)	(2.15)	(−0.89)	(2.29)	(2.35)
High price× Post–FID$_t$	0.197***	0.400***	0.056**	0.171***	0.235***
	(4.33)	(2.93)	(2.52)	(5.88)	(3.41)
ln(Market cap)$_{t-1}$	0.151***	0.138	0.165***	0.092***	0.216**
	(2.78)	(0.71)	(3.98)	(2.68)	(2.28)
Book to market$_{q-1}$	0.172	0.294	0.039	−0.019	0.165
	(1.32)	(0.68)	(0.65)	(−0.29)	(1.08)
Earnings announcement$_t$	0.093***	0.137***	0.063***	0.068***	0.117***
	(11.36)	(7.21)	(11.88)	(12.57)	(8.77)
Past month volatility$_t$	0.028***	0.036*	0.030***	0.026***	0.037***
	(4.52)	(1.71)	(5.56)	(4.31)	(3.69)
Past month max return$_t$	−0.296***	−0.093	−0.225***	−0.134	−0.387*
	(−2.75)	(−0.20)	(−2.75)	(−1.48)	(−1.92)
Past week return$_t$	0.005	0.057	−0.037**	0.029	−0.032
	(0.17)	(0.90)	(−2.46)	(1.50)	(−0.84)
Past month return$_t$	−0.059**	−0.182*	−0.048	−0.036	−0.052
	(−1.98)	(−1.67)	(−1.58)	(−1.48)	(−0.99)
Past year return$_t$	0.079**	0.220*	−0.008	0.042**	0.044
	(2.06)	(1.86)	(−0.42)	(2.40)	(1.21)
Observations	354,000	141,000	171,000	425,000	180,000
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.658	.602	.595	.653	.649

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 $150 for column 5) at the end of November 2019 and into the low-priced group otherwise. The pooled sample, from January 2, 2019, to December 31, 2020, includes observations pulled from both groups that are matched on Fama-French industry, book-to-market, stock popularity, institutional ownership, and growth in the daily number of off-exchange one-share trades pre-FT. The two subsamples in columns 2 and 3 are divided within high- and low-priced groups based on how a stock's institutional ownership compares to the group median at the end of November 2019 and then matched applying the same PSM procedure. Column 1 uses the pooled sample; column 2 uses the subsample of low–IO stocks; column 3 uses the subsample of high–IO stocks; and columns 4 and 5 use different price cutoffs, respectively. *# of one-share trades$_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. 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. *p < .1; **p < .05; ***p < .01

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 (197, or 138.7%), 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 and 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 coefficient estimates on the two DiD estimators of interest remain statistically significant in column 2 but they become weaker in column 3. Within the low-IO subsample, high-priced stocks experience a larger increase of 50 (or 26.0%) 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 400 (or 208.3%) after Fidelity began FT. In further analyses, we check the robustness of the baseline finding to using alternative price cutoffs. As columns 4 and 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 is likely representative rather than an exception.

2.2 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 ($Post\text{–}ZCT\text{–}FT_t$) 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 $Post\text{–}ZCT\text{–}FT_t$. Table 3, panel A, reports the results.

Table 3
FT and retail trading: Additional analyses

A. Effect of ZCT

	# of one-share trades$_t$				
	(1) Pooled ($100)	(2) Low–IO	(3) High–IO	(4) $75	(5) $150
High price × *Post–ZCT–FT$_t$*	−0.012**	−0.008	−0.016**	−0.016***	−0.009
	(−2.31)	(−0.63)	(−2.45)	(−3.47)	(−1.13)
High price × *Post–IB–FID$_t$*	0.017**	0.048*	−0.008	0.010	0.033**
	(1.97)	(1.91)	(−1.15)	(1.63)	(2.08)
High price × *Post–FID$_t$*	0.194***	0.398***	0.053**	0.168***	0.234***
	(4.26)	(2.90)	(2.37)	(5.77)	(3.35)
Observations	354,000	141,000	171,000	425,000	180,000
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	.658	.602	.595	.653	.649

B. Effect of the COVID-19 pandemic

	# of one-share trades$_t$				
	(1) Pooled ($100)	(2) Low–IO	(3) High–IO	(4) $75	(5) $150
High price × *Post–IB–FID$_t$*	0.020**	0.050**	−0.006	0.013**	0.034**
	(2.40)	(2.15)	(−0.89)	(2.29)	(2.35)
High price × *Post–FID–COVID$_t$*	0.069***	0.170***	0.014	0.058***	0.106***
	(2.96)	(2.67)	(1.22)	(3.19)	(2.79)
High price × *Post–COVID$_t$*	0.210***	0.424***	0.060**	0.183***	0.249***
	(4.34)	(2.92)	(2.53)	(5.89)	(3.40)
Observations	354,000	141,000	171,000	425,000	180,000
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	.658	.602	.596	.654	.649

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; 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$*. Controls and fixed effects are as in Table 2. Detailed variable definitions are in Appendix. Standard errors are clustered by firm and date. All continuous variables are winsorized at the top and bottom 1% by trading days. t-statistics are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$

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 facilitated 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 $Post\text{–}FID\text{–}COVID_t$, 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.[9] We then code an indicator, labeled $Post\text{–}COVID_t$, 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 $High\ price \times Post\text{–}FID_t$ with *High price* interacted with the two COVID-related indicators, respectively. In all columns, the coefficient estimates on the first DiD estimator, $High\ price \times Post\text{–}FID\text{–}COVID_t$, 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, $High\ price \times Post\text{–}COVID_t$, 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-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.[10] 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

9 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.

10 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).

Table 4
FT and retail trading: Exchange-specific analyses

A. Evidence from Robinhood

	RH trading intensity$_t$				
	(1) Pooled ($100)	(2) Low–IO	(3) High–IO	(4) $75	(5) $150
High price × *Post–RH$_t$*	0.002***	0.002**	0.001	0.002***	0.002***
	(3.18)	(2.58)	(1.56)	(5.05)	(3.59)
Observations	265,990	106,396	131,010	377,150	134,980
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	.265	.221	.231	.242	.268

B: Evidence from Charles Schwab

	# of one-share trades$_t$			
	(1) S&P 500	(2) Non-S&P 500	(3) High-Priced	(4) Low-Priced
High price$_{CS}$ × *Post–CS$_t$*	0.167*	−0.015		
	(1.93)	(−1.16)		
S&P 500 × *Post–CS$_t$*			0.218*	−0.001
			(1.91)	(−0.01)
Observations	6,230	26,418	5,180	27,468
Controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	.895	.857	.910	.917

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- versus 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; 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$* indicates whether trading day t falls in the period after Robinhood began FT. The DiD estimator is *High price*×*Post–RH$_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 $100, and into the low-priced group otherwise. The sample period is from May 29, 2020 (7 trading days before Charles Schwab introduced FT) to June 17, 2020 (7 trading days after Charles Schwab introduced FT). *# of one-share trades$_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$* × *High price$_{CS}$* and *S&P 500* × *Post CS$_t$*. In both panels, controls and fixed effects are as in Table 2. Detailed variable definitions are in Appendix. Standard errors are clustered by firm and date. All continuous variables are winsorized at the top and bottom 1% by trading days. t-statistics are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$

changes, and then sum them up. The resultant variable, labeled *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 *RH trading intensity$_t$* on a DiD estimator interacting *High price* with *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 facilitated 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 IA5 of the Internet Appendix, we show that the results are also consistent if we instead measure *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. Since Charles Schwab is the second largest broker in the U.S., this event may have resulted in a measurable change in tiny trades of high-priced S&P 500 stocks by easing access to these stocks for its own retail clients. However, we do not expect the effect, if any, to be substantial since FT of S&P 500 stocks was already available through two smaller but more retail-friendly exchanges (i.e., Interactive Brokers and Robinhood) and as well as the largest exchange (Fidelity) at the time. Thus, to sharpen identification and maximize the chance that we pick up the effect of Charles Schwab's partial FT introduction, we hone in on a 14-trading-day window centered on June 9, 2020. Table 4, panel B, reports the results regressing *# of one-share trades*$_t$ on a DiD 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. As shown, the DiD estimator exhibits a positive coefficient estimate in columns 1 and 3 (albeit significant only at the 10% level), 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 7 trading days after Charles Schwab began FT compared to the 7 trading days before. The coefficient estimate on the DiD estimator is statistically insignificant in columns 2 and 4, which suggests that there is no measurable change in the number of off-exchange one-share trades between low- and high-priced non-S&P 500 stocks or between low-priced S&P 500 and non-S&P 500 stocks after the broker began FT.

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 facilitating a greater increase of tiny trades in high-priced stocks.

2.3 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 relative to low-priced stocks. Prior research suggests that such an increase is often associated with greater stock price fluctuations. Because retail investors rarely short (or are restricted from doing so by brokers), 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, Engelberg, and Gao 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, Ruenzi, and Ungeheuer (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 facilitating retail herding. We conjecture that high-priced stocks are more likely to experience attention-induced price pressure than low-priced stocks after FT introduction compared to before. 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 top-100 winners and losers. Table IA6 of the Internet Appendix reports results of these robustness checks.

We conduct three analyses using this super set. In the first analysis, we check whether the volume of tiny trades during attention-grabbing events increases more for high-priced stocks than low-priced stocks from the pre-FT period to the post-FT period. Specifically, we estimate the following OLS model analogous to Equation (1):

$$\#\ of\ one\text{-}share\ trades_{t+1} = \alpha + \beta_1 High\ price_t \times Post\text{–}FT_{t+1} + \gamma\ Controls_t + \epsilon_t, \tag{2}$$

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

Table 5
FT and price pressure: Retail herding

A. Tiny trades

	# of one-share trades$_{t+1}$				
	(1) Pooled ($100)	(2) Low–IO	(3) High–IO	(4) $75	(5) $150
High price$_t$	−0.004	0.075	−0.046	−0.045	0.062
	(−0.04)	(0.20)	(−1.54)	(−0.67)	(0.47)
High price$_t$ × Post–FT$_{t+1}$	0.430***	1.043***	0.149***	0.361***	0.548***
	(5.30)	(3.83)	(4.19)	(5.50)	(4.32)
ln(Market cap)$_{t-1}$	0.229***	0.278***	0.111***	0.229***	0.236***
	(5.24)	(3.88)	(4.36)	(5.23)	(5.43)
Book to market$_{q-1}$	0.104	0.191	0.032	0.102	0.107
	(1.00)	(1.29)	(0.49)	(0.98)	(1.04)
Earnings announcement$_t$	0.068***	0.081***	0.063***	0.068***	0.069***
	(5.66)	(3.18)	(8.16)	(5.65)	(5.72)
Past month volatility$_t$	0.059***	0.057***	0.039***	0.059***	0.058***
	(6.92)	(4.26)	(7.74)	(6.95)	(6.91)
Past month max return$_t$	−0.947***	−1.193***	−0.422***	−0.952***	−0.948***
	(−4.55)	(−3.58)	(−3.88)	(−4.59)	(−4.56)
Past week return$_t$	0.359***	0.550***	0.022	0.360***	0.358***
	(6.76)	(6.49)	(0.70)	(6.79)	(6.75)
Past month return$_t$	0.012	0.027	0.032	0.012	0.012
	(0.31)	(0.46)	(1.30)	(0.31)	(0.31)
Past year return$_t$	0.042**	0.044*	0.008	0.042**	0.042**
	(2.21)	(1.89)	(0.87)	(2.19)	(2.17)
Observations	73,964	36,863	36,941	73,964	73,964
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.639	.656	.582	.639	.640

This panel reports the OLS regression results on differences in high- and low-priced firms' number of off-exchange one-share trades during 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 stock price on trading day t equals or exceeds $100 for columns 1–3 ($75 for column 4 and $150 for column 5) and into the low-priced group otherwise. The two subsamples in columns 2 and 3 are divided within high- and low-priced groups based on how a stock's institutional ownership compares to the group median on trading day t. The sample period is from January 2018 to December 2021. *# of one-share trades$_{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$_t$ × Post–FT$_{t+1}$*. Controls are as in Table 2. Detailed variable definitions are in Appendix. Standard errors are clustered by firm and date. All continuous variables are winsorized at the top and bottom 1%. t-statistics are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$

on trading day $t+1$, which is measured 1 day forward to allow adequate time for attention-induced retail herding to take place. *High price$_t$* is an indicator denoting whether a stock's closing price on day t equals or exceeds $100. For simplicity, we define a single indicator, *Post–FT$_{t+1}$*, to denote whether day $t+1$ falls on or after November 25, 2019, when Interactive Brokers introduced FT. The DiD estimator is the interaction of the two. Controls are defined the same as in Table 2. Because *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.

Column 1 of Table 5, panel A, 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,

Table 5
(Continued)

B. Reddit discussions

	$WSB\ mention_{t+1}$				
	(1) Pooled ($100)	(2) Low–IO	(3) High–IO	(4) $75	(5) $150
$High\ price_t$	0.019	0.111	−0.024	0.002	−0.032
	(0.12)	(0.15)	(−0.47)	(0.02)	(−0.15)
$High\ price_t \times Post\text{–}FT_{t+1}$	0.352**	1.192**	0.067	0.286**	0.494**
	(2.56)	(2.17)	(1.06)	(2.51)	(2.21)
$ln(Market\ cap)_{t-1}$	0.323***	0.474**	0.161***	0.321***	0.331***
	(3.52)	(2.46)	(2.84)	(3.46)	(3.69)
$Book\ to\ market_{q-1}$	0.080	0.314	−0.038	0.078	0.083
	(0.40)	(0.96)	(−0.25)	(0.39)	(0.41)
$Earnings\ announcement_t$	0.057**	0.054	0.056***	0.056**	0.058**
	(2.03)	(0.81)	(2.89)	(2.03)	(2.07)
$Past\ month\ volatility_t$	0.068***	0.055***	0.057***	0.068***	0.068***
	(4.96)	(2.71)	(4.87)	(4.98)	(4.95)
$Past\ month\ max\ return_t$	−1.192***	−1.119*	−0.764***	−1.198***	−1.192***
	(−2.98)	(−1.92)	(−2.69)	(−2.99)	(−2.98)
$Past\ week\ return_t$	0.589***	0.856***	0.090	0.590***	0.589***
	(4.04)	(3.63)	(1.10)	(4.04)	(4.04)
$Past\ month\ return_t$	0.015	−0.026	0.154**	0.016	0.015
	(0.14)	(−0.17)	(2.26)	(0.15)	(0.14)
$Past\ year\ return_t$	0.069*	0.043	0.024	0.069*	0.069*
	(1.89)	(0.81)	(1.04)	(1.89)	(1.88)
Observations	73,964	36,863	36,941	73,964	73,964
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.553	.567	.535	.553	.553

This panel reports the OLS regression results on differences in high- and low-priced firms' number of Reddit discussions during 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 stock 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 how a stock's institutional ownership compares to the group median on trading day t. The sample period is from January 2018 to December 2021. $WSB\ mention_{t+1}$ is the number of the stock's Reddit discussions on day $t+1$. $High\ price_t$ indicates whether the firm is in the high-priced group. $Post\text{–}FT_{t+1}$ indicates whether trading day $t+1$ falls in the period after FT first became available in the market. The DiD estimator is $High\ price_t \times Post\text{–}FT_{t+1}$. Controls are as in Table 2. Detailed variable definitions are in Appendix. Standard errors are clustered by firm and date. All continuous variables are winsorized at the top and bottom 1%. t-statistics are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$

the magnitude of the coefficient estimate nearly doubles the corresponding number in column 1 of Table 2 (430 vs. 217=(20+197) trades). This contrast indicates that FT introduction facilitates 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, panel A, for the low-IO subsample, as its magnitude is nearly seven times the corresponding number in column 3 of Table 5, panel A (1,043 vs. 149 trades), and more than doubles the corresponding number in column 2 of Table 2 (1,043 vs. 450=(50+400) trades). This result again confirms that retail investors are driving the surge of tiny trades in high-priced stocks during attention-grabbing events post-FT. Columns 4 and 5 of Table 5, panel A, report consistent results using alternative price cutoffs of \$75 and \$150.

Second, we check whether FT triggers more social media discussions. We follow Bryzgalova, Pavlova, and Sikorskaya (2023) to manually collect the number of times that a stock was discussed via the Reddit WSB forum during a day. Table 5, panel B, reports the results of estimating Equation (2) with $WSB\ mention_{t+1}$, the number of the stock's Reddit discussions during day $t+1$, as the dependent variable. In column 1, the coefficient estimate on the DiD estimator is positive and significant at the 5% level. This result confirms that FT introduction leads to increases in Reddit discussion of high-priced stocks relative to low-priced stocks, which facilitates herding by retail investors. Additionally, the significant result concentrates on the subsample of stocks with below-median institutional ownership. The significantly positive coefficient estimate on the DiD estimator in columns 4 and 5 suggests that the result is robust to using alternative price cutoffs.

Third, 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:

$$BHAR_{[+2,+6]} = \alpha + \beta_1 High\ price_t \times Post\text{–}FT_{t+1} + \gamma\, Controls_t + \epsilon_t. \qquad (3)$$

Again, t denotes the trading day on which the super set is created. The dependent variable, $BHAR_{[+2,+6]}$, measures a stock's 5-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, that is, $\prod_{\tau=t+2}^{\tau=t+6}(1+r_\tau) - \prod_{\tau=t+2}^{\tau=t+6}(1+r_{m\tau})$. 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 stand-alone 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 experience a larger increase in price pressure from the pre-FT period to the post-FT period than low-priced stocks. 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 5-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 16 bps than low-priced stocks over the 5-trading-day window of $[t+2, t+6]$. As before, the result is also robust to using

Table 6
FT and price pressure: Price reversals

	$BHAR_{[+2,+6]}$				
	(1) Pooled ($100)	(2) Low–IO	(3) High–IO	(4) $75	(5) $150
High price$_t$	0.003	0.008	0.006*	0.003	−0.006
	(0.96)	(0.93)	(1.78)	(1.03)	(−1.42)
High price$_t$ × Post–FT$_{t+1}$	−0.008***	−0.016***	−0.004	−0.007***	−0.007*
	(−2.71)	(−3.32)	(−1.10)	(−2.88)	(−1.90)
ln(Market cap)$_{t-1}$	−0.018***	−0.018***	−0.021***	−0.018***	−0.018***
	(−7.99)	(−4.61)	(−8.65)	(−7.91)	(−8.00)
Book to market$_{q-1}$	0.005	0.002	0.005	0.005	0.005
	(0.73)	(0.22)	(0.76)	(0.74)	(0.73)
Earnings announcement$_t$	0.001	0.001	0.002	0.001	0.001
	(0.75)	(0.52)	(1.11)	(0.75)	(0.73)
Past month volatility$_t$	−0.002***	−0.002***	−0.001	−0.002***	−0.002***
	(−3.02)	(−2.80)	(−1.49)	(−3.02)	(−3.01)
Past month max return$_t$	0.048***	0.050**	0.055*	0.048***	0.048***
	(2.78)	(2.47)	(1.90)	(2.78)	(2.78)
Past week return$_t$	−0.025***	−0.026***	−0.019*	−0.025***	−0.025***
	(−3.66)	(−3.51)	(−1.71)	(−3.66)	(−3.65)
Past month return$_t$	−0.010**	−0.005	−0.019**	−0.010**	−0.010**
	(−2.29)	(−1.18)	(−2.52)	(−2.29)	(−2.30)
Past year return$_t$	0.001	−0.000	0.002**	0.001	0.001
	(0.75)	(−0.40)	(2.07)	(0.74)	(0.77)
Observations	73,964	36,863	36,941	73,964	73,964
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.083	.084	.094	.083	.083

This table reports the OLS regression results on differences in high- and low-priced firms' 5-day buy-and-hold abnormal returns (BHAR) during 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 stock 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 how a stock's institutional ownership compares to the group 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$_t$ × Post–FT$_{t+1}$*. Controls are as in Table 2. Detailed variable definitions are in Appendix. Standard errors are clustered by firm and date. All continuous variables are winsorized at the top and bottom 1%. t-statistics are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$

alternative price cutoffs, as shown in columns 4 and 5. As additional robustness checks, Table IA7 of the Internet Appendix confirms that the results in Table 6 are robust to using the 10-day buy-and-hold abnormal return. Panels A and B of Table IA8 further confirm that the main results on FT-facilitated retail herding in high-priced stocks reported in this section are robust to excluding FANG-like stocks.

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.

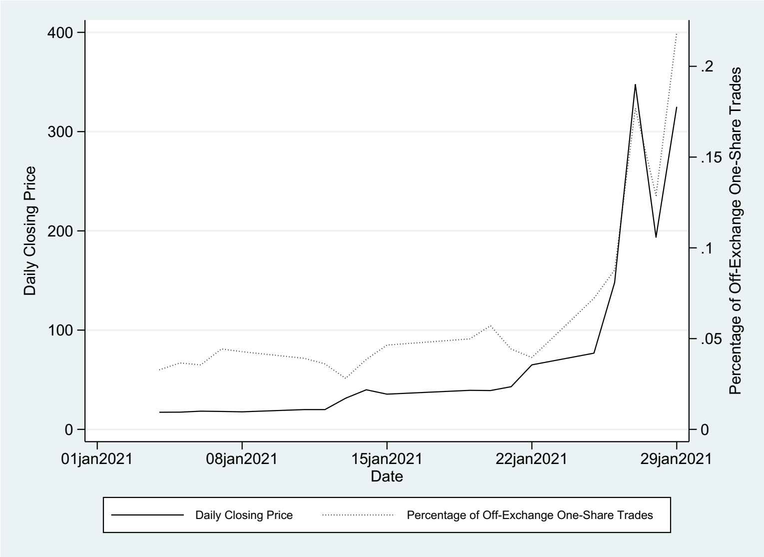

Figure 3
Stock bubbles and percentage of off-exchange one-share trades
This figure plots GameStop's daily closing price (in solid line) and the daily number of off-exchange one-share trades as a percentage of the daily total number of trades (dotted line) during January 2021.

2.4 FT, trading frenzies, and price bubbles

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, Ozdenoren, and Yuan (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 2 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 orchestrate 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:

$$\begin{aligned} Prob(Bubble{=}1)_m = {} & \alpha + \beta_1 High\ price_m + \beta_2 Post\text{–}FT_m \\ & + \beta_3 High\ price_m \times Post\text{–}FT_m + \gamma\, Controls_m + \epsilon_m . \end{aligned} \tag{4}$$

The dependent variable, $Prob(Bubble{=}1)_m$, is an indicator that denotes whether the stock experiences a price bubble over a maximum period of 6 months. Specifically, we define bubble occurrence as when the stock's peak price during the first 3 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 3 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 6 months in-between to avoid overlapping.[11] Using this method, we identify 27 unique bubbles during the pre-FT period. In sharp contrast, the number of unique bubbles increased to 206 after the introduction of FT. Our method of identifying a price bubble is similar to that of Greenwood, Shleifer, and You (2019) except that we define peak and trough prices over a shorter horizon, given relatively short post-FT period and the fact that we focus on bubbles in individual stocks rather than at the industry level.

Among the regressors, $High\ price_m$ is an indicator denoting whether the nominal stock price equals or exceeds \$100 at the end of month m, $Post\text{–}FT_m$ 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 month m ($ln(Market\ cap)_m$), book-to-market of the prior 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 $Post\text{–}FT_m$ is significantly

[11] 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.

Table 7
FT and stock bubbles

	$Prob(Bubble{=}1)_m$					
	(1) Pooled ($100)	(2) Low–IO	(3) High–IO	(4) $75	(5) $150	(6) Alternative Pre
High price$_m$	−2.452***	−2.598***	−1.782***	−2.808***	−2.449***	−2.379***
	(−28.77)	(−25.66)	(−7.18)	(−31.93)	(−28.60)	(−13.93)
Post–FT$_m$	0.522***	0.502***	0.813***	0.519***	0.527***	0.351***
	(4.96)	(4.51)	(2.95)	(4.92)	(5.11)	(2.72)
High price$_m$ × Post–FT$_m$	2.411***	2.463***	1.922***	2.700***	2.344***	2.303***
	(15.40)	(11.92)	(5.76)	(19.29)	(11.50)	(10.44)
ln(Market cap)$_m$	−0.204***	−0.166***	−0.242***	−0.199***	−0.204***	−0.159***
	(−8.82)	(−6.78)	(−2.72)	(−8.38)	(−9.34)	(−9.45)
Book to market$_{q-1}$	−0.460***	−0.531***	−0.201	−0.463***	−0.460***	−0.435***
	(−4.73)	(−4.93)	(−0.82)	(−4.75)	(−4.78)	(−5.35)
Earnings announcement$_m$	−0.010	−0.019	0.024	−0.010	−0.010	−0.025
	(−0.08)	(−0.13)	(0.21)	(−0.08)	(−0.08)	(−0.18)
Past year volatility$_m$	0.017***	0.011**	0.056***	0.017***	0.017***	0.031***
	(2.69)	(2.06)	(3.97)	(2.61)	(2.70)	(4.69)
Past year max return$_m$	−0.050	0.023	−1.537***	−0.040	−0.050	−0.308
	(−0.24)	(0.14)	(−2.83)	(−0.19)	(−0.24)	(−1.52)
Past month return$_m$	0.521***	0.446***	0.654***	0.522***	0.521***	0.390***
	(3.21)	(2.90)	(3.59)	(3.21)	(3.20)	(2.87)
Past year return$_m$	−0.014	−0.019	0.082	−0.013	−0.014	−0.036
	(−0.56)	(−0.87)	(1.05)	(−0.55)	(−0.56)	(−1.58)
Observations	134,240	67,120	67,120	134,240	134,240	176,298
Pseudo R^2	.188	.162	.175	.188	.188	.147

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 at the end of month m equals or exceeds $100 for columns 1–3 and 6 ($75 for column 4 and $150 for column 5) and into the low-priced group otherwise. Columns 1, 4, 5, and 6 use the pooled sample; column 2 uses the subsample of low-IO stocks; and column 3 uses the subsample of high-IO stocks, respectively. The two subsamples in columns 2 and 3 are divided within high- and low-priced groups based on how a stock's institutional ownership compares to the group median in month m. *Prob(Bubble=1)$_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$ ×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. 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. *$p < .1$; **$p < .05$; ***$p < .01$

positive, which is consistent with bubbles occurring more often for all stocks post-FT presumably because of 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 increase in the likelihood of experiencing a bubble from the pre-FT period to the post-FT period is 21% higher for a high-priced stock than a low-priced stock. 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 10% 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.

We conduct three robustness checks of Table 7. First, we verify that the results are robust to excluding FANG-like stocks in Table IA8, panel C, of the Internet Appendix. Second, we use alternative return cutoffs to define the peak price (+80%, +100%, +120%) of a bubble and report similar baseline results in Table IA9 of the Internet Appendix. Third, we show that the results are robust to the inclusion of industry and year-month fixed effects in Table IA10 of the Internet Appendix.

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 bubble events and estimate the following OLS regression:

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

For each bubble event, the event window runs from 5 trading days before the peak day to 5 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 stand-alone 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 $\#\ of\ one\text{-}share\ trades\ \%_t$. 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 $\#\ of\ one\text{-}share\ trades\ \%_t$ 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

Table 8
FT and stock bubbles: Percentage of tiny trades

	Ret_t	
	(1)	(2)
# of one-share trades $\%_t$	−0.267	
	(−0.75)	
High price$_m$ × *# of one-share trades* $\%_t$	2.501**	
	(2.32)	
# of fractional trades $\%_t$		−0.406
		(−0.58)
High price$_m$ × *# of fractional trades* $\%_t$		5.142**
		(2.39)
ln(Market cap)$_{t-1}$	−0.028	−0.265***
	(−1.10)	(−2.69)
Book to market$_{q-1}$	0.414**	−0.094
	(2.34)	(−0.27)
Earnings announcement$_t$	0.004	0.053
	(0.17)	(0.91)
Past month volatility$_t$	−0.013***	−0.025**
	(−3.80)	(−2.67)
Past month max return$_t$	0.225**	0.360*
	(2.60)	(1.71)
Past week return$_t$	−0.055***	−0.010
	(−4.46)	(−0.24)
Past month return$_t$	−0.036***	−0.008
	(−3.26)	(−0.29)
Past year return$_t$	−0.002	−0.002
	(−1.24)	(−0.71)
Observations	2,144	620
Firm fixed effects	Yes	Yes
Date fixed effects	Yes	Yes
Adjusted R^2	.198	.239

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, McCrary, and O'Hara (2023b) to measure tiny trades and the sample period for the trading day is after March 2021 because of data limitations. A firm-month bubble event is classified into the high-priced group if the firm's nominal stock price at the end of month m equals or exceeds \$100. For each bubble event, we include 5 trading days before and after the peak day in the regression analysis. Ret_t is the firm's raw stock 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 daily 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. Standard errors are clustered by firm and date. All continuous variables are winsorized at the top and bottom 1%. t-statistics are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$

measure tiny trades using the number of fractional trades detected by Bartlett, McCrary, and O'Hara (2023b) and label the variable *# of fractional trades* $\%_t$. As explained in Section 1.1, 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 71% 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 among high-priced stocks during bubble events post-FT.

We expect to see a stronger link between tiny trades and price movements among high-priced stocks than low-priced stocks because our tiny trade measures intend to capture only trading by capital-constrained retail investors. To see this, consider a marginal capital-constrained investor at Robinhood with $240 (the median Robinhood account balance) to invest. With FT, she can purchase 0.8 shares of a $300 stock (a high-priced stock), which will result in one off-exchange one-share trade (per rounded-up rule). This trade also will be counted as one fractional trade according to the BMO measure. She can also purchase 4.8 shares of a $50 stock (a low-priced stock). In this case, however, only the fractional component (0.8) will result in one off-exchange one-share trade and be counted as one fractional trade according to the BMO measure. Thus, by design, our tiny trade measures exclude the whole-share component (4 shares) of the trade in the low-priced stock.

In the final set of analyses, we study the role that feedback plays in facilitating trading frenzies and price bubbles among high-priced stocks post-FT. Goldstein, Ozdenoren, and Yuan (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, Ozdenoren, and Yuan (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, Ozdenoren, and Yuan (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, Ozdenoren, and Yuan 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 follow Bryzgalova, Pavlova, and Sikorskaya (2023) to 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*). Since the median number of mentions is only one, we are essentially comparing stocks with Reddit WSB discussion to stocks without. We augment Equation (4) with this indicator, its respective interactions with

Table 9
FT and stock bubbles: Feedback effect

	Prob(Bubble=1)$_m$		
	(1) WSB posts	(2) Credit rating	(3) Feedback
High price$_m$	−2.513***	−2.545***	−2.441***
	(−20.29)	(−8.29)	(−20.96)
Post–FT$_m$	0.473***	0.197	0.500***
	(3.75)	(0.72)	(3.61)
Subsample indicator	0.313**	−0.796*	0.050
	(2.06)	(−1.79)	(0.36)
High price$_m$ × *Post–FT$_m$*	−0.478***	−0.272	2.000***
	(−3.40)	(−0.80)	(8.97)
High price$_m$ × *Subsample indicator*	−0.029	0.415	−0.057
	(−0.17)	(0.97)	(−0.36)
Post–FT$_m$ × *Subsample indicator*	0.131	0.145	−0.062
	(0.84)	(0.33)	(−0.40)
High price$_m$ × *Post–FT$_m$* × *Subsample indicator*	3.039***	3.093***	0.751***
	(13.57)	(7.22)	(2.71)
ln(Market cap)$_m$	−0.243***	−0.240**	−0.204***
	(−10.34)	(−2.34)	(−8.39)
Book to market$_{q-1}$	−0.412***	0.170	−0.471***
	(−4.15)	(0.70)	(−4.26)
Earnings announcement$_m$	−0.025	−0.067	−0.007
	(−0.20)	(−0.61)	(−0.06)
Past year volatility$_m$	0.014**	0.055**	0.026***
	(2.09)	(2.41)	(3.85)
Past year max return$_m$	−0.017	−0.572	−0.297
	(−0.08)	(−0.69)	(−1.30)
Past month return$_m$	0.526***	0.574*	0.573***
	(3.22)	(1.78)	(3.28)
Past year return$_m$	−0.024	0.033	−0.007
	(−0.95)	(0.43)	(−0.29)
Observations	128,761	45,969	130,835
Pseudo R^2	.208	.328	.210

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 excluding stocks with tickers that have special meanings. *Subsample indicator* in column 1 indicates whether the total number of times of a stock 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 with available capital-to-price sensitivity estimated over the past eight quarters. *Subsample indicator* in column 3 indicates whether the firm exhibits a capital-to-price sensitivity that equals or exceeds the sample median. *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. 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. *$p < .1$; **$p < .05$; ***$p < .01$

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, Ozdenoren, and Yuan (2013)'s 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, Ozdenoren, and Yuan (2013)'s prediction.

The third prediction posits that the feedback effect is stronger in firms where capital providers are more sensitive to price changes, as their decisions rely more heavily on common price signals. We estimate this capital-to-price sensitivity by regressing each firm's net equity issuance in quarter q, measured as the change in common equity from quarter q-1 (net of retained earnings) scaled by book value of assets (Baker and Xuan 2016), on its raw stock return during quarter q-1 over a rolling-window of eight quarters and obtaining the coefficient estimates. We then cut the sample based on the median coefficient estimate and create an indicator denoting the two subsamples (labeled *Subsample indicator*). Column 3 of Table 9 reports results with this indicator. The triple interaction again exhibits a significantly positive coefficient estimate, which supports Goldstein, Ozdenoren, and Yuan (2013)'s 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.

3. 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.[12] 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

[12] The survey finds that 57% of Gen Z adults began investing between the ages 18 and 24. This compares to 14% of the Millennials surveyed and 8% of Baby Boomers surveyed.

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, Ozdenoren, and Yuan (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 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.

Code Availability: The replication code is available in the Harvard Dataverse at `https://doi.org/10.7910/DVN/WMKPXJ`.

Appendix

Table A1
Variable definitions

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 ($\underline{\text{PRC}} \times \underline{\text{SHROUT}}$) on trading day $t-1$
Book to market$_{q-1}$	Book value of assets ($\underline{\text{ATQ}}$) divided by market value of assets ($\underline{\text{PRCCQ}} \times \underline{\text{CSHOQ}} + \underline{\text{LTQ}}$) at the end of quarter $q-1$
Earnings announcement$_t$	An indicator that equals one if day t falls within a 3 day window centered on a quarterly earnings announcement and zero otherwise
Past month 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, Cakici, and Whitelaw (2011)
Past week return$_t$	The stock's cumulative return of the past week by compounding the stock's daily returns over the past 7 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
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

Table A1
(Continued)

Variable	Definition
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
WSB mention$_{t+1}$	The number of the stock's Reddit discussions on day $t+1$
$BHAR_{[+2,+6]}$	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 6 months and zero otherwise. We define bubble occurrence as when the stock's peak price during the first 3 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 3 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 exhibits a high capital-to-price sensitivity over the past eight quarters equal to or exceeding the sample median 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, McCrary, and O'Hara (2023b) as a percentage of total number of trades on trading day t
ln(Market cap)$_m$	Natural logarithm of market capitalization ($\underline{\text{PRC}} \times \underline{\text{SHROUT}}$) at the end of month m
Book to market$_{q-1}$	Book value of assets ($\underline{\text{ATQ}}$) divided by market value of assets ($\underline{\text{PRCCQ}} \times \underline{\text{CSHOQ}} + \underline{\text{LTQ}}$) 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

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.

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