Revisit Fractional Shares: The Real Effect on Market Quality*

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Abstract

This paper examines the real effect of fractional trading on market quality. Fractional trades constitute 23% of one-share trades and 4% of odd-lots for large stocks, yet are generally liquidity-driven and uninformed. Exploiting the introduction of fractional trading in 2019 and a new reporting policy in 2026 as two quasi-natural experiments, we find that fractional trading widened the quoted spreads and harmed price efficiency. To reconcile the uninformedness of fractional trading and widened quoted spreads, we find evidence that the opaque disclosure of fractional trading elevated market makers' inventory risks and retail brokers "cream skim" fractional traders by routing the whole-share part of fractional trading to wholesalers with worse execution quality. We further document that fractional trading distorts optimal split outcomes by widening realized quoted spreads *ex post*.

Keywords: Fractional trading, retail trading, liquidity, price efficiency, stock splits

JEL Codes: G10, G12, G14, G18, G30, G41

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1. Introduction

The democratization of equity markets has been one of the most significant structural shifts in modern finance. Retail brokers, such as Robinhood, Fidelity, and Charles Schwab, attracted large retail order flows due to eliminated commission fees (Bryzgalova, Pavlova, and Sikorskaya 2023; Jain et al. 2024), simplified access to security markets (Barber et al. 2022; Welch 2022), and, critically, allowed their users to purchase fractional shares of a stock. As shown in Figure 1, the value of Robinhood's user-held fractional shares reached $3.82 billion as of March 2026, a 51% year-on-year increase.[1] Despite the growing importance of fractional trading, empirical researches has been severely constrained by its opaque disclosure.

The source of this constraint is regulatory. Prior to January 2021, the execution information on fractional trading were entirely invisible on the consolidated tape as retail brokers did not realize that they should report fractional trading. In that month, the Financial Industry Regulatory Authority (FINRA) began explicitly requiring retail brokers to report fractional trades to the Trade Reporting Facility (TRF), yet all fractional quantities below one share were rounded up to one share. This regulation resulted in contaminated data, where a substantial fraction of reported one-share trades were in fact fractional trades with very different economic characteristics.[2] To further enhance the transparency, effective February 23, 2026, FINRA mandated that fractional quantities be reported to up to six decimal places, rendering fractional trades individually identifiable for the first time.[3] Leveraging these two updates of reporting policy, this paper revisits an important empirical question: how fractional trading affects market quality, i.e., liquidity and price efficiency.

This paper begins by documenting a set of stylized facts about fractional trading after February 23, 2026. First, fractional shares account for an economically significant proportion of overall trading activity, particularly when measured on a value-weighted basis: 48.6% of

[1] Data source: Form 10-Q/10-K and Form S-1 of Robinhood Markets, Inc.

[2] A small body of existing research on fractional shares has attempted to work around these data limitations in creative but necessarily imperfect ways. Bartlett, McCrary, and O'Hara (2024) obtained proprietary data from Robinhood and Drivewealth to study fractional share trading patterns and developed an algorithm to partially detect fractional trades in Trade and Quote (TAQ) based on latency signatures. Da, Fang, and Lin (2025) adopted a different approach, using one-share trades as a proxy for fractional trading activity.

[3] For example, a fractional trading of 1/3 share, previously reported as one share, is now reported as 0.333333 share in TAQ labelled with `EX='D'` (off-exchange). Fractional trading is not permitted on exchanges.

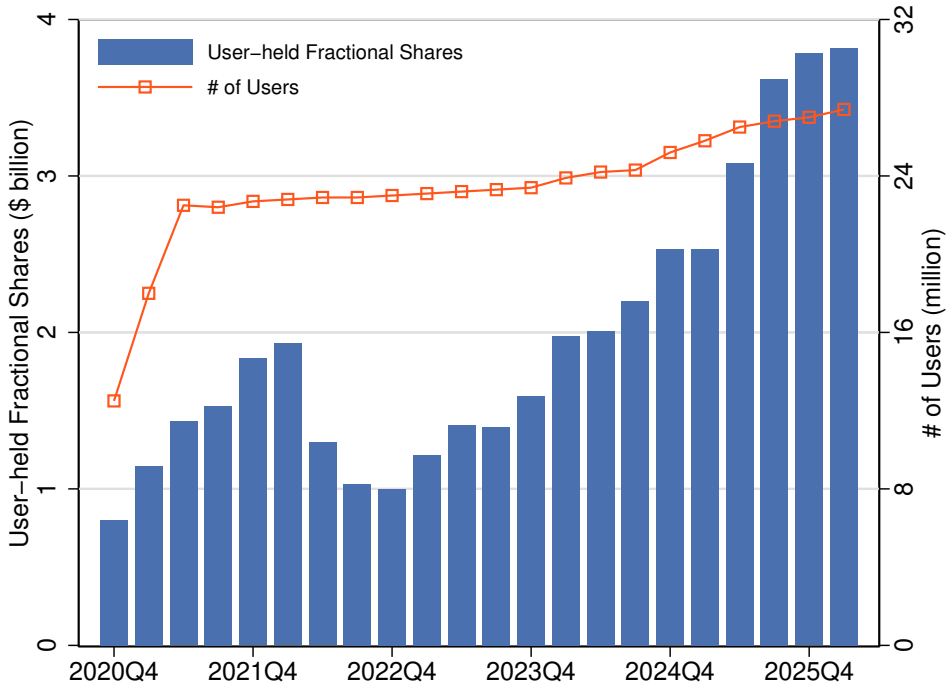


Figure 1. The value of user-held fractional shares and the number of users on Robinhood. The gray bar indicates the value of Robinhood user-held fractional shares in $ million. The solid black line depicts the number of Robinhood users in million. The time period spans from 2020Q4 to 2026Q1.

all trades with sizes below or at one share, 13.9% of odd-lot trades, and 10.5% of all trades. Second, the fractional trading concentrates on large-capitalization, high-priced stocks, than small or medium stocks, consistent with the intuition that fractional shares are most valuable to retail investors to bypass the capital constraints of high-price stocks (Bartlett, McCrary, and O'Hara 2024; Bartlett, McCrary, and O'Hara 2025a; Da, Fang, and Lin 2025). Third, fractional share trading exhibits a distinctive intraday pattern, spiking sharply at market open and declining gradually throughout the trading day. This pattern differs markedly from the well-known U-shaped intraday pattern of overall trading volume. It is consistent with the attention channel that retail investors, attracted by overnight announcements, submit orders overnight or in the early morning for execution around the market open (Da, Fang, and Lin 2025). Fourth, the dollar volume of fractional share trades are highly likely to be round integers, providing strong evidence that these trades originate from dollar-based orders placed by retail investors. The fractional dollar volume indicates that fractional traders may

use portfolio trading strategies, and fractional trading allows them to conduct more precise portfolio balancing (FINRA 2025). Fifth, the millisecond-level timestamps of fractional share trades are approximately uniformly distributed, in contrast to the concentration of overall trade timestamps at low-latency intervals documented by Hasbrouck and Saar (2013). This uniform distribution is consistent with fractional trading being manually and randomly generated by retail order flow rather than by agency algorithm to split large orders.

With these stylized facts established, I turn to the question of whether fractional trading contribute to price discovery. Using the weighted price contribution (WPC) methodology of Barclay and Warner (1993), I decompose cumulative daily stock price change into contributions from different trade size categories. The results are striking: fractional trading has a mean WPC of -0.912, indicating that they are uninformed, liquidity motivated that is systematically on the wrong side of the market, consistent with the behavioral finance literature on retail investor trading (Barber and Odean 2000, 2008). By contrast, one-share trades executed on exchanges have a mean WPC of $+0.880$, following round-lot and mixed-lot trades below 100 shares on exchanges contribute the most to price discovery with WPC of $+1.310$. Our findings are robust to controlling for the proportion of trades or trading volume accounted for by each category. These patterns are consistent with that informed traders may split their orders over time to better hide their trades among uninformed traders (e.g., Kyle 1985; Easley and O'Hara 1987; O'Hara, Yao, and Ye 2014). The substantial price discovery by round-lot and mixed-lot trades below 100 shares is also in line with Brogaard and Landsberg (2026), who show that the new definition of round-lots contribute to better price informativeness by including previous odd-lot quotes (Bartlett, McCrary, and O'Hara 2025b). The high (low) price discovery in on-exchange (off-exchange) tiny trades is also consistent with the pattern discovered by Lu, Guo, and Zou (2023).

I further complement the price contribution analysis with a detailed examination of liquidity metrics, including effective spread, price impact, and realized spread, estimated separately for each trade size category. Fractional trading below one share exhibit the highest average effective spreads of 0.644% and the highest realized spreads of 0.546% among all trade size categories, but relatively low price impact of 0.095%. In comparison, the on-exchange one-share trading encounters an average effective and realized spread of only

0.375% and 0.181%, but impose a significant price impact of 0.189%. The combination of high effective spreads, high realized spreads, and low price impact is the classic signature of uninformed order flow: market makers earn large profits from trading against fractional share orders because these orders do not contain private information. The high spreads on fractional trades indicate that retail investors trading fractional shares face substantially worse execution quality than traders in other size categories. It suggests that retail brokers "cream skim" uninformed liquidity trades, leaving the informed trades to established markets (Easley, Kiefer, and O'Hara 1996; Bolton, Santos, and Scheinkman 2016).[4]

To establish causal effect, I explore the new reporting policy effective February 23, 2026, required by which the reported fractional trading quantities should contain up to six decimal points. This regulatory shift created a quasi-natural experiment: after that date, the exact size of every fractional share trade became publicly visible, whereas previously this information was hidden behind the one-share rounding convention. On the first stage, I examine whether the transparency shock affected the willingness of retail investors to trade fractional shares, for example, if investors valued the anonymity provided by the rounding convention. I employ a difference-in-differences (DID) design using the propensity-score-matched sample of Da, Fang, and Lin (2025), in which high-priced treatment stocks (those most affected by fractional share disclosure) are matched to low-priced control stocks on observable characteristics. Because fractional share trading was not directly observable before the disclosure date, I proxy pre-event fractional trading using the Bartlett, McCrary, and O'Hara (2024) algorithm. The results suggest that the disclosure event led to a statistically significant reduction in fractional share trading volume for treatment stocks relative to control stocks.

On the second stage, I examine whether the disclosure-induced reduction in fractional trading affected market quality. Regressing spreads and intraday volatility on predicted fractional trading from the first stage, an exogenous reduction in fractional trading significantly reduced both contemporaneous and next-day spreads and intraday volatility. Because the disclosure shock reduced fractional trading (or tiny trades) without directly affecting other

[4]Unlike the execution of OTC non-fractional trades which are routed to market makers (or wholesalers) by retail brokers, fractional shares are internalized by retail brokers' own order book. The absence of competitions among market makers may further aggravate the moral hazard of retail brokers. See more discussions in Section 2.1.

aspects of market structure, the observed improvements in market quality can be attributed primarily to the reduction in fractional trading. Though these findings model fractional traders remarkably different from informed retail traders documented by prior literature (e.g., Foucault, Sraer, and Thesmar 2011; Barrot, Kaniel, and Sraer 2016; Boehmer et al. 2021), they are consistent with the low liquidity accompanied by Robinhood-type investors (Eaton et al. 2022; Jones et al. 2022).[5]

Next, this paper studies how the widespread adoption of fractional trading reshapes the economic role and market consequences of stock splits. In the traditional literature, stock splits are explained by the optimal trading range hypothesis (Copeland 1979; Lakonishok and Lev 1987; Angel 1997), signaling motives (Grinblatt, Masulis, and Titman 1984; Brennan and Copeland 1988; McNichols and Dravid 1990; Ikenberry, Rankine, and Stice 1996), and investor attention (Barber and Odean 2008; Da, Fang, and Lin 2025). Fractional trading fundamentally alters this environment by eliminating the price barrier to entry, allowing investors to purchase arbitrary dollar amounts regardless of share price. This institutional change provides a clean setting to disentangle these competing explanations and reassess whether stock splits remain value-relevant in modern markets.

Using a comprehensive sample of stock splits from 2003 to 2025, I document a sharp divergence in split announcement effects following the introduction of fractional trading. Prior to 2019, high- and low-price stocks exhibit similar announcement returns, consistent with the existing evidence that split-induced abnormal returns are broadly shared across firms (Fama et al. 1969; Lamoureux and Poon 1987; Asquith, Healy, and Palepu 1989). In contrast, in the post-fractional-trading period, high-price stocks experience significantly stronger short-run and long-run abnormal returns, while low-price stocks see their split premium largely dissipate. Difference-in-differences estimates confirm a sizable and persistent wedge between the two groups. These findings contradict with the optimal trading range and signaling hypothesis, which predicts a diminished role for splits once price accessibility is no longer binding, and instead point to an attention-driven mechanism in which fractional traders amplify demand for salient, high-price split announcements (Barber and Odean 2008;

[5]I do acknowledge another possibility that fractional trading became uninformed because of the enhanced transparency and more strict reporting policy.

Da, Fang, and Lin 2025).

Beyond announcement effects, fractional trading also distorts the real outcomes of rational stock splits. Replicating the benchmark result that predicted and realized spread changes map nearly one-for-one before 2020 (Li and Ye 2026), I show that this relationship breaks down in the post-2020 period for high-price stocks. Specifically, splits of high-price firms are associated with higher realized spreads *ex post*, consistent with evidence that retail trading can widen spreads and impair price discovery. Moreover, firms do not adjust split ratios to offset these effects. Taken together, the results suggest that attention-driven fractional trading introduces correlated order flow that undermines the traditional liquidity benefits of stock splits and disrupts the rational price-management mechanism.

Contributions to related literature. This paper contributes to the literature on fractional trading. To my best knowledge, I provide the first direct, comprehensive measurement of fractional trading in U.S. equity markets, resolving the data limitation that has constrained prior research. For example, Bartlett, McCrary, and O'Hara (2024) obtained proprietary data from Robinhood and Drivewealth to study fractional share trading patterns and developed an algorithm to partially detect fractional trades in Trade and Quote (TAQ) based on latency signatures. Da, Fang, and Lin (2025) adopted a different approach, using one-share trades as a proxy for fractional trading activity. This paper documents a rich set of stylized facts about fractional trading that inform our understanding of retail investor behavior, off-exchange trading, and the market for fractional shares.

Our results complement the open discussion on the information content conveyed by small trades. A stream of studies argues that small trades, such as odd-lots, on exchange contain disproportional private information, stemming from order-split by informed traders to reduce adverse selection risks (O'Hara, Yao, and Ye 2014). Foucault, Sraer, and Thesmar (2011) and Barrot, Kaniel, and Sraer (2016) find that retail trading enhances liquidity and lowers volatility. Bartlett, McCrary, and O'Hara (2024) find that fractional trading positively predict future bid-ask spreads, and interpret it as informed fractional trading. Another stream of literature, on the other hand, argues that the retail trading and fractional trading from Robinhood, are accompanied with low liquidity (Eaton et al. 2022; Jones et al. 2022). This paper shows that fractional trades carry negative weighted price contributions

and exhibit the liquidity signature of uninformed order flow. Beyond correlation, I also provide causal evidence on the effects of fractional trading on market quality, contributing to the literature on market transparency and disclosure regulation (Bartlett, McCrary, and O'Hara 2025a). The uninformed small trades in OTC (compared to informed small trades on exchanges) is also consistent with the systematic pattern documented by Lu, Guo, and Zou (2023).

This paper also contributes to the broader retail trading literature by focusing on fractional trading (Barber and Odean 2000, 2008; Kaniel, Saar, and Titman 2008; Welch 2022; Pavlova 2025). A growing body of literature focus on the retail trading from retail platforms such as Robinhood (Ozik, Sadka, and Shen 2021; Eaton, Green, Roseman, and Wu 2022; Welch 2022). Moreover, I provide a new, directly measured proxy for retail investor activity that can be used in future research (Barber et al. 2022; Boehmer et al. 2021).

Finally, this paper contributes to the literature on market microstructure and corporate stock-split outcomes. First, it revisits the long-standing debate on the economic role of stock splits. Prior studies attribute split-related abnormal returns to optimal trading range considerations (Copeland 1979; Lakonishok and Lev 1987; Angel 1997), signaling (Grinblatt, Masulis, and Titman 1984; Brennan and Copeland 1988; McNichols and Dravid 1990; Ikenberry, Rankine, and Stice 1996), and attention-driven demand (Barber and Odean 2008; Da et al. 2025). I provide new evidence that the accessibility channel becomes largely obsolete in the presence of fractional trading, while the attention channel not only persists but becomes more pronounced. This result complements and extends the nominal share price puzzle documented by Weld et al. (2009), showing that nominal prices continue to matter even when mechanical barriers to entry are removed.

Existing market microstructure studies also rationalize stock splits to improve liquidity by moving prices toward an optimal tick-size range (Angel 1997; Li and Ye 2026). I demonstrate that in the era of fractional trading, attention-driven order flow from fractional traders widens spreads and offsets the predicted liquidity gains. This finding complements evidence that retail trading can degrade market quality and increase volatility (Bartlett, McCrary, and O'Hara 2024; Da, Fang, and Lin 2025), and highlights a novel channel through which behavioral demand shocks interfere with firms' rational price-setting decisions.

The remainder of the paper is organized as follows. Section 2 describes the institutional background of fractional trading and sample construction, and presents five stylized facts about fractional trading. Section 3 examines the correlation between fractional shares and price discovery. Section 4 establishes causal effect of fractional trades on harming market quality using the introduction of fractional trading in 2019 and the new reporting policy of fractional trading in 2026. Section 5 shows how the spikes of fractional trading contribute to the stock-split announcement returns and distort the rational stock-split outcomes on bid-ask spread. Section 6 discusses the policy implications on regulating fractional trading. Finally, Section 7 concludes.

2. Institutional Background and Stylized Facts

2.1 Institutional Background

Fractional trading allows investors to buy or sell less than one whole share of a stock. Fractional trading has its origins in dividend reinvestment plans (DRIPs) and direct stock purchase plans offered by transfer agents, but the modern incarnation, where retail investors can buy and sell arbitrary dollar amounts of eligible publicly traded stock, is a product of the Fintech revolution of the late 2010s. Platforms such as Interactive Brokers, which launched fractional trading for its users in December 2019, and subsequently Robinhood, Fidelity, and Charles Schwab, have made fractional share investing a standard feature of retail brokerage accounts.

Instead of choosing the number of shares to buy, a retail investor can specify a dollar amount, and the broker converts the order into a fractional-share quantity. This feature lowers the capital required to obtain exposure to high-price stocks and makes nominal share prices less binding for retail participation. Figure 2 illustrates the basic execution mechanism. Whole-share orders can be routed by the retail broker to wholesalers and then either internalized or routed to exchanges on an *agency* basis. There are multiple wholesalers compete with each other through, e.g., payment for order flow (PFOF). Fractional-share orders, by contrast, cannot be directly routed to exchanges as fractional quantities. They are instead

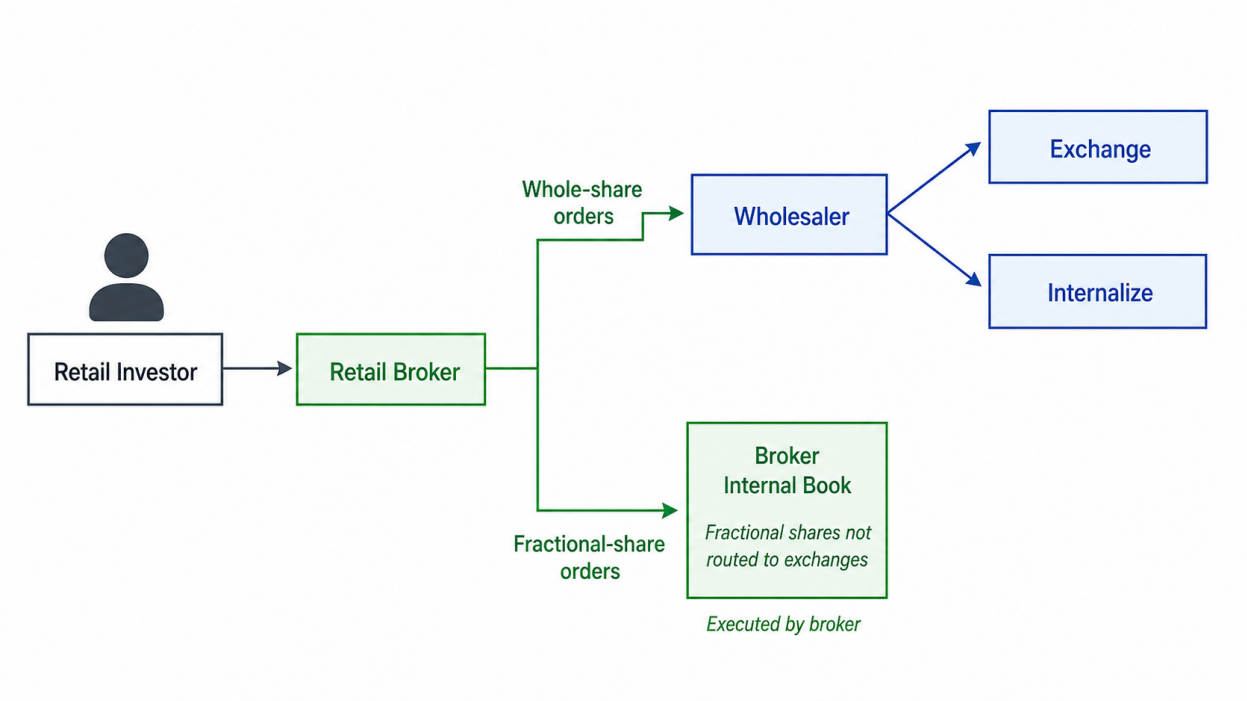


Figure 2. Execution of whole-share and fractional-share orders by retail brokers. This figure illustrates the order-routing and execution process for retail brokerage orders. Whole-share orders may be routed from the retail broker to a wholesaler and then either executed internally by the wholesaler or routed to an exchange (agency basis). Fractional-share orders, in contrast, are not directly routed to exchanges as fractional quantities. They are executed through the broker's internal book (principal basis).

executed by the retail broker through an internal fractional-share book on a *principal* basis, with the broker managing the residual inventory needed to provide fractional exposure to customers. As discussed later, the absence of order-routing and competitions would result in worse execution qualities of retail orders.

Identification of fractional trading. A central empirical challenge is that fractional trading was historically difficult to observe in public transaction data. Before the recent reporting reform, fractional-share trades were not separately identifiable on the consolidated tape. In particular, trades with quantities below one share were reported as one share, while trades with both whole and fractional components were reported only in whole-share quantities. As a result, reported one-share trades contained a mixture of true one-share trades and rounded-up fractional-share trades. Effective February 23, 2026, FINRA enhanced its equity trade-reporting facilities by adding a new *Fractional Share Quantity* field for NMS

stock transactions reported to the TRFs or ADF. Under the new guidance, firms that engage in fractional trading must report the full fractional-share quantity in decimal format, up to six digits after the decimal point, without rounding up.[6] This rule change makes fractional trades directly observable for the first time and provides the institutional setting for the empirical analysis.

New definition of round lots. A separate but related regulatory development occurred on November 3, 2025, when the SEC implemented a revised definition of round lots under Regulation NMS. Historically, a round lot was generally treated as 100 shares, regardless of the stock's nominal price. The new definition makes the round-lot size depend on the stock's average closing price: Effective November 3, 2025, the Securities and Exchange Commission (SEC) altered the definition of round-lots based on stock price levels:[7]

$$1 \text{ round-lot} = \begin{cases} 100 \text{ shares}, & \text{if } \bar{p} \leq \$250.00 \\ 40 \text{ shares}, & \text{if } \$1{,}000.00 \geq \bar{p} \geq \$250.01 \\ 10 \text{ shares}, & \text{if } \$10{,}000.00 \geq \bar{p} \geq \$1{,}000.01 \\ 1 \text{ share}, & \text{if } \bar{p} \geq \$10{,}000.01 \end{cases} \tag{1}$$

where $\bar{p}$ is the average closing price over the prior evaluation period. The evaluation period is March for revisions effective in May and September for revisions effective in November. Any order with a size below the round-lot threshold is classified as an odd-lot under the new definition. In other words, some previous odd-lots quotes are now NBBO-eligible. Brogaard and Landsberg (2026) find this regulatory shift increasing price informativeness and reducing noise in the price, consistent with the conjecture by Bartlett, McCrary, and O'Hara (2025b). This reform is conceptually distinct from the fractional-share reporting rule, but both changes reflect the increasing importance of small-size trading in modern equity markets. The round-lot reform changes how displayed liquidity is measured and disseminated for high-priced

[6] See FINRA (2026). For example, a transaction of one-third of a share is reported in the new fractional quantity field as a decimal quantity, rather than being observable only as a one-share trade in the standard quantity field.

[7] The revised definition of round-lots as set forth in Rule 600(b)(93) of Regulation National Market System (NMS), is part of SEC's proposal "Tick size and Access Fees and the Transparency of Better Priced Orders." See more details in SEC (2025b).

stocks, while the fractional-reporting reform makes sub-share retail trading directly visible in transaction data. Together, these developments improve the measurement of retail trading activity, small trades, and market quality in high-price stocks. An implication of this new definition is that fractional shares will account for an even higher proportion of odd-lot trades for high-priced stocks, since the odd-lot threshold is now lower.

2.2 Data and Sample Construction

The primary data source for this study is the Daily TAQ database, which provides intraday transaction- and quote-level data for equity trades reported on U.S. exchanges and off-exchange venues. I focus on off-exchange transactions identified by the exchange code "D" in TAQ (`EX='D'`), since fractional share trades by definition cannot be executed on exchanges. The data cleaning procedures follow Holden and Jacobsen (2014). The daily stock-level quoted spreads and intraday volatility are obtained from Millisecond Intraday Indicators (IID) from Wharton Research Data Services (WRDS).

The daily stock trading information before 2025 is obtained from the Center for Research in Security Prices (CRSP); information of 2025 is obtained from the CRSP Version 2 (CIZ); information of 2026 is obtained from daily security file of CRSP/Compustat Merged database. I also collect the stock-splits information, including declaration date, ex-date, and split ratio from CRSP Distribution file.

The sample consists of U.S. common stocks satisfying the following criteria based on the most recent CRSP record as of 2025: `ShareType = 'NS,' SecurityType = 'EQTY,' SecuritySubType = 'COM,' USIncFlg = 'Y,'` and `IssuerType in ('ACOR', 'CORP')`.[8] I restrict the sample to stocks listed on the three major exchanges, NASDAQ, NYSE, and AMEX, and exclude penny stocks with prices below \$1. Our main conclusion remains robust with alternative threshold of \$5. These filters generate a final sample of 3,343 stocks. Stocks are assigned into small, medium, and large group based on 30% and 70% NYSE breakpoints in June 2025, which are collected from Kenneth French's Data Library. The primary sample period spans 48 trading days from February 23, 2026 to April 30, 2026.

[8]These conditions effectively are equivalent to `SHRCD in (10,11)` in the latency CRSP data. A SAS program recoding CRSP CIZ version to the latency verion can be found on WRDS.

Unless otherwise noted, the analysis focuses on regular trading hours, although selected results are also presented for extended trading hours. To mitigate the potential influence of extreme values, I winsorize the continuous variables at the 1st and 99th percentiles.

2.3 Stylized Facts

This section documents five stylized facts about fractional share trading that emerge from the newly granular TAQ data.

Fact 1: Fractional Shares as a Substantial Fraction of Trading Activity

The first finding is that the vast majority of fractional share trades involve quantities less than one share. Column (1) and (2) of Table 1 Panel A indicates that, across the full sample, 96.7% (89.8%) of all fractional trades are sub-one-share trades on a value-weighted (equal-weighted) basis. The ratio is highest for large stocks (97.2% value-weighted, 95.1% equal-weighted) and somewhat lower for small stocks (88.3% value-weighted, 88.1% equal-weighted), though the overwhelming majority of fractional trades are still below one share.

The next question is how significantly the fractional shares account for different types of trades. Specifically, we are interested in the number of one-share trades, odd-lots, and total trades. Column (3) to (8) of Table 1 Panel A reports the proportion of fractional trading. On a value-weighted average basis, fractional shares account for 48.6% of all trades with sizes at or below one share, 13.9% of all odd-lot trades (using the new SEC definition from equation (1)), and 10.5% of total trades. These are economically large proportions, indicating that fractional share trading is not a trivial phenomenon. This finding confirms that the pre-February 2026 rounding convention obscured a large volume of trading activity by collapsing sub-one-share trades into the one-share bucket. The value-weighted figures are substantially higher than the equal-weighted figures (13.7%, 1.7%, and 1.3%, respectively), reflecting the concentration of fractional trading in large, high-priced stocks. Figure 3 displays the time series of these proportions over the sample period, showing that they are relatively stable, with fractional shares consistently accounting for a significant share of total trading activity, especially on a value-weighted basis.

Table 1
Proportion of Fractional Shares by Size Groups

This table shows the proportion of fractional shares by size groups (Small, Medium, Large). Panel A reports value-weighted (VW) and equal-weighted (EW) averages of four ratios fo each size group. Stocks are assigned based on 30% and 70% NYSE breakpoints in June 2025. "FS" is the number of fractional trades that are below one share. "FS_TOTAL" is the number of total fractional trades. "1-SHARE" is the number of trades with shares ≤ 1. "OL" is the number of odd-lot trades. "TOTAL" is the number of total trades. Panel B reports tests of differences across size groups. The robust t-statistics are shown in square brackets.

	FS/FS_TOTAL		FS/1-SHARE		FS/OL		FS/TOTAL	
	VW	EW	VW	EW	VW	EW	VW	EW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Summary statistics								
All	0.967	0.898	0.486	0.137	0.139	0.017	0.105	0.013
Large[a]	0.972	0.951	0.519	0.231	0.150	0.037	0.113	0.027
Medium[b]	0.904	0.901	0.096	0.089	0.009	0.009	0.007	0.007
Small[c]	0.883	0.881	0.090	0.133	0.009	0.015	0.007	0.011
Panel B: Test of differences								
$a - c$	0.090	0.070	0.429	0.098	0.140	0.021	0.106	0.016
	[59.34]	[52.63]	[170.07]	[36.05]	[57.03]	[35.98]	[49.23]	[32.15]
$a - b$	0.068	0.050	0.423	0.142	0.140	0.028	0.106	0.020
	[35.03]	[39.57]	[187.48]	[71.48]	[58.09]	[52.98]	[50.00]	[45.67]
$b - c$	0.021	0.020	0.006	−0.044	0.000	−0.006	0.000	−0.004
	[11.50]	[13.78]	[7.39]	[−32.39]	[0.56]	[−24.45]	[1.18]	[−21.61]

Fact 2: Larger Stocks Witness More Fractional Trading

Panel A of Table 1 decomposes the fractional share proportions by size group, using the 30th and 70th NYSE market capitalization percentiles as of June 2025 as breakpoints. The results reveal a striking size gradient. For large stocks, fractional shares account for 51.9% (23.1%) of one-share-or-below trades on a value-weighted (equal-weighted) basis, compared to only 9.0% (13.3%) for small stocks. As shown in panel B of Table 1, the differences between large and small stocks, and between large and medium stocks, are statistically significant with t-statistics exceeding 30 in all cases. This pattern is consistent with the economic intuition that fractional shares are most valuable to budget-constrained retail investors when individual share prices are high (Bartlett, McCrary, and O'Hara 2024; Bartlett, McCrary, and O'Hara

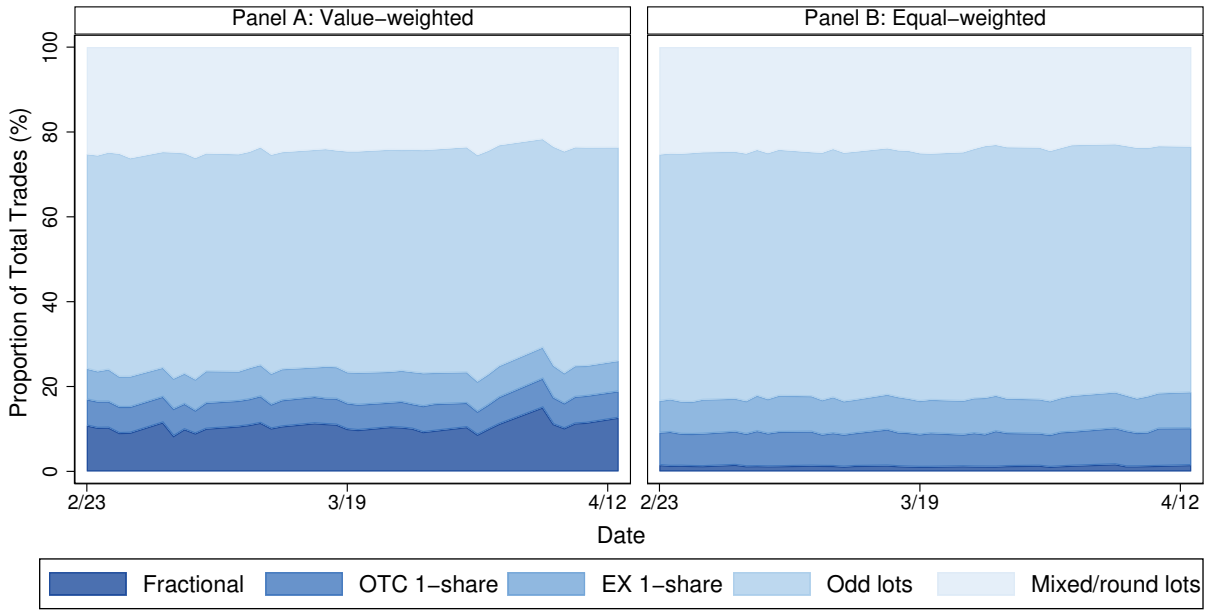


Figure 3. Proportion of Fractional Shares: Time-series. This figure shows the proportion of total trades accounted for by fractional shares (<1 share), off-exchange 1-share trades, exchange 1-share trades, odd-lots, and mixed-/round-lots. Panel A: Value-weighted. Panel B: Equal-weighted. Sample period: February 23 to April 12, 2026.

2025a; Da et al. 2025).

Fact 3: Fractional Trading Spikes around Market Open

Figure 4 illustrates the third stylized facts: the intraday distribution of fractional share trading is markedly different from that of overall trading activity. While total off-exchange trades exhibit a pattern with spikes at market open and close and elevated activity during the pre-market session, fractional share trades below one share exhibit a dramatic spike at the 9:30 a.m. market open that dwarfs all other intraday activity, followed by a gradual decline over the remainder of the trading day. This pattern suggests that many fractional share orders are submitted by retail investors during non-market hours (evenings, overnight, or early morning) and are accumulated by brokers for execution at or shortly after the market open. By contrast, the relatively muted activity during the middle of the trading day and the absence of a strong close-of-day spike suggest that fractional share trading is not driven by the same institutional forces (e.g., index rebalancing, closing auctions) that generate the

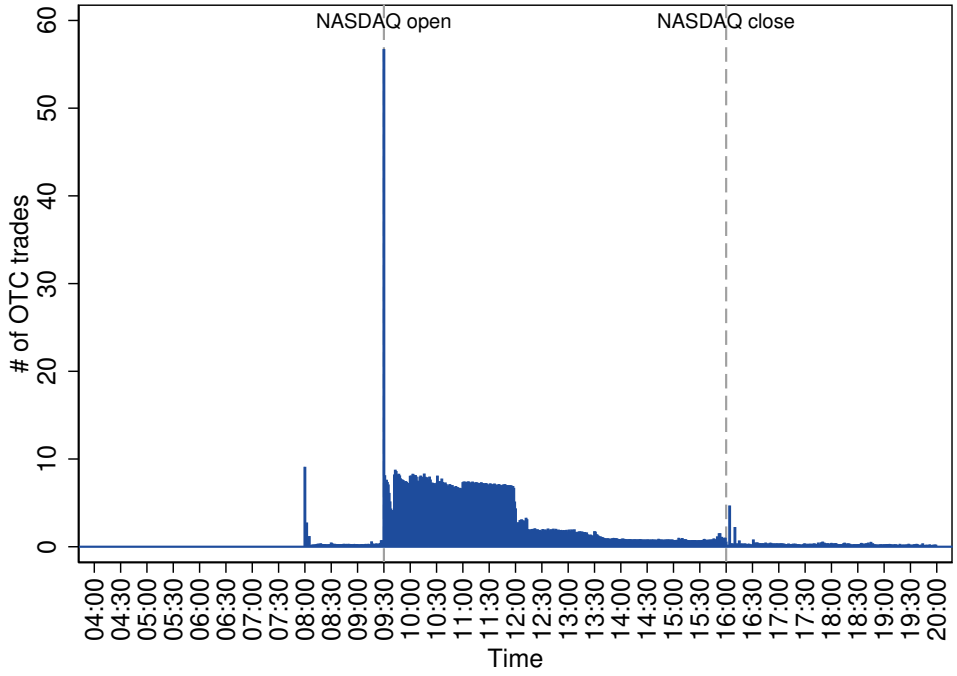


Figure 4. Intraday Distribution of Total Trades and Fractional Share Trades. This figure depicts the average number of trades per minute throughout the extended trading day (4:00 a.m. to 8:00 p.m. EST). Left panel: Total trades, showing spikes at pre-market open, market open (9:30 a.m.), and market close (4:00 p.m.), with a U-shaped pattern during regular hours. Right panel: Fractional shares < 1, showing a dramatic spike at 9:30 AM that dwarfs all other intraday activity, followed by gradual decline.

well-known U-shaped intraday volume pattern (e.g., Lou, Polk, and Skouras 2019; Jiang, Wu, and Yao 2026).

Fact 4: Dollar-based Fractional Shares

To preliminarily pin down the incentives of fractional trading, I compute the dollar value of each fractional share trade (price times quantity) and examine the distribution of the fractional part (cents) of these dollar values. If trades originate from dollar-based orders, the dollar values should cluster at round numbers, and the fractional cents should be concentrated near 100 cents (i.e., the dollar values should be approximately integers). The data strongly support the dollar-denomination hypothesis. Figure 5 displays the histogram of the cents of fractional dollar volume shows pronounced spikes at 100, i.e., at values corresponding to round dollar amounts. This pattern provides direct evidence that fractional share orders

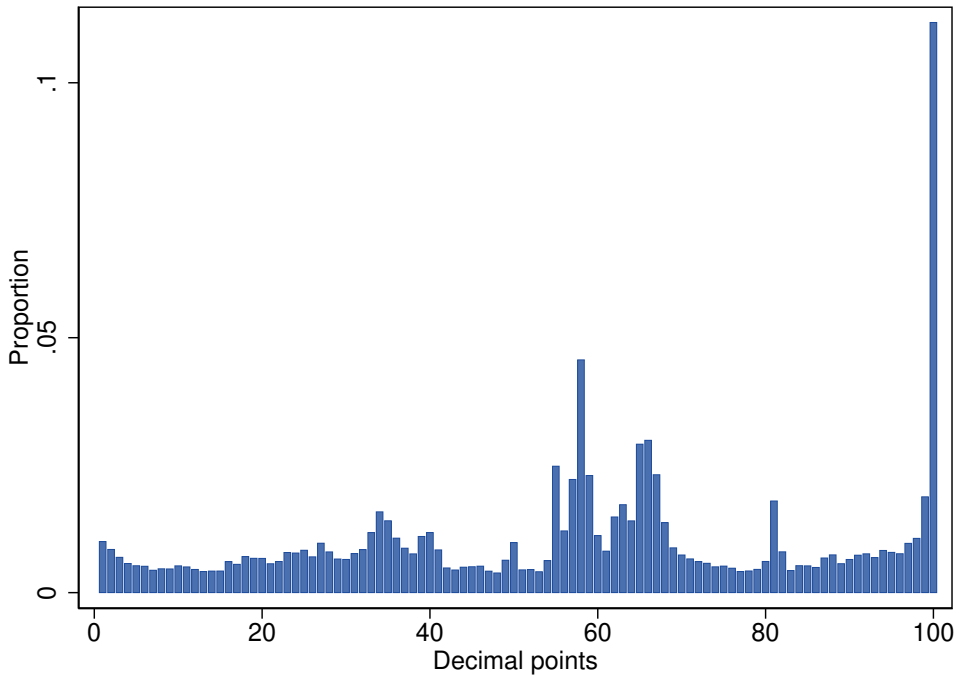


Figure 5. Distribution of Decimal Points in Fractional Share Dollar Volume. This figure shows the histogram of the cents (1–100) in the dollar volume of fractional trading.

are overwhelmingly placed in dollar terms, consistent with the user interface design of retail trading platforms. In addition, the rest 90% fractional trading with fractional dollar volume indicates that fractional traders may use portfolio trading strategies as fractional trading allows them to conduct more precise portfolio balancing (FINRA 2025).

Fact 5: Fractional Shares Do Not Correlate with Algorithmic Trading

A natural question is whether some fractional trades generated by algorithmic trading strategies that split large orders into small pieces, some of which happen to be non-integer quantities. To investigate this possibility, I examine the millisecond-level timestamps of fractional share trades. Hasbrouck and Saar (2013) document that the timestamps of all trades exhibit a characteristic pattern of concentration close to the start of each second, reflecting the prevalence of high-frequency, low-latency trading. If fractional trades were generated by similar algorithms, they should exhibit a similar pattern. Instead, Figure 6 shows that the millisecond timestamps of fractional share trades below one share are approximately

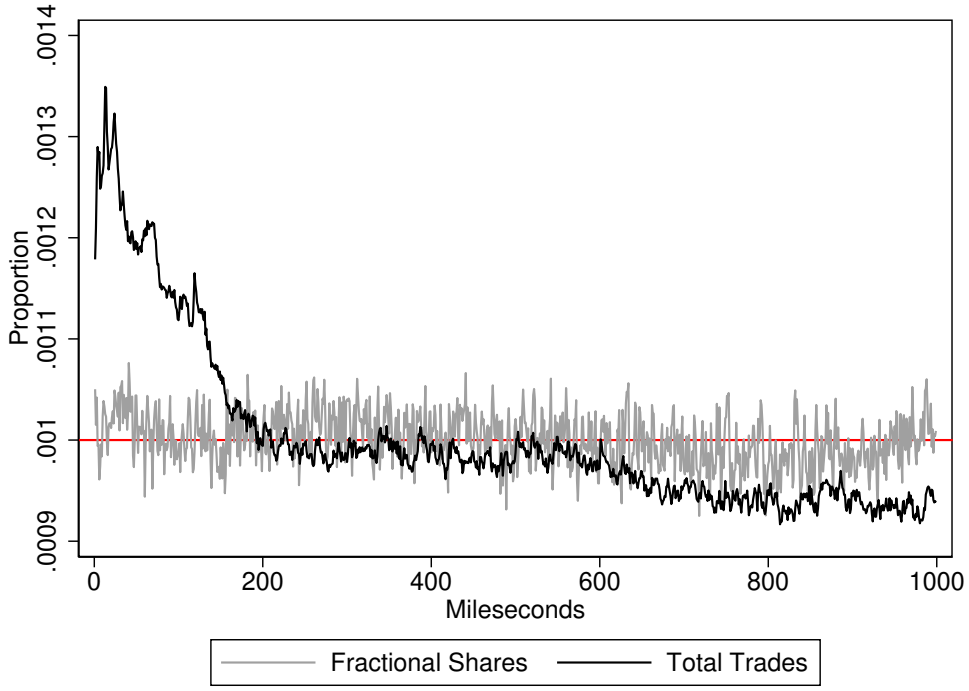


Figure 6. Millisecond Distribution of Trade Timestamps. This figure plots the proportion of trades at each millisecond (1–1,000) within a second, separately for fractional share trades (solid black line) and total trades (gray line). The horizontal reference line denotes a uniform distribution at 1/1000.

uniformly distributed across a second, with no lwo-latency concentration. This uniform distribution is inconsistent with algorithmic order splitting and strongly suggests that fractional trades are generated by the execution of retail dollar-based orders.

3. Price Discovery

The results so far show that fractional trading accounts for a substantial proportion of stock trading activities, especially for large stocks. Whether such trades have private information content remains an open question. On one hand, the retail trading and fractional trading from retail platform, such as Robinhood, are accompanied with low liquidity (Eaton et al. 2022; Jones et al. 2022). Bartlett, McCrary, and O'Hara (2024) interpret it as an evidence of informed fractional trading. On the other hand, Foucault, Sraer, and Thesmar (2011) and Barrot, Kaniel, and Sraer (2016) find that retail trading enhances liquidity and lowers

volatility. O'Hara, Yao, and Ye (2014) show that small on-exchange trades, i.e., odd-lots, contribute 35% of price discovery, consistent with informed traders using odd-lots to avoid detection. To investigate the informativeness of fractional trading, I first use WPC, which measures how much of a stock's cumulative price change is attributable to trades in particular trade-size categories (see, e.g., Barclay and Warner 1993; Chakravarty 2001; Choe and Hansch 2005; Alexander and Peterson 2007; O'Hara, Yao, and Ye 2014; Lu, Guo, and Zou 2023). Next, I examine and compare the liquidity metrics, including effective spread, realized spreads, and price impact, of fractional trading with other trade-size categories. Finally, I provide causal evidence on how fractional trading affect market quality by exploring the new reporting policy effective February 23, 2026.

3.1 Weighted Price Contribution

To assess the contribution of fractional share trades to price discovery, I employ the WPC methodology introduced by Barclay and Warner (1993). The WPC decomposes the cumulative daily price change of each stock into contributions from different trade size categories, weighted by the stock's contribution to overall price movement.

Formally, let j denote one of J trade size categories, t denote the trading day, i denote the stock, and N denote the total number of trades, respectively. The WPC for category j on day t is defined as:

$$WPC_{j,t} = \sum_{i=1}^{I} w_{i,t}\, PC_{i,j,t}, \tag{2}$$

where the stock weight $w_{i,t}$ and the price contribution $PC_{i,j,t}$ are given by:

$$w_{i,t} = \frac{\left|\sum_{n=1}^{N} r_{n,i,t}\right|}{\sum_{i=1}^{S}\left|\sum_{n=1}^{N} r_{n,i,t}\right|}, \text{ and } PC_{i,j,t} = \frac{\sum_{n=1}^{N} \delta_{n,j}\, r_{n,i,t}}{\sum_{n=1}^{N} r_{n,i,t}}, \tag{3}$$

where $\delta_{n,j}$ is an indicator variable equal to one if the n-th trade belongs to category j and zero otherwise, and $r_{n,i,t}$ denotes the price change between trade n and trade $n-1$ for stock i on day t. Following Barclay and Warner (1993), I define $r_{n,i,t}$ as the simple price difference, though I also verify that using log price differences as in Choe and Hansch (2005) yields

similar results.

The trade size categories are defined as follows. Fractional shares are divided into two subcategories: those with quantities below one share and those with quantities above one share. Integer-share trades are categorized by exchange versus off-exchange execution and by trade size: one-share trades on exchange, one-share trades off-exchange (OTC), two-share OTC, three-share OTC, five-share OTC, odd-lots, round- and mixed-lots below 100 shares, 101–500 shares, 501–1,000 shares, 1,001–2,000 shares, 2,001–5,000 shares, 5,001–10,000 shares, and trades exceeding 10,000 shares.

Table 2 presents the summary statistics of the WPC for each category over the 48 trading days from February 23 to April 30, 2026. The most striking finding is that fractional trading below one share have a mean (median) WPC of −0.912 (−0.384) with a large standard deviation of 3.002. The negative mean indicates that, on average, fractional share trades move prices in the direction *opposite* to the cumulative daily return. This is the hallmark of uninformed, contrarian, and liquidity-motivated order flow. Fractional trading above one share also have a negative mean WPC of −0.066, a magnitude is much more conservative. Though beyond the scope of this paper, the high WPC standard deviation of fractional trading below one share and the difference between tiny and large fractional trading size may suggest a substantial heterogeneity in the informational content conveyed by fractional trading (Johnson, Van Ness, and Van Ness 2017).

Off-exchange one-share trades also have a negative mean WPC of −0.735, consistent with the interpretation that many off-exchange one-share trades are in fact associated with uninformed retail order flow (Da, Fang, and Lin 2025). By contrast, one-share trades executed on exchanges have a strongly positive mean WPC of +0.880, indicating that informed traders may split their orders over time to better hide their trades among uninformed traders (Easley and O'Hara 1987; O'Hara, Yao, and Ye 2014). Among larger trade categories, the highest price contribution comes from round- and mixed-lot trades between the odd-lot threshold and 100 shares ("Oddlots–100"), with a mean WPC of +1.310. This finding is consistent with Bartlett, McCrary, and O'Hara (2025b) and Brogaard and Landsberg (2026), who show that the odd-lot quotes contribute to higher price informativeness. The 101–500 share category also contributes positively (+0.404), with declining contributions for larger

Table 2
Weighted Price Contribution by Trade Size Categories

This table reports the summary statistics of weighted price contribution (WPC) for each order size category using individual trades. Fractional shares are divided into those with quantities below one share and those with quantities above one share. Integer-share trades are categorized by one-share trades on exchange, one-share trades off-exchange (OTC), two-share OTC, three-share OTC, five-share OTC, odd-lots, round- and mixed-lots below 100 shares, 101–500 shares, 501–1,000 shares, 1,001–2,000 shares, 2,001–5,000 shares, 5,001–10,000 shares, and trades exceeding 10,000 shares. Categories other than fractional shares contain rounded shares only. Unless otherwise noted, categories contain orders reported by both exchanges and off-exchanges. The data period is 48 trading days from February 23, 2026 to April 30, 2026.

	Mean	SD	Min.	Q1	Median	Q3	Max.
Fractional Shares:							
<1 share	−0.912	3.002	−6.663	−3.562	−0.384	0.792	4.750
>1 share	−0.066	0.112	−0.374	−0.105	−0.055	0.003	0.148
1 (OTC)	−0.735	0.332	−1.449	−0.913	−0.724	−0.483	−0.053
1 (Exchange)	0.880	0.326	0.123	0.676	0.877	1.118	1.528
2 (OTC)	−0.447	0.217	−0.863	−0.600	−0.436	−0.275	0.019
3 (OTC)	−0.242	0.160	−0.540	−0.383	−0.278	−0.092	0.082
5 (OTC)	−0.172	0.155	−0.515	−0.245	−0.161	−0.070	0.191
Oddlots	0.395	2.191	−3.847	−1.178	0.126	2.441	4.605
Oddlots–100	1.310	1.005	−0.704	0.614	1.583	2.128	2.937
101–500	0.404	0.286	−0.101	0.147	0.404	0.628	0.972
501–1,000	0.040	0.041	−0.027	0.017	0.034	0.064	0.137
1,001–2,000	0.012	0.017	−0.024	0.001	0.010	0.022	0.052
2,001–5,000	0.008	0.011	−0.017	0.000	0.010	0.016	0.027
5,001–10,000	0.003	0.007	−0.012	−0.001	0.003	0.006	0.016
>10,000	−0.001	0.008	−0.021	−0.004	0.000	0.002	0.016

trade sizes. Trades exceeding 10,000 shares have a slightly negative mean WPC of −0.001, consistent with the stealth trading hypothesis that informed traders avoid the very largest trade sizes (Barclay and Warner 1993).

Besides the stealth trading hypothesis, the public information hypothesis and the trading volume hypothesis, also address the relation between price contribution and percentage of transactions or total trading volume in each trade-size category. The public information hypothesis posits that the release of public information causes most stock price changes. The testable implication of this theory is that the price contribution in a trade-size category

is proportional to the percentage of trades in that category. The stealth trading hypothesis, in contrast, implies that the price contributions would not be proportional. To exclude the confounding public information hypothesis, I estimate a weighted least squares (WLS) regression of the price contribution on trade size category indicators and control variables:

$$PC_{i,j,t} = \sum_{j=1}^{J} \beta_j \delta_{i,j,t} + \psi_1 PctNum_{i,j,t} + \psi_2 PctQty_{i,j,t} + \varepsilon_{i,j,t}, \tag{4}$$

where $\delta_{i,j,t}$ is an indicator equal to one if the price contribution observation belongs to category j for stock i on day t, and $PctNum_{i,j,t}$ and $PctQty_{i,j,t}$ denote the proportion of category j to total trades with respect to the number of trades and trading volume, respectively. The regression weight is the ratio of the absolute cumulative price change of stock i on day t to the sum of all stocks' absolute cumulative price changes on day t, defined as in equation (3). If the public information hypothesis holds, the coefficient on the percentage of transactions (ψ_1) or the percentage of trading volume (ψ_2) in that category should equal one and the coefficient on the dummy variable ($\beta_j, j = 1, 2, ..., J$) should equal zero.

Table 3 comes down in favor of stealth trading hypothesis and goes agains the public information hypothesis. In the specification with pecentage of number of trades (column 1), the coefficient on fractional shares below one share is -0.894 ($t = -8.94$), confirming the univariate finding. Replacing with the proportion of trading volume instead (column 2) yields a nearly identical coefficient of -0.913 ($t = -8.30$). The coefficients on off-exchange one-share trades, two-share OTC trades, three-share OTC trades, and five-share OTC trades are all significantly negative, while the coefficient on exchange one-share trades is significantly positive (+0.864 to +0.959). The oddlots-to-100 category retains its strong positive contribution (+0.640 to +1.422). More importantly, both ψ_1 and ψ_2 are significantly different from one. These results reinforce the interpretation that off-exchange small trades, and fractional share trades in particular, represent uninformed order flow that detracts from price discovery. The high (low) price discovery in on-exchange (off-exchange) tiny trades is also consistent with the pattern discovered in Chinese FX market (Lu, Guo, and Zou 2023).

Table 3
Weighted Least Squares Regression of Price Contribution

This table reports WLS regression estimates of equation (4). The dependent variable is the price contribution of each trade size category for each stock-day. All category indicators are included without an intercept. The regression weight is the ratio of the stock s absolute cumulative price change to the sum of all stocks' absolute cumulative price changes on day t. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$PC_{i,j,t}$	
	(1)	(2)
Fractional Shares:		
< 1 (a)	−0.894***	−0.913***
	(0.10)	(0.11)
> 1 (b)	−0.065***	−0.067***
	(0.01)	(0.01)
1 (OTC)	−0.672***	−0.744***
	(0.10)	(0.04)
1 (EX)	0.959***	0.864***
	(0.10)	(0.03)
2 (OTC)	−0.419***	−0.454***
	(0.05)	(0.02)
3 (OTC)	−0.227***	−0.248***
	(0.03)	(0.01)
5 (OTC)	−0.157***	−0.180***
	(0.03)	(0.01)
Oddlots	0.987	−0.297
	(0.79)	(0.19)
Oddlots–100	1.422***	0.640***
	(0.16)	(0.12)
101–500	0.434***	0.030
	(0.05)	(0.07)
> 500	0.013***	−0.050***
	(0.00)	(0.01)
$PctNum_{i,j,t}$ (c)	−0.757	
	(0.91)	
$PctQty_{i,j,t}$ (d)		2.046***
		(0.34)
Test of (a) = (b)	< 0.01	< 0.01
Test of (c) = 1	< 0.01	
Test of (d) = 1		< 0.01
Observations	2,017,065	2,017,065
R^2	0.005	0.005

3.2 Liquidity Metrics

To further characterize the information content of fractional share trades, I compute three standard liquidity metrics for each trade size category: the percentage effective spread, the percentage price impact, and the percentage realized spread.

The effective spread is defined as:

$$ESpread_n = 2\, D_n \frac{P_n - M_n}{M_n}, \tag{5}$$

where $D_n = +1$ (-1) if trade n is classified as a buy (sell) using the Lee and Ready (1991) algorithm,[9] P_n is the trade price, and M_n is the NBBO midpoint immediately preceding trade n. The price impact is defined as:

$$PriceImpact_n = 2\, D_n \frac{M_{n,+5} - M_n}{M_n}, \tag{6}$$

where $M_{n,+5}$ is the NBBO midpoint five minutes after trade n. The realized spread is defined as:

$$RSpread_n = 2\, D_n \frac{P_n - M_{n,+5}}{M_n}. \tag{7}$$

For each stock-day-category, I compute the dollar-weighted average of each metric across all trades in that category. The estimation procedures follow Holden and Jacobsen (2014).

Table 4 reports the mean and median of each metric by trade size category. Fractional share trades below one share exhibit the highest mean effective spread of 0.669%, the highest mean realized spread of 0.557%, but a modest mean price impact of 0.104%. The combination of high effective and realized spreads with low price impact is the defining characteristic of uninformed order flow: market makers extract large rents from fractional share traders because these trades carry little information about future price movements. By comparison, exchange one-share trades have lower effective spreads of 0.387% and much higher price impact of 0.196%, consistent with informed trading. This pattern is consistent with the theoretical predictions of models of informed and uninformed trading (e.g., Kyle

[9]The main results remain virtually unchanged using alternative classification algorithms, e.g., Ellis, Michaely, and O'Hara (2000) and Chakrabarty et al. (2007).

Table 4
Liquidity Metrics by Trade Size Categories

This table reports the mean and median of three liquidity metrics for each order size category. Effective spread, realized spread, and price impact are computed following Holden and Jacobsen (2014). Trade direction is classified using the Lee and Ready (1991) algorithm. The data period is 48 trading days from February 23, 2026 to April 30, 2026.

	$ESpread_{i,j,t}$ (%)		$RSpread_{i,j,t}$ (%)		$PriceImpact_{i,j,t}$ (%)	
	Mean (1)	Median (2)	Mean (3)	Median (4)	Mean (5)	Median (6)
Fractional Shares:						
$<$ 1 share	0.644	0.326	0.546	0.244	0.095	0.026
$>$ 1 share	0.288	0.068	0.300	0.106	-0.003	0.000
1 (OTC)	0.437	0.127	0.417	0.105	0.021	0.011
1 (Exchange)	0.375	0.142	0.181	0.015	0.189	0.106
2 (OTC)	0.357	0.107	0.339	0.087	0.022	0.007
3 (OTC)	0.327	0.104	0.307	0.083	0.024	0.009
5 (OTC)	0.316	0.099	0.294	0.081	0.025	0.009
Oddlots	0.401	0.142	0.236	0.038	0.156	0.088
Oddlots–100	0.379	0.150	0.167	0.031	0.205	0.099
101–500	0.401	0.150	0.169	0.037	0.220	0.090
501–1,000	0.398	0.149	0.166	0.045	0.223	0.080
1,001–2,000	0.386	0.139	0.155	0.045	0.223	0.075
2,001–5,000	0.405	0.148	0.141	0.042	0.250	0.084
5,001–10,000	0.407	0.145	0.130	0.038	0.263	0.078
$>$10,000	0.511	0.270	0.181	0.068	0.300	0.095

1985; Glosten and Milgrom 1985).

These findings have important implications for the welfare of retail investors. The high effective and realized spreads on fractional share trades indicate that retail investors trading fractional shares face substantially worse execution quality than traders in other size categories. It suggests that retail brokers "cream skim" uninformed liquidity trades, leaving the information-based trades to established markets (Easley, Kiefer, and O'Hara 1996; Bolton, Santos, and Scheinkman 2016). While the elimination of explicit commission fees by retail brokers has been widely celebrated as a benefit for retail investors, the implicit costs embedded in the execution of fractional share orders reflected in the wide effective spreads, partially offset these gains.

4. Causal Effect

Having established the correlation between fractional trading and price discovery, this section provides causality evidence. We leverage two quasi-natural experiments: (i) two waves of introduction of fractional trading by major retail brokers in 2019; (ii) the new reporting policy of fractional trading quantity up to six decimal points in 2026.

4.1 Introduction of Fractional Trading in 2019

As described in Section 2.1, fractional share is not a new invention and typically arises following dividend reinvestment. In recent years, to attract retail clientele, some major brokers in U.S. updated their system and allowed their users to directly trade fractional shares of eligible stocks. Interactive Brokers was the first major U.S. broker to announce FT offerings on November 25, 2019, joined by Robinhood on December 12, 2019 and Fidelity on January 29, 2020.[10] The introduction of fractional trading stems from the competition among retail brokers and is therefore not endogenously determined by stock characteristics.

To estimate the causal effect of introducing fractional trading on market quality, I employ a DID design using a propensity-score-matched (PSM) sample. The matched sample follows Da, Fang, and Lin (2025). Each treatment stock, defined as a stock with a price above $100, is matched to a control stock with a price below $100 using one-to-one nearest-neighbor matching without replacement based on *ex ante* matching covariates. The matching procedure ensures that treatment and control stocks are similar on observable characteristics, so that any differential change in market quality around the events can be attributed to fractional trading *per se* rather than to pre-existing differences between high-priced and low-priced stocks.[11] The DID specification is:

$$Y_{i,t} = \beta_1 \times Treat_i \times Post_IB_FID_t + \beta_2 \times Treat_i \times Post_FID_t + \boldsymbol{\gamma' X_{i,t}} + \alpha_i + \eta_t + \epsilon_{i,t} \quad (8)$$

[10] Charles Schwab introduced fractional trading on June 9, 2020 but restricted to S&P 500 index constituents. We thus exclude this shock from our sample period.

[11] The details of matching covariates, matching procedure, and test of balance on covariates are provided in Section A.2.

where $Y_{i,t}$ denote two metrics of market quality: (i) liquidity measures, including percentage quoted ($QSpread_{i,t}$), effective ($ESpread_{i,t}$), and realized spreads ($RSpread_{i,t}$); (ii) price inefficiency measures, including autocorrelation ($AutoCorr_{i,t}$), price delay ($Delay_{i,t}$), and intraday volatility ($Volatility_{i,t}$) (e.g., Foley and Putniņš 2016). $AutoCorr_{i,t}$ denotes the absolute value of autocorrelation of 1-minute midquote stock returns (Hendershott and Jones 2005). $Delay_{i,t}$ reflects how slowly the stock price reflects market-wide information (Hou and Moskowitz 2005). $Volatility_{i,t}$ is the volatility of 1-minute midquote stock returns (O'Hara and Ye 2011). An efficient market implies that stock price follows a random walk, quickly incorporate market-wide information, and less deviate from fair values. Therefore, lower values of price inefficiency measures indicate more efficient price.

We define $Treat_i$ as an indicator equals to one (zero) if firm i is a treatment (control) stock. $Post_IB_FID_t$ is an indicator equals to one if day t falls between November 25, 2019, and January 28, 2020, and zero otherwise. $Post_FID_t$ is an indicator equals to one (zero) if day t falls on or after January 29, 2020, and zero otherwise. $\boldsymbol{X}_{i,t}$ denotes a battery of control variables including the inverse of stock closing price and natural logarithm of market capitalization. Finally, we include firm fixed effects (α_i) to control for time-invariant heterogeneity across firms and year-quarter fixed effects (η_t) to absorb time-varying shocks. The robust standard errors are clustered at the stock and day levels.

Table 5 reports the estimates of equation (8). Panel A shows that liquidity in high-priced stocks got worse after brokers introduced fractional trading. Relative to matched control stocks, the percentage quoted spread of treatment stocks rose by 4.5 bps (significant at the 1% level) during the initial window, when only Interactive Brokers and Robinhood offered fractional trading. Effective and realized spreads rose by 1.9 bps and 0.9 bps over the same window (significant at the 1% and 5% levels). After Fidelity entered on January 29, 2020, the effect on quoted spreads became small of 0.8 bps and statistically insignificant. Effective and realized spreads stayed significantly higher, by 1.0 bps and 0.8 bps, both significant at the 5% level. The economic magnitudes of quoted, effective, and realized spreads account for 20%, 22%, and 33% of the sample mean, respectively. These results suggest that liquidity takers payed higher transaction costs and liquidity providers earned higher rents after fractional trading was available.

Table 5
Effect of Introduction of Fractional Trading on Market Quality

This table reports the effect of introduction of fractional trading on market quality. In panel A, dependent variables are respectively the percentage quoted spreads, effective spreads, and realized spreads. $Treat_i$ is an indicator equals to one (zero) if firm i is a treatment (control) stock. $Post_IB_FID_t$ is an indicator equals to one if day t falls b/w November 25, 2019, and January 28, 2020, zero otherwise. $Post_FID_t$ is an indicator equals to one (zero) if day t falls on or after January 29, 2020, zero otherwise. Control variables include the inverse of stock closing price and natural logarithm of market capitalization. In panel B, dependent variables are the return autocorrelation, price delay, and volatility. The robust standard errors clustered at the stock and day levels are show in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Liquidity Metrics	$QSpread_{i,t}$	$ESpread_{i,t}$	$RSpread_{i,t}$
	(1)	(2)	(3)
$\boldsymbol{Treat_i \times Post_IB_FID_t}$	**0.045*** **	**0.019*** **	**0.009** **
	(0.01)	**(0.01)**	**(0.00)**
$\boldsymbol{Treat_i \times Post_FID_t}$	**0.008**	**0.010** **	**0.008** **
	(0.01)	**(0.00)**	**(0.00)**
$Inv_Prc_{i,t}$	1.082**	0.880***	−0.058
	(0.42)	(0.22)	(0.19)
$Size_{i,t}$	−0.021*	−0.008	−0.006
	(0.01)	(0.01)	(0.00)
Stock FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	346,850	346,680	345,855
Adjusted R^2	0.815	0.830	0.682
Panel B: Price Efficiency	$AutoCorr_{i,t}$	$Delay_{i,t}$	$Volatility_{i,t}$
	(1)	(2)	(3)
$\boldsymbol{Treat_i \times Post_IB_FID_t}$	**0.792*** **	**3.869*** **	**0.588** *
	(0.16)	**(0.78)**	**(0.35)**
$\boldsymbol{Treat_i \times Post_FID_t}$	**0.434*** **	**3.143*** **	**1.940*** **
	(0.10)	**(0.60)**	**(0.37)**
Controls	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	345,032	341,848	346,552
Adjusted R^2	0.069	0.566	0.687

Panel B shows that price efficiency also declined for treatment stocks. In the first event window, autocorrelation of 1-minute midquote returns rose by 0.792% and price delay rose by 3.869%, both significant at the 1% level. Intraday volatility rose by 0.588% at 10% significance level. The declines persisted after Fidelity introduced fractional trading. Relative to the pre-treatment period, autocorrelation, price delay, and volatility were higher by 0.434%, 3.143%, and 1.940%, all significant at the 1% level. Taken together, the results in Table 5 show that fractional trading was followed by wider spreads and less efficient prices. This is consistent with the view that fractional trading brings in a new retail clientele whose order flow harms market quality in high-priced stocks.

4.2 New Reporting Policy of Fractional Trading in 2026

The new reporting policy effective February 23, 2026 made the exact quantity of every fractional trade publicly visible in TAQ for the first time. This transparency shock created another quasi-natural experiment for studying the causal effects of fractional trading on market quality. Several channels could lead disclosure to affect fractional trading activity and subsequent market outcome. First, retail investors or their brokers may have valued the anonymity provided by the rounding convention, and the loss of this anonymity could reduce the willingness to trade fractional shares. Second, the visibility of fractional share order flow could affect the pricing behavior of market makers, who might adjust quotes or internalization practices in response to better information about the composition of small-order flow.

To mitigate the concern that the new reporting policy may affect other unobservables, we instrument the daily percentage of fractional trading ($\widehat{FS}_{i,t}$) in the first stage, and estimate the effect on market quality using a 2SLS regression:

$$\begin{aligned} \text{First stage: } & FS_{i,t} = \beta\ Treat_i \times Post_t + \boldsymbol{\gamma'} \boldsymbol{X}_{i,t} + \alpha_i + \gamma_t + \varepsilon_{i,t} \\ \text{Second stage: } & Y_{i,t} = \beta\ \widehat{FS}_{i,t} + \boldsymbol{\gamma'} \boldsymbol{X}_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t} \end{aligned} \tag{9}$$

where $FS_{i,t}$ is either $\frac{\text{number of fractional trades}}{\text{number of total trades}}$ or $\log(1 + \text{number of fractional trades})$ for stock i on day t; $Treat_i$ is an indicator equal to one for treatment stocks (price $\geq$ \$100) and

zero for control stocks; $Post_t$ is an indicator equal to one for trading days from February 23 to March 31, 2026 and zero for trading days from January 2 to February 20, 2026; $\boldsymbol{X}_{i,t}$ is a vector of time-varying stock characteristics including the inverse of stock closing price and natural logarithm of market capitalization. α_i and γ_t denote stock and day fixed effects, respectively. The robust standard errors are clustered at the stock and day levels.

A challenge for causal identification is that fractional share trading was not directly observable before the disclosure date. I address this challenge using the algorithm by Bartlett, McCrary, and O'Hara (2024) to detect potential fractional trading from Robinhood and Drivewealth in TAQ based on trade reporting facility and latency between the trade execution time and the participant reporting time. The algorithm is applied to OTC one-share trades: exchange code "D," (`EX='D'`) and trade size equal to one (`SIZE=1` before February 23; `SIZE`$\leq$`1` afterwards). Further, for Nasdaq TRF (`TRF in ('T','Q')`), the trades with latency (`TIME_M`$-$`PART_TIME`) between 135 and 300 milliseconds or greater than 20 milliseconds are classified as fractional trading. For NYSE TRF (`TRF in ('N')`), the trades with latency greater than 20 milliseconds are classified as fractional trading. An implicit assumption is that the technology and routing practices underlying these latency signatures did not change significantly between the algorithm's calibration period (around March 2022) and the study period.[12]

Panel A of Table 6 reports the first-stage results. In the odd columns, the coefficient on $Treat_i \times Post_t$ is negative and statistically significant across all specifications without control variables, indicating that the policy reduces fractional trading activity. Specifically, the share of fractional trades declines by 0.568%, and the log number of fractional trades decreases by 0.184, both significant at the 1% level. The magnitudes are economically significant as well, which account for 32% and 38% of the pre-treatment sample mean (1.770% and 0.485), respectively. These results are robust to the inclusion of control variables as shown in the even columns.

To ensure that the estimated effects are not driven by spurious time trends or unobserved confounding shocks unrelated to the policy, panel B of Table 6 conducts several placebo tests. Column (1) presents a placebo test using a pseudo-event date (January 31, 2026) and finds no

[12]I provide a detailed discussion on the algorithm and this assumption in Section A.1.

Table 6
Effect of Disclosure on Fractional Trading

This table reports the effect of new reporting policy on fractional trading. In panel A, the dependent variables are respectively the percentage of the number of fractional trades to the number of total trades (column (1) and (2)) and log(1+number of fractional trades) (column (3) and (4)), measured using the Bartlett, McCrary, and O'Hara (2024) algorithm. $Treat_i$ equals one (zero) for treatment (control) stocks in the PSM sample of Da, Fang, and Lin (2025). $Post_t$ equals one for trading days from February 23 to March 31, 2026 and zero for trading days from January 2 to February 20, 2026. Control variables include the inverse of stock closing price and natural logarithm of market capitalization. In panel B, column (1) adopts a placebo shock on January 31, 2026, and uses January 2 to 30, 2026 (February 2 to 22, 2026) as pre-(post-) treatment period. The dependent variables are the percentage of fractional trades, on-exchange one-share trades, off-exchange tiny trades (one-, two-, three-, and five-share trades), and odd-lots, respectively. The robust standard errors clustered at the stock and day levels are show in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect of disclosure on fractional trading

	$FS_{i,t}$			
	Percentage		log(1+# of Fractional Trades)	
	(1)	(2)	(3)	(4)
$\boldsymbol{Treat_i \times Post_t}$	**−0.568*** **	**−0.572*** **	**−0.184*** **	**−0.184*** **
	(0.13)	**(0.13)**	**(0.03)**	**(0.04)**
$Inv_Prc_{i,t}$		−1.078		−0.231
		(0.99)		(0.25)
$Size_{i,t}$		−0.176		−0.104*
		(0.23)		(0.06)
Stock FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	36,276	36,271	36,276	36,271
Adjusted R^2	0.418	0.418	0.724	0.724

Panel B: Placebo tests

	$FS_{i,t}$	$Ex_One_{i,t}$	$Tiny_{i,t}$	$Oddlots_{i,t}$
	(1)	(2)	(3)	(4)
$\boldsymbol{Treat_i \times Post_t}$	**−0.071**	**0.190**	**−0.028**	**−0.042**
	(0.06)	**(0.14)**	**(0.10)**	**(0.26)**
Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	20,240	36,271	36,271	36,271
Adjusted R^2	0.771	0.739	0.511	0.849

statistically significant effects on fractional trading measures. Column (2) to (4) find that the new reporting policy had no significant impact on other types of small trades, including on-exchange one-share trades, off-exchange tiny trades, and odd-lot trades, respectively.[13] The coefficients on $Treat_i \times Post_t$ are small and insignificant across all specifications, supporting the validity of the identification strategy.

The identification of the DID estimation in equation (9) relies on the assumption that, absent treatment, the dependent variable would have followed parallel trends across treatment and control firms. Figure 7 provides visual confirmation of the parallel trend assumption. Prior to the effectiveness date February 23, 2026, treatment stocks exhibit higher levels of proxied fractional trading than control stocks, but the gap between the two groups is relatively stable, consistent with the parallel trends assumption. At the effectiveness date, treatment stocks experience a sharp and immediate decline in proxied fractional trading, while control stocks show no comparable change. The gap between treatment and control narrows substantially in the post-disclosure period and remains at the reduced level throughout the remainder of the sample. Overall, the evidence suggests that the disclosure policy leads to a meaningful reduction in fractional trading, with no indication of confounding or spurious effects.

Next, we examine whether this reduction affected market quality. I replace the dependent variable in equation (9) with several *contemporaneous* measures of price efficiency and market quality.[14] The set includes the quoted spread, effective spread, realized spread, price impact, and intraday volatility. Because the disclosure shock reduced fractional share trading without directly affecting other aspects of market structure (e.g., exchange matching engines, order types, or fee schedules), any observed changes in market quality for treatment stocks relative to control stocks around the disclosure date can be attributed primarily to the reduction in fractional share activity. Table 7 reports the effect of the disclosure on market quality. In Panel A, the DID estimates show that $Treat_i \times Post_t$ is associated with

[13] A caveat is that, since the dependent variable is in percentage, there must exist some types of trades being mechanically increased after the new reporting policy. Though I cannot exhaust every type, they are at least not other off-exchange tiny trades or informative on-exchange small trades, which should partially address the concern of confounding effect.

[14] In the untabulated results, I replace the dependent variables by *next-day* liquidity and volatility, and find similar results.

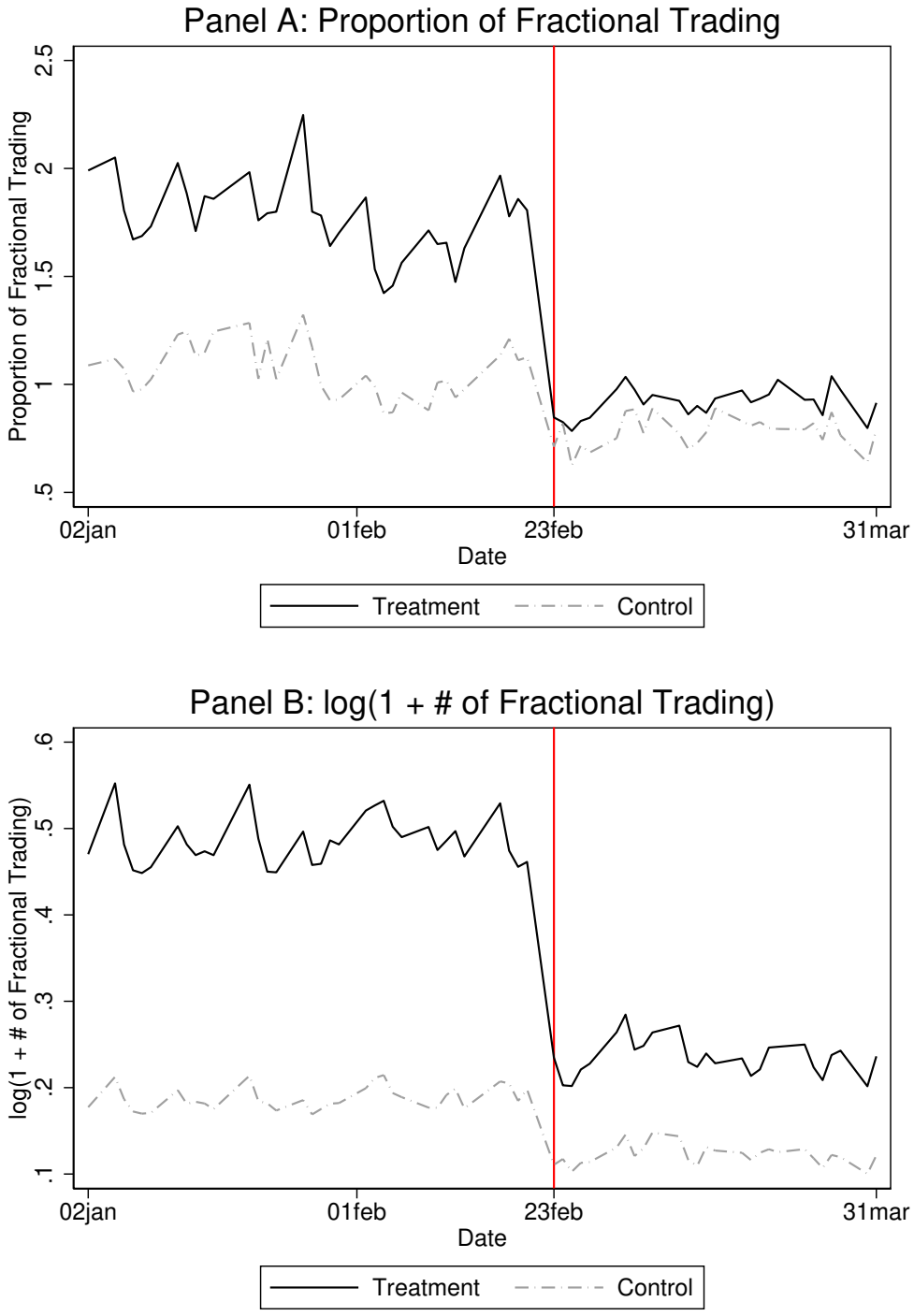


Figure 7. Event Study: Effect of Disclosure on Fractional Trading. This figure depicts the time series fractional trading for treatment stocks (solid line) and control stocks (dashed line) from January 2 to March 31, 2026. A vertical red line marks the February 23, 2026, the effectiveness date.

Table 7
Effect of Disclosure on Market Quality

This table reports the effect of new reporting policy on market quality. In panel A, the dependent variables are quoted spread (%), effective spread (%), realized spread (%), price impact (%), and intraday volatility (bps). $Treat_i$ equals one (zero) for treatment (control) stocks in the PSM sample of Da, Fang, and Lin (2025). $Post_t$ equals one for trading days from February 23 to March 31, 2026 and zero for trading days from January 2 to February 20, 2026. Control variables include the inverse of stock closing price and natural logarithm of market capitalization. In panel B, the main independent variable is the predicted percentage of the number of fractional trades to total trades, estimated by equation (9). The robust standard errors clustered at the stock and day levels are show in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Difference-in-differences regression	$QSpread_{i,t}$	$ESpread_{i,t}$	$RSpread_{i,t}$	$PriceImpact_{i,t}$	$Vola_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{Treat_i \times Post_t}$	**−0.022*** **	**−0.007** **	**−0.007*** **	**−0.001**	**−0.003** **
	(0.01)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
Controls	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Observations	36,233	36,219	36,120	36,107	36,231
Adjusted R^2	0.913	0.903	0.714	0.695	0.788
Panel B: Two-stage least squares regression	$QSpread_{i,t}$	$ESpread_{i,t}$	$RSpread_{i,t}$	$PriceImpact_{i,t}$	$Vola_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{\widehat{FS}_{i,t}}$	**0.038*** **	**0.012** **	**0.012*** **	**0.001**	**0.005** **
	(0.01)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
First-stage F-statistics			17.91		
Controls	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Observations	36,233	36,219	36,120	36,107	36,231
Adjusted R^2	0.913	0.903	0.714	0.695	0.788

a statistically significant reduction in quoted, effective, and realized spreads by 2.2 bps, 0.7 bps, and 0.7 bps, respectively. The magnitudes are economically meaningful by respectively accounting for 8.4%, 7.7%, and 21.9% of the pre-treatment sample mean. The intraday volatility also significantly decreases by 0.003 bps, around 39% of the pre-treatment sample

mean. In contrast, the coefficient on price impact is small and statistically insignificant. These results suggest that the policy improves liquidity without affecting the price impact, and substantially reduces short-term volatility by disciplining the fractional trading.

Panel B of Table 7 reports the results of 2SLS regression. The first-stage F-statistic of 17.91 exceeds conventional weak-instrument thresholds (Stock and Yogo 2005), supporting instrument relevance. The results indicate that higher fractional trading is associated with wider spreads and higher volatility: a one-unit increase in predicted fractional trading increases quoted spreads by 3.8 basis points (bps) and effective and realized spreads by 1.2 bps, all statistically significant at conventional levels. The effect on price impact remains insignificant, while intraday volatility increases by 0.005 bps Taken together, these findings suggest that the reduction in fractional trading induced by the disclosure policy improves overall market quality, primarily through narrower spreads and lower volatility.

4.3 Economic Mechanisms

Though our results are consistent with Bartlett, McCrary, and O'Hara (2024), this section proposes different economic mechanisms on the higher quoted spreads related to fractional trading. Bartlett, McCrary, and O'Hara (2024) interpret it as an evidence that fractional trading contains private information, thus market makers quote higher bid-ask spreads to compensate the adverse selection risks (Kyle 1985; Glosten and Milgrom 1985). Or, the introduction of fractional trading attracts large noisy order flow from exchanges to the OTC market, which mechanically increase the share of informed trading in the lit venues. The market makers, instead, quote higher bid-ask spread to hedge the adverse selection risks.[15] This paper, however, finds opposite empirical evidence in Section 3: fractional trading are generally liquidity-driven and represent uninformed order flow, so a reduction in fractional trading reduces the volume of noise trading and potentially improves price efficiency.

In this section, we propose two alternative hypotheses to reconcile this "inconsistency." The first mechanism is inventory management by market makers (dealers). As retail orders

[15]Section 5.2 will later show that on-exchange informed trading and fractional trading coincident simultaneously around important corporate events such as stock splits. Hu et al. (2025) also provide supportive evidence that a typical type of informed traders, short sellers, also actively trade around the market open, in parallel with the intraday pattern of fraction trading in Figure 4.

are highly correlated, higher retail order flow tends to increase market makers' inventory risks (Baldauf, Mollner, and Yueshen 2024). Da, Fang, and Lin (2025) find the introduction of fractional trading also increased tiny trades off-exchange. Though market makers cannot know the information of retail order flow to every market makers, they may perceive an increase of off-exchange retail orders from FINRA weekly public report. To compensate for this risk, market makers will widen quoted spreads.

To examine this hypothesis, we leverage the updated reporting policy in March 2021 as a quasi-natural experiments. Though retail brokers introduced FT in late 2019, they didn't realize that they need to report fractional trading to FINRA until March 2021. After March 2021, FINRA explicitly required brokers to report fractional trading, but rounding fractional quantity up to one whole share. Therefore, there was suddenly more one-share off-exchange trading (see Figure 11). On the one hand, if dealers perceived them as more uninformed trading, they would decrease quoted spreads because of lower adverse selection risks. On the other hand, if dealers perceived them as correlated order flow, they would increase quoted spreads because of higher inventory management risks.

To separate these two competing stories, we replace the $Post_{i,t}$ in the first stage of equation (9) by a new indicator that equals one if date t falls between April and December 2021, and zero if date t falls between January and February 2021. Table 8 report the results. After the new report policy in March 2021, dealers thought more correlated order flow upcoming, so that they widened the spreads to compensate for higher inventory risks.[16]

Second, the opaque reporting policy of fractional trading prior to February 23, 2026 may propagate moral hazard of retail brokers, who "cream skim" uninformed fractional trades, leaving the informed trades to established markets (Easley, Kiefer, and O'Hara 1996; Bolton, Santos, and Scheinkman 2016). In our context, brokers may route whole-share part of fractional trading (greater than one share) to wholesalers paying PFOF but with lower execution quality (higher spreads). To provide suggestive evidence, we compare the quoted spreads between the whole-share part of fractional trading and other whole-share trading

[16]This channel also reconciles the effect of the new reporting policy in 2026, which further revealed that these one-share trades are in fact fractional trading with much smaller quantity and can only be internalized and executed by retail brokers. Dealers therefore decreased quoted spreads as the true inventory risks are lower than expectation.

Table 8
Effect of 2021 Reporting Policy of Fractional Trading on Liquidity

This table reports the effect of 2021 reporting policy of fractional trading on liquidity. The dependent variables are quoted spread (%), effective spread (%), and realized spread (%) (bps). $Treat_i$ equals one (zero) for treatment (control) stocks in the PSM sample of Da, Fang, and Lin (2025). $Post_t$ equals one if date t falls between April and December 2021, and zero if date t falls between January and February 2021. Control variables include the inverse of stock closing price and natural logarithm of market capitalization. The robust standard errors clustered at the stock and day levels are show in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$QSpread_{i,t}$	$ESpread_{i,t}$	$RSpread_{i,t}$
	(1)	(2)	(3)
$\boldsymbol{Treat_i \times Post_t}$	**0.034*** **	**0.019*** **	**0.004*** **
	(0.01)	**(0.00)**	**(0.00)**
Controls	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	69,561	69,541	69,375
Adjusted R^2	0.892	0.883	0.776

with the same quantity at the first 30-minute (9:30 a.m. to 10:00 a.m.) for each stock-day. If there is no selective routing or "cream-skimming" behavior, both trading types should be charged by the similar spreads. Alternatively, if fractional trading is charged by higher spreads, it may suggest that retail brokers route whole-share part of fractional trading to a dealer with lower quality. Figure 8 comes down in favor of the second explanation. We find both realized and effective spreads are higher for fractional trading than whole-share trading with the same whole-share quantity, across different size groups.

5. Real Effect of Fractional Trading on Stock Splits

This section investigates the real effect of fractional trading on corporate decisions. Stock-split is a natural laboratory for two reasons. First, the *optimal trading range hypothesis* posits that managers split their stock to bring the share price back to a preferred trading range, thereby making shares more accessible to small, liquidity-constrained investors (Copeland

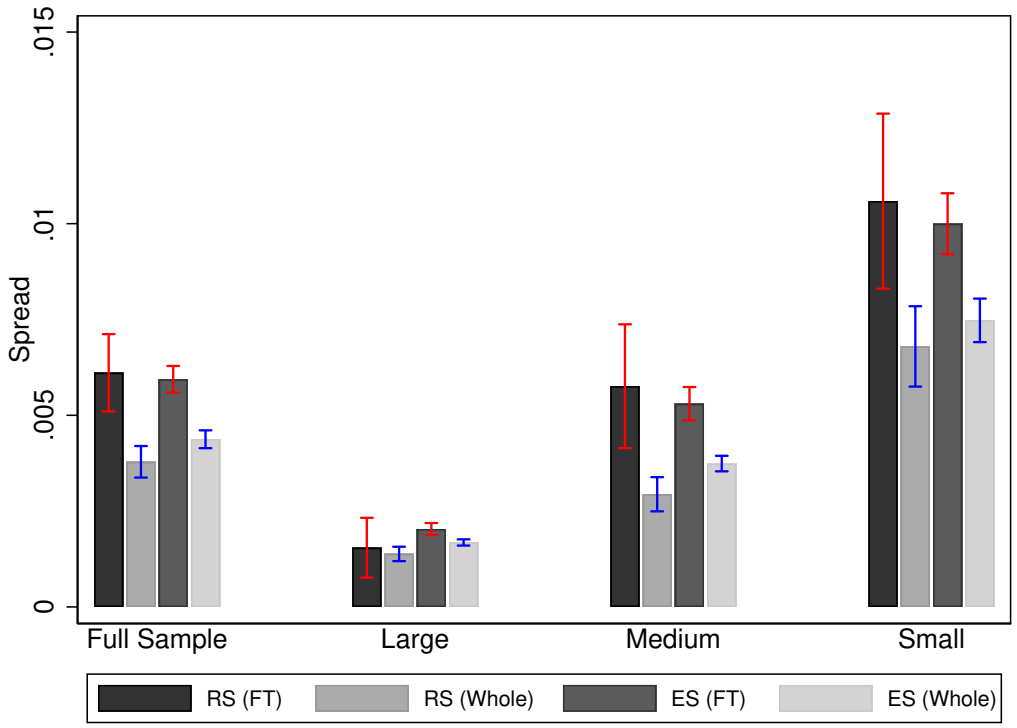


Figure 8. Comparison of quoted spreads between fractional and whole-share trading with the same whole-share quantity.. This figure compares the average realized spreads (RS) and effective spreads (ES) between fractional (dark bars) and whole-share trading (gray bars) with the same whole-share quantity. The sample period spans from February 23 to April 30, 2026.

1979; Baker and Gallagher 1980; Lakonishok and Lev 1987). The fractional trading, however, allows households to access to the high-price and large stocks even with very high trading range. The information content of stock splits, e.g., the stock-split announcement abnormal returns, could be reshaped in the fractional trading era. Second, retail traders, especially fractional traders, actively engaged in attention-grabbing events.[17] This irrational investor behavior is likely to distort rational manager's optimal stock-split outcomes discussed by Li and Ye (2026). This section first reviews the literature on stock splits, and further establish the causal effects of fractional trading on stock-splits outcomes, including announcement abnormal returns and optimal reduced quoted spreads following actual stock splits.

[17]Figure 11 shows that off-exchange trades at or below one share accounted for a substantial proportion of trading activities during GameStop episodes. Barber and Odean (2008) hypothesize that individual investors tend to purchase only stocks that have first caught their attention. Da, Fang, and Lin (2025) empirically document that the number of tiny trades spikes around attention-grabbing events and contribute to the short-term stock bubble.

5.1 Stock-Split Announcement Abnormal Returns

A large body of research documents that stock splits are associated with abnormal announcement returns, increased trading activity, and a wider investor base (Fama et al. 1969; Grinblatt, Masulis, and Titman 1984; Lamoureux and Poon 1987; Ikenberry, Rankine, and Stice 1996). Explaining *why* a purely cosmetic change in the number of shares outstanding should affect firm value has proven surprisingly difficult, and several competing hypotheses have emerged over the past half century.

The *optimal trading range hypothesis* posits that managers split their stock to bring the share price back to a preferred trading range, thereby making shares more accessible to small, liquidity-constrained investors (Copeland 1979; Lakonishok and Lev 1987; Angel 1997). Under this view, splits are value-relevant because they lower the effective barrier to entry: imagine that a retail investor with limited capital can purchase round lots of a $50 stock but not a $500 stock. The *signaling hypothesis*, by contrast, argues that only managers confident about future earnings are willing to incur the transaction costs of a split, so the announcement conveys positive private information to the market (Grinblatt, Masulis, and Titman 1984; Brennan and Copeland 1988; McNichols and Dravid 1990; Ikenberry, Rankine, and Stice 1996). Fama et al. (1969), Lakonishok and Lev (1987), and Asquith, Healy, and Palepu (1989) find, however, that stock prices, earnings, and profits rise significantly before splits but not after them. The skyrocketing of retail investors and fractional traders suggests a third class of explanations, which emphasize the *attention* channel: splits generate media coverage and brokerage reports, temporarily placing the stock in investors' choice sets and increasing demand through the attention channel (Barber and Odean 2008; Da, Fang, and Lin 2025). Several prominent recent splits provide suggestive motivation. Apple (August 31, 2020), Tesla (August 31, 2020 and August 25, 2022), Amazon (June 6, 2022), and Alphabet (July 15, 2022) all announced stock splits during a period in which fractional trading was already widely available. Yet each announcement generated substantial abnormal returns and media attention, consistent with the attention channels continuing to operate even when the price-barrier channel may have been largely neutralized by fractional trading.[18]

[18]See, e.g., "The Biggest Stock Splits of 2022 and What They Mean for Investors" discussing the wave of high-profile splits and their strong investor attention in the era of fractional trading. See also "Why Stock

Disentangling these explanations has been empirically challenging because, in a world of whole-share trading, all three channels are activated simultaneously on the split announcement date. The rapid adoption of fractional trading on major retail brokerage platforms—most notably since late 2019 and 2020—offers a powerful new setting in which to separate them. When investors can purchase arbitrary dollar amounts of any stock regardless of its nominal price, the accessibility rationale for splits is substantially weakened, if not eliminated entirely. A retail investor with $50 can now own exposure to a stock trading at $3,000 per share just as easily as one trading at $30. If the optimal trading range hypothesis is the dominant driver of split announcement returns, we should observe a decline in those returns as fractional trading penetration grows. If, on the other hand, signaling or attention effects dominate, the split premium should remain largely intact even as fractional trading renders the price-barrier argument moot.

I trace back the common stock–split announcements (CRSP event code 5523) and the split ratio from January 2003 to December 2025 for our sample stocks. Following Li and Ye (2026), I exclude reverse splits. I also require the declaration date, the ex-date (i.e., the actual split date), and the split ratio to be neither missing nor duplicated by CRSP. Following Grinblatt, Masulis, and Titman (1984), I require that stock-split ratios be greater than or equal to 1.25. We end up with 875 unique stock splits. Table 9 presents the summary statistics. The average split ratio is around 2.072, with the most common splits are 2-for-1 splits and 1.5-for-1 splits. The average price before a split announcement is $79.57 and the average price after a split is $39.66. An average stock-split stock has a market capitalization of $8.9 billion and 2.53% of announcement abnormal returns. The stock splits on average successfully decrease the bid-ask spread from 22.83 cents to 11 cents.

The identification strategy hinges on the adoption of fractional trading by major retail brokers in 2019 and 2020, Interactive Brokers (November 2019), Robinhood (December 2019), Fidelity (January 2020), and Schwab (June 2020). I exploit both time-series and cross-sectional variation in stock-split events. Specifically, I will compare the three-day CAR around stock-split announcements between high- and low-price stocks, before 2019 and after

Splits like Amazon's are an Antiquated Move" on Amazon's split generating a price reaction despite the prevalence of fractional trading.

Table 9
Summary Statistics of Stock Splits

This table presents the summary statistics for main variables of interests on stock splits. Gap is the number of days between the declaration (announcement) date and ex-date. Pre-split (ex-ante) variables are estimated as the average value from 180 days to 60 days before the declaration date. Post-split (ex-post) variables are estimated as the average value from 60 days to 180 days after the ex-date. To mitigate the potential influence of extreme values, I winsorize the continuous variables at the 1st and 99th percentiles.

	N	Mean	*SD*	Q1	Median	Q3
Split Ratio	875	2.072	1.144	1.500	2.000	2.000
Gap (# of days)	875	38.494	20.266	27.000	33.000	46.000
Pre-split price ($)	875	79.566	129.523	32.729	50.471	77.136
Post-split price ($)	875	39.658	27.665	24.034	33.075	47.113
Market cap ($b)	875	8.935	22.440	0.446	1.673	5.560
Ann. CAR (%)	875	2.531	4.857	−0.121	1.736	4.466
Ex-ante spread (cents)	875	22.829	36.950	4.493	8.753	23.007
Ex-post spread (cents)	875	10.996	16.252	2.695	4.728	11.856

2020. If the optimal trading range hypothesis drives the split premium, the announcement return should be *smaller* for stocks with high pre-existing fractional participation. A finding of no difference or in the opposite way would favor the signaling or attention hypotheses.

5.2 Effect of Fractional Trading on Announcement Returns

Figure 9 shows the three-day CAR for stock-split announcements declared from 2003 to 2025, separately for high-price stocks ($\geq$ \$100, solid blue line) and low-price stocks ($<$ \$100, dashed red line). The vertical dashed lines denote the adoption period of fractional trading between 2019 and 2020. Before 2019, two groups largely co-move with similar magnitudes, both fluctuating between approximately 0% and 5%. There is no systematic wedge between high-price and low-price split announcements, consistent with the traditional view that split announcement returns are driven by common factors—signaling, optimal trading range, or attention—regardless of price level. After 2020, a visible divergence emerges. While the CAR of high-price stocks maintains or even increases, that of low-price stocks declines sharply, frequently approaching zero or turning negative. The spread between the two groups widens persistently.

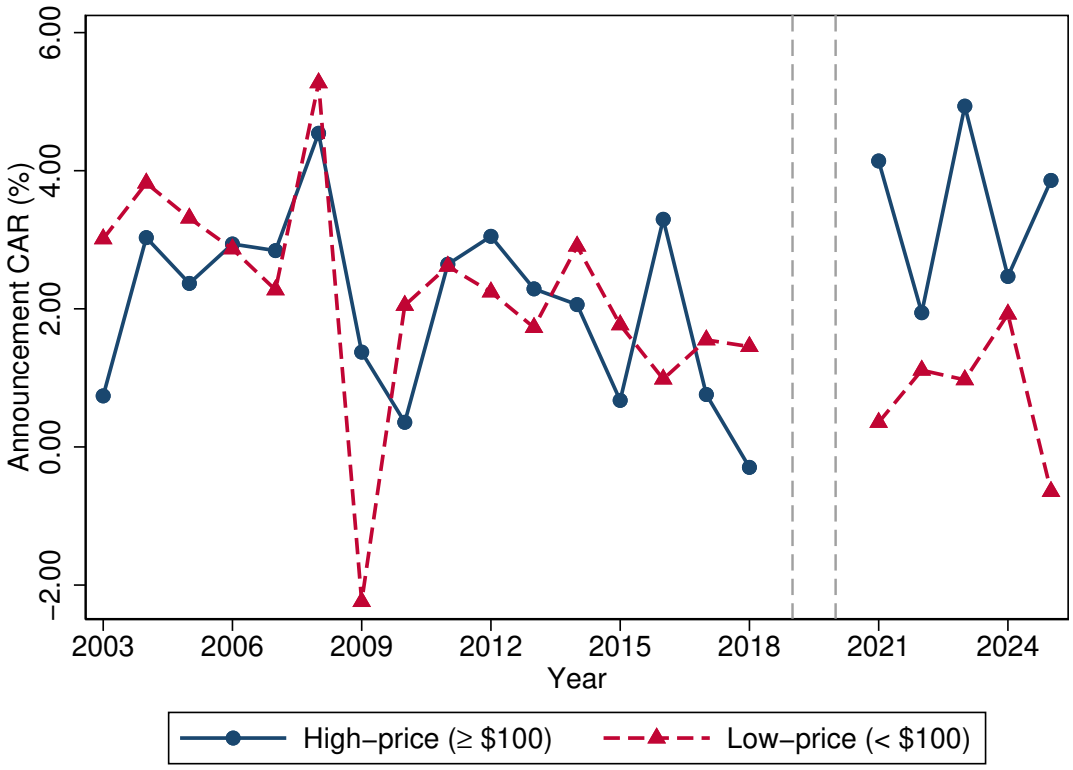


Figure 9. Proportion of Fractional Shares: Time-series. This figure shows the proportion of total trades accounted for by fractional shares (<1 share), off-exchange 1-share trades, exchange 1-share trades, odd-lots, and mixed-/round-lots. Panel A: Value-weighted. Panel B: Equal-weighted. Sample period: February 23 to April 12, 2026.

Table 10 displays a formal analysis. Panel A reports short-run three-day CARs over the announcement window $[-1, +1]$ based on raw stock returns, excess returns over value-weighted market returns, and CAPM. Across all benchmarks, the DID estimates (Column 7) are positive and significant, ranging from 1.953% to 3.022%, indicating that the widespread of fractional trading differentially amplifies announcement returns for high-price stocks relative to low-price stocks. These results suggest that, once fractional trading allows investors to purchase partial shares at any price, the traditional optimal trading range rationale for splits becomes obsolete, and the market discounts the informational value of low-price splits accordingly. Meanwhile, high-price split announcements attract disproportionate attention from fractional traders who already hold fractional positions in these stocks, inflating short-run returns through an attention-momentum channel consistent with Grinblatt, Masulis, and Titman (1984) and Barber and Odean (2000).

Table 10
Effect of Fractional Trading on Stock-Split Abnormal Returns

This table presents the univariate difference-in-differences analysis of cumulative abnormal returns (CAR) in percentage points around stock split announcements. Panel A and B respectively compare three-day CAR$[-1,+1]$ and long-run CAR$[+2,+252]$ for high-price ($\geq$ \$100) and low-price stocks ($<$ \$100) before (January 2003–November 2019) and after (January 2021–December 2025) the widespread availability of fractional trading. Difference (Diff.) reports within-group changes, and DID shows the estimates (3)−(6). The t-statistics are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	High-price			Low-Price			
	Before (1)	After (2)	Diff. (3)	Before (4)	After (5)	Diff. (6)	DID (7)
Panel A: Announcement $CAR[-1,+1]$							
Raw	2.446	3.395	0.966	2.784	0.972	−2.056***	3.022***
			[1.20]			[-3.06]	[2.61]
Market	1.963	2.382	0.480	2.262	0.882	−1.473**	1.953*
			[0.63]			[-2.42]	[1.84]
CAPM	2.319	2.966	0.677	2.743	0.943	−1.973***	2.650**
			[0.90]			[-3.16]	[2.46]
Panel B: Long-run $CAR[+2,+252]$							
CAPM	8.565	24.839	13.917**	3.501	-8.861	−12.487**	26.404***
			[2.12]			[-2.58]	[3.14]

Panel B extends the analysis to long-run CARs over $[+2,+252]$. The DID estimate of 26.404% ($t = 3.14$) reveals a persistent and economically large wedge: high-price stocks experience significant positive drift (13.917%) after fractional trading. This pattern aligns with the post-split drift documented by Desai and Jain (1997), but is substantially amplified by fractional traders' momentum behavior. For high-price stocks, attention-driven net-buying by fractional traders, who behave as momentum traders, sustains upward price pressure well beyond the announcement window (Welch 2022). For low-price stocks, the absence of a genuine accessibility motive, combined with the liquidity deterioration induced by fractional trading (i.e., wider realized quoted spreads), generates a negative feedback loop that depresses long-run returns. The negative long-run returns for low-price stocks also contradict with the signaling hypothesis, which conjecture that firm managers signal positive private

information through stock-split announcements.

To further confirm the underlying mechanism that the fractional traders are attention-driven momentum traders, and subsequently contribute to both short-run and long-run abnormal returns of high-price stocks. Figure 10 depicts the trend of abnormal fractional trading (proxied by one-share off-exchange trading following Da, Fang, and Lin (2025)) around the stock-split announcement by Apple Inc. declared on July 30, 2020. I define the abnormal number of trades as the natural logarithm of daily number of trades minus the median value over $[-200, -100)$ event window.

Panel A closely tracks the increase in announcement-period abnormal returns around 12%. Off-exchange and exchange one-share trades increase by 250% and 200% from day -1 to day $+1$, respectively. The rise is especially pronounced for off-exchange one-share trades, consistent with stock-split announcements attracting fractional trading demand. Panel B shows that this increase is not confined to the three-day announcement window. One-share trading activity spikes immediately after the announcement and at the ex-date. The off-exchange and on-exchange one-share trades begins to diverge after the announcement date, consistent with momentum trading behavior of fractional traders. The pattern suggests that stock splits generate investor attention attracting fractional traders respond strongly to these salient corporate events, and that the momentum trading behavior of fractional traders may explain the long-run abnormal returns for high-price stocks in Table 10.

Taken together, the results suggest that fractional trading fundamentally disrupts the traditional signaling equilibrium of stock splits, stripping low-price splits of their economic rationale while supercharging high-price splits through an attention-momentum mechanism.

5.3 Effect of Fractional Trading on Rational Split Outcomes

Besides the stock-split announcement abnormal returns, there are two additional puzzles in the behavioral finance literature on stock splits. The volatility puzzle states that it is puzzling for volatile firms to be more likely to split their stocks because they have a "greater chance of reaching a low price anyway" (Baker, Greenwood, and Wurgler 2009). The social-norm puzzle states that firms set stock prices that are similar to those set by similarly sized firms and industry peers (Weld et al. 2009). In contrast, Li and Ye (2026) rationalize

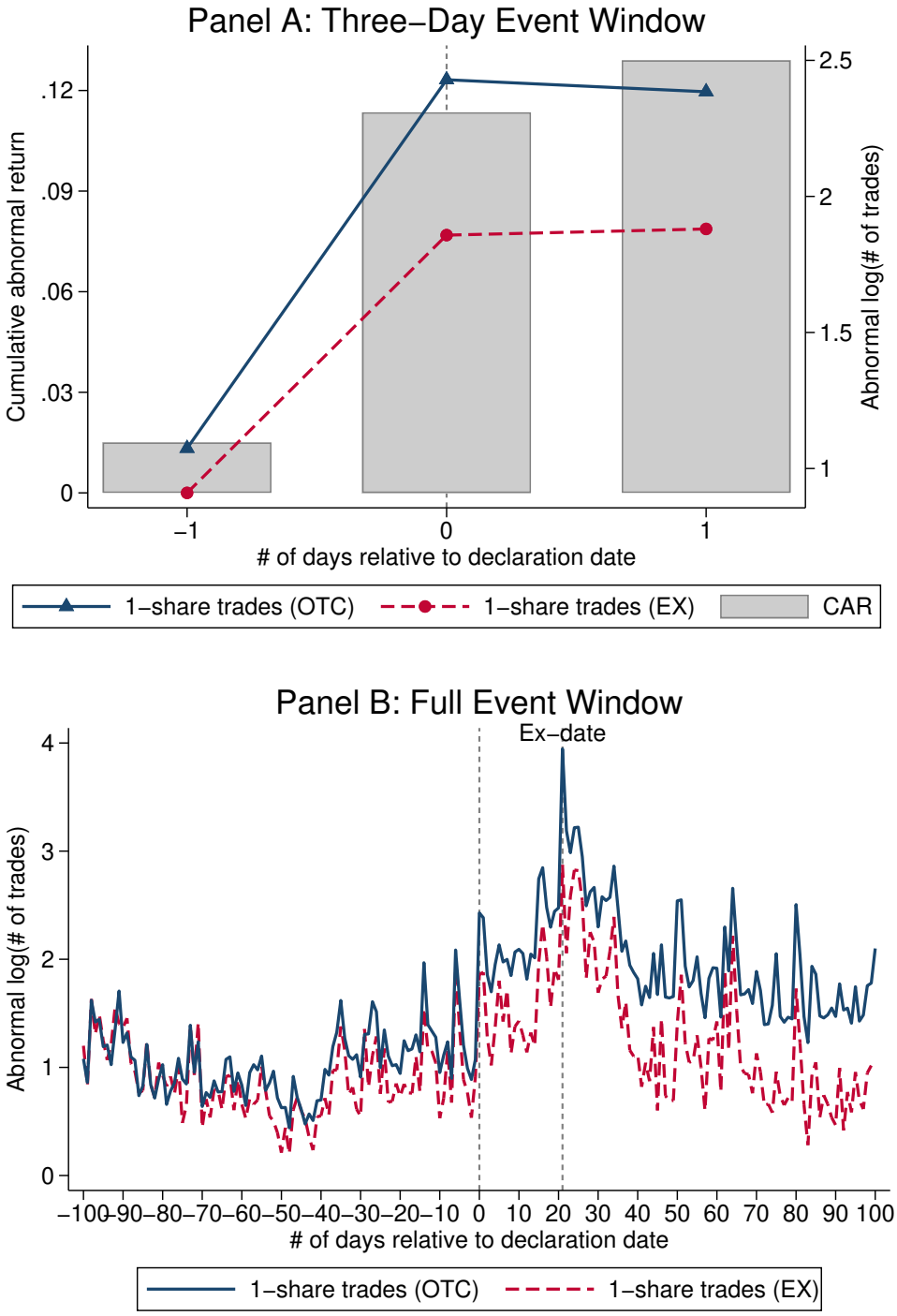


Figure 10. Trading activity around stock-split announcements. This figure plots abnormal log trading activity around the stock-split of Apple Inc. declared on July 30, 2020. Panel A focuses on the three-day announcement window $[-1, +1]$ and reports abnormal log trades for off-exchange one-share trades, which proxy for fractional trading, and exchange one-share trades, together with cumulative abnormal returns. Panel B plots the full event window from 100 trading days before to 100 trading days after the declaration date. Day 0 denotes the stock-split declaration date.

these two puzzles by arguing that firms split the stocks to lower prices because they tend to lower the adverse selection risks and bid-ask spreads due to high volatility, and similar stocks appear to have similar volatilities. Their model implies that splits move stock prices toward a spread-minimizing optimum: a predicted 1 bps increase in the spread (R_i) maps nearly one-for-one into a realized one bps increase ($\Delta\mathcal{S}_i$). In their data sample, 91% of stock splits are "correct" in that they move the percentage spread closer to the optimum. The key empirical implication is that the microstructure-based rationale should fully explain realized post-split spread changes, leaving no residual role for other variables.

Leveraging this rational framework, I examine whether the introduction of fractional trading disrupts the mapping between model-predicted and realized spread changes. My hypothesis is that attention-driven momentum trading by fractional traders who disproportionately target high-price splitting stocks, introduces post-split liquidity dynamics not captured by the rational split decisions, thereby distorting optimal split outcomes.

I begin with replicating Li and Ye (2026) by estimating the following specification:

$$\Delta\mathcal{S}_{i,t} = \beta_1\ R_{i,t} + \beta_2\ H_{i,t} + \boldsymbol{\psi}'\boldsymbol{X}_{i,t} + \alpha_j \times \gamma_t + \varepsilon_{i,t} \tag{10}$$

where $\Delta\mathcal{S}_{i,t}$ is the realized change in the percentage quoted spread, measured as the difference between the average percentage spread in the $[-180, -60]$ window before the announcement and the $[+60, +180]$ window after the ex-date; $R_{i,t}$ is the model-predicted (expected) change in the percentage spread from the Modified Square Rule (Corollary 2 in Li and Ye (2026)); $H_{i,t}$ is the natural logarithm of the split ratio. Control variables $\mathbf{X}_{i,t}$ include the natural logarithm of stock price, market capitalization, dollar volume, and turnover ratio, following Weld et al. (2009).

Column (1) of Table 11 replicates the baseline finding of Li and Ye (2026): the coefficient on $R_{i,t}$ is 0.915 ($p < 0.01$), which is indistinguishable from one, confirming that model-predicted spread changes map nearly one-for-one into realized spread changes in our sample.

Section 3 shows that an increase of fractional trading widens the bid-ask spreads. A natural follow-up question is whether fractional trading attracted by stock splits increases the realized quoted spreads *ex post*. I next investigate this question by estimating the following

Table 11
Effect of Fractional Trading on Stock-Split Realized Quoted Spreads

This table reports the effect of fractional trading on realized reduction in the percentage quoted spread. $\Delta\mathcal{S}_{i,t}$ is the realized change in the percentage quoted spread, measured as the difference between the average percentage spread in the $[-180, -60]$ window before the announcement and the $[+60, +180]$ window after the ex-date. $R_{i,t}$ is the model-predicted (expected) change in the percentage spread from the Modified Square Rule (Corollary 2 in Li and Ye (2026)); $H_{i,t}$ is the natural logarithm of the split ratio (1+`FACSHR`). Control variables $\mathbf{X}_{i,t}$ include the natural logarithm of stock price, market capitalization, dollar volume, and turnover ratio, following Weld et al. (2009). We include either industry (2-digit SIC)-year or year fixed effects to absorb any common shocks. The robust standard errors clustered at year level are show in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$\Delta\mathcal{S}_{i,t}$		
	(1)	(2)	(3)
$\boldsymbol{HighPrice_i \times Post_t \times R_{i,t}}$			**-0.741***
			(0.41)
$\boldsymbol{HighPrice_i \times Post_t}$		**0.203****	**0.001**
		(0.07)	**(0.07)**
$\boldsymbol{R_{i,t}}$	**0.915*****		**0.807*****
	(0.18)		**(0.13)**
$H_{i,t}$	0.154		0.003
	(0.09)		(0.05)
$HighPrice_i \times R_t$	No	No	Yes
$HighPrice_i \times R_t$	No	No	Yes
$HighPrice_i$	No	Yes	Yes
Controls	Yes	No	Yes
Industry×Year FE	Yes	No	No
Year FE	No	Yes	Yes
Observations	756	880	848
Adjusted R^2	0.351	0.036	0.289

regression:

$$\Delta\mathcal{S}_{i,t} = \beta\ HighPrice_i \times Post_t + \boldsymbol{\psi'}\boldsymbol{X}_{i,t} + HighPrice_i + \gamma_t + \varepsilon_{i,t} \tag{11}$$

where $HighPrice_i$ is an indicator equal to one if the pre-split stock price is at or above \$100; and $Post_t$ is an indicator equal to one for splits announced after the widespread adoption of fractional trading (January 2021 to December 2025) and zero for splits announced before

(January 2003 to October 2019). Column (2) of Table 11 shows that high-price stocks experience a 0.203 bps larger increase in realized spreads after fractional trading ($p < 0.05$), consistent with attention-driven order flow degrading liquidity for these stocks.

Finally, I investigate whether the spikes of fractional trading affect managerial stock-split decisions and distorts the outcome of rational optimal stock splits by estimating the following specification:

$$\Delta \mathcal{S}_{i,t} = \beta_1 \; HighPrice_i \times Post_t \times R_{i,t} + \beta_2 \; R_{i,t} + \boldsymbol{\psi}' \boldsymbol{X}_{i,t} + \gamma_t + \varepsilon_{i,t}, \tag{12}$$

If firm managers expect the impact of fractional trading on bid-ask spreads, they should increase the split-ratio after 2020. In other words, β_1 should be insignificant or significantly positive. Column (3) of Table 11 rejects this hypothesis. The coefficient on $HighPrice_i \times Post_t \times R_{i,t}$ is -0.741 ($p < 0.10$), while the coefficient on $R_{i,t}$ alone remains 0.807 ($p < 0.01$). It suggests that managers did not offset the effect of fractional trading on bid-ask spreads by adopting more aggressive split ratio.

These findings support our hypothesis that attention-driven momentum trading by fractional traders distorts optimal split outcomes. When high-price firms split to approach their *ex-ante* spread-minimizing price, the resulting attention shock attracts fractional traders whose correlated order flow widens the realized quoted spread *ex post*. The one-for-one mapping between predicted and realized spread improvements—the hallmark of a well-functioning price-management mechanism—breaks down precisely for the stocks most targeted by fractional traders. In economic terms, the liquidity benefit that historically justified stock splits is substantially attenuated for high-price stocks in the fractional-trading era, as the gains from moving toward the tick-size optimum are offset by the liquidity costs imposed by attention-driven trading.

6. Policy Implications and Discussion

Regulation is a key research topic in market microstructure (Ernst and Spatt 2025). This section discusses three aspects on regulating fractional trading: (i) transparency; (ii) exe-

cution quality; (iii) real effects on high-price stocks. Fractional trading has expanded retail access to high-priced stocks and made dollar-based investing more convenient. At the same time, the evidence in this paper shows that fractional trades are not merely a mechanical innovation in order size. They represent a distinct segment of retail order flow: they are concentrated in high-price and large-cap stocks, spike around attention-grabbing events, exhibit patterns consistent with dollar-based retail orders, and differ sharply from exchange-executed tiny trades in their contribution to price discovery. Most importantly, fractional trades carry little price-relevant information but face relatively high trading costs, as reflected in high effective and realized spreads and low price impact. These findings suggest that fractional trading creates a central regulatory tradeoff: it democratizes market access, but it may also expose retail investors to weaker execution quality in a less competitive execution environment than traditional retail traders (Barber and Odean 2000; Eaton et al. 2022).

Transparency. The first policy implication concerns transparency. The February 23, 2026 FINRA reporting enhancement, which requires fractional share quantities to be reported up to six decimal places, is an important step toward making fractional trading observable. Before this reform, sub-one-share trades were rounded up to one share, making genuine one-share trades indistinguishable from fractional trades in public transaction data, which created a "mystery" documented by Bartlett, McCrary, and O'Hara (2025a). They study the sudden surge in trading volume of Berkshire Hathaway Class A shares after 2021 (as shown in panel A of Figure 11). BRK.A had historically traded only a few hundred shares per day, but reported volume suddenly increased dramatically. Bartlett, McCrary, and O'Hara (2025a) show that much of this increase was not real economic trading volume. Instead, it was "phantom volume" created by the interaction of fractional-share trading and FINRA's trade-reporting rules: sub-one-share trades were rounded up and reported as one-share trades, causing tiny fractional trades to appear in public data as full-share transactions.

The key point is that poor transparency made the market data misleading. A small dollar-based purchase of BRK.A through a retail broker could involve only a tiny fraction of one share, but the consolidated tape recorded it as a one-share trade. For an extremely high-priced stock such as BRK.A, this rounding error was economically enormous: a few dollars

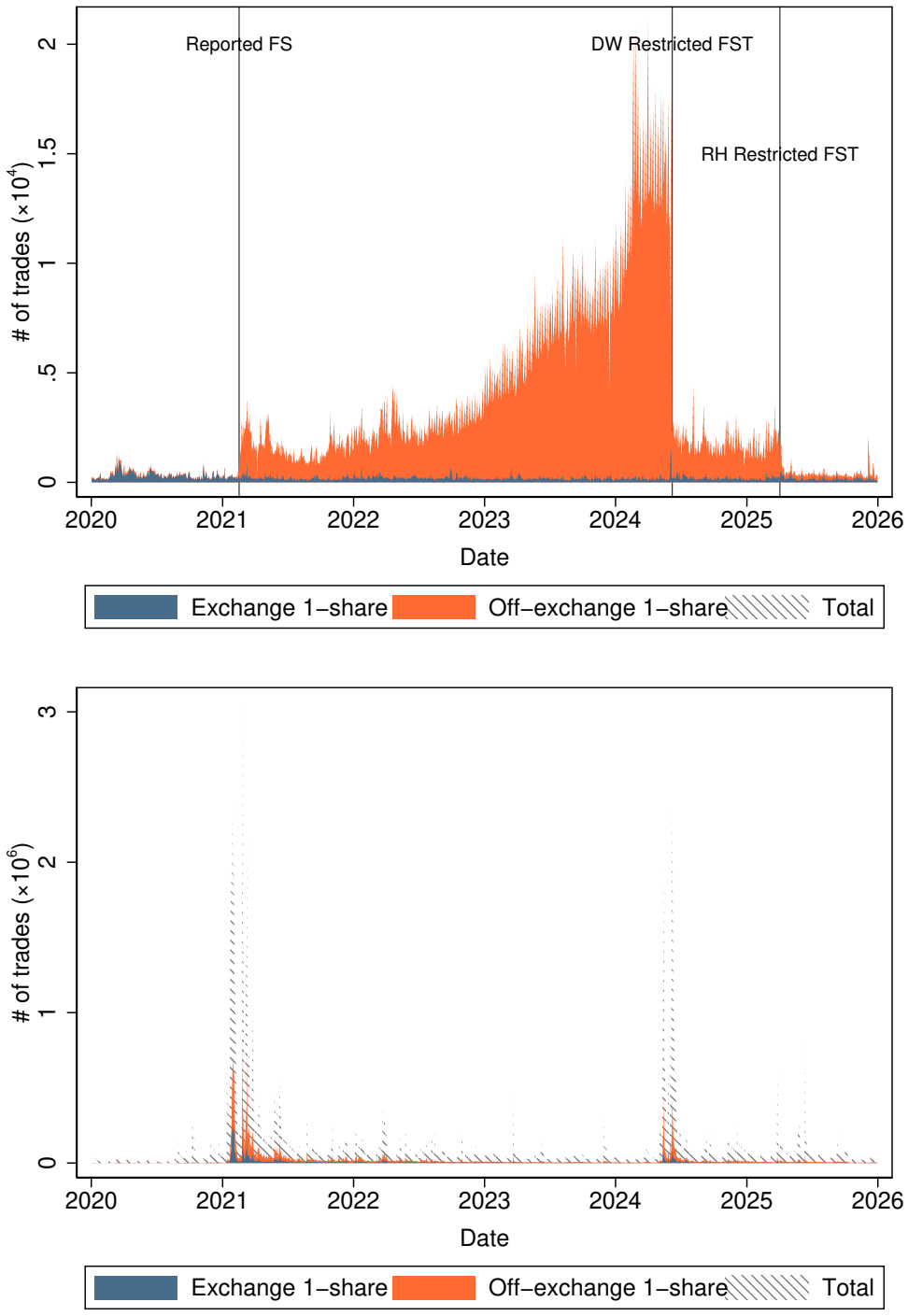


Figure 11. Trend of 1-Share Trading for Selected Stocks. Two panels showing the daily number of 1-share trades (exchange, off-exchange, and total) for BRK.A (NYSE) and GME (NYSE) from 2020 to 2026. Vertical lines indicate the Robinhood started to report fractional trading, Drivewealth restricted FST date, and Robinhood restricted FST date.

of fractional exposure could be reported as hundreds of thousands of dollars of volume.[19] Bartlett, McCrary, and O'Hara (2025a) also argue that this distorted reported volume, created apparent dislocations between BRK.A and BRK.B, increased trading costs, and even generated incentives for manipulation.

By rendering fractional trades directly identifiable, the new reporting regime allows regulators, researchers, and market participants to evaluate the size, timing, and execution quality of fractional trades, especially during extreme market episodes (e.g., GameStop short squeezing, as shown in panel B of Figure 11). The results in this paper show that this transparency is not merely cosmetic: the disclosure shock reduces fractional trading in treated stocks and is associated with narrower spreads and lower intraday volatility. These findings support the view that disclosure can discipline trading behavior and improve market quality in a relatively nonintrusive way.

Execution quality. The second implication concerns execution quality. Unlike whole-share orders, which can be routed to wholesalers and may ultimately be internalized or routed to exchanges, fractional-share orders are executed off-exchange through the broker's internal book. This institutional feature limits direct competition for fractional order flow. Because fractional orders are often small, dollar-based, and liquidity-motivated, retail investors may be less sensitive to small differences in execution quality. The combination of low information content and high realized spreads suggests that brokers or affiliated liquidity providers may earn substantial rents from fractional order execution. Regulators should therefore consider requiring standardized execution-quality statistics for fractional orders, including effective spreads, realized spreads, price improvement relative to the NBBO, execution speed, and the extent to which fractional orders are filled from broker inventory. Such disclosures would make fractional execution quality comparable across brokers and would help ensure that the benefits of expanded market access are not offset by hidden trading costs.

Two related regulatory developments are the SEC's broader attention to retail order execution. In December 2022, the SEC under former Chair Gary Gensler proposed an amendment on SEC Rule 615, the Order Competition Rule, which would have required

[19] In Section B.1.3, I show that the rounding error induce 60% overestimation bias on the fractional trading order imbalance measures, especially for large stocks.

"segmented orders", predominantly marketable retail orders, to be exposed to order-by-order (OBO) competition through qualified auctions before being internalized by wholesale market makers (SEC 2025a). The proposal aimed to address concerns that PFOF arrangements and internalization reduce price improvement for retail investors by insulating wholesalers from direct competition on individual orders. Subsequently, however, Ernst, Spatt, and Sun (2025) aruge that the auction mechanism breeds the winner's curse problem, which may further discourage the competition. I do not take a position on whether such auctions should be applied to fractional trades. Fractional orders have distinctive economics: they are typically very small, cannot be routed to exchanges as fractional quantities, and may involve operational costs that are large relative to the notional value of the order. The more relevant point for this paper is that the proposal reflects a broader regulatory concern that retail execution mechanisms may not always deliver competitive outcomes. Fractional trading raises a particularly sharp version of this concern because the execution process is even less transparent than ordinary whole-share retail internalization. Rather than imposing an auction mechanism designed for whole-share orders, a more targeted approach would be to strengthen fractional-specific reporting and execution-quality disclosure (SEC 2024).

Real effects on high-price stocks. The third implication concerns the interaction between fractional trading and corporate decisions. This paper shows that fractional trading reshapes the economic role of stock splits. Once investors can purchase arbitrary dollar amounts, the traditional accessibility motive for stock splits becomes less relevant. Yet high-price split announcements generate stronger short- and long-run abnormal returns in the fractional-trading era, consistent with an attention-driven demand channel. At the same time, fractional trading weakens the liquidity benefits of splits by increasing realized quoted spreads ex post. These findings imply that fractional trading affects not only secondary-market execution quality but also the equilibrium consequences of corporate price-management decisions, especially for large stocks. Considering the Magnificent 7 stocks account for accounted for roughly one-third of the S&P 500's total market capitalization and historically the largest upcoming IPO by SpaceX,[20] regulators and exchanges should there-

[20]See, e.g., "What are the Magnificent 7 stocks?" and "Musk's SpaceX Files to Go Public in One of the Biggest IPOs Ever."

fore recognize that changes in retail trading technology can alter the economic meaning of nominal share prices, stock splits, odd-lot trading, and displayed liquidity.

Overall, the evidence suggests that fractional trading should not be regulated simply as a benign access technology. It is a growing and economically important form of retail trading with distinct execution mechanics, information content, and market-quality consequences. The appropriate regulatory response is not necessarily to restrict fractional trading, but to make its execution transparent, comparable, and contestable. Stronger fractional-specific disclosure, broker-level execution-quality reporting, and continued monitoring of broker internalization would preserve the access benefits of fractional shares while reducing the hidden costs borne by retail investors.

7. Conclusion

This paper provides the first comprehensive analysis on the fractional trading in U.S. equity markets and its effect on market quality. Exploiting the 2026 enhancement in FINRA trade-reporting requirements, I show that fractional shares represent a substantial share of retail trading activity, concentrate in high-priced and large-cap stocks, and display patterns consistent with dollar-based, attention-driven retail order flow. Despite their role in expanding market access, fractional trades contribute negatively to price discovery and exhibit the liquidity signature of uninformed order flow: high effective and realized spreads, low price impact, and poor execution quality.

Using the reporting change as a quasi-natural experiment, I further establish the causal effects on market quality. The disclosure shock reduces fractional trading in treated stocks, and this reduction leads to narrower spreads and lower intraday volatility. These results suggest that fractional trading creates an important tradeoff in modern market design. It democratizes access to expensive stocks, but it also generates uninformed order flow that can weaken liquidity and impair market efficiency.

Finally, I show that fractional trading reshapes the economic role of stock splits. Once investors can buy arbitrary dollar amounts, the traditional accessibility motive for stock splits becomes less relevant. Yet high-price split announcements earn larger short- and

long-run abnormal returns in the fractional-trading era, consistent with an attention-driven demand channel. At the same time, fractional trading weakens the liquidity benefits of splits by widening realized spreads after the split. Taken together, the evidence shows that fractional trading is not merely a new trading technology; it changes retail participation, market quality, and the equilibrium consequences of corporate price-management decisions.

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A. Additional Institutional Details

A.1 Detection Algorithm for Fractional Shares

Following Bartlett, McCrary, and O'Hara (2024), I identify likely fractional share trades from Robinhood and Drivewealth in the pre-disclosure TAQ data using the following criteria.

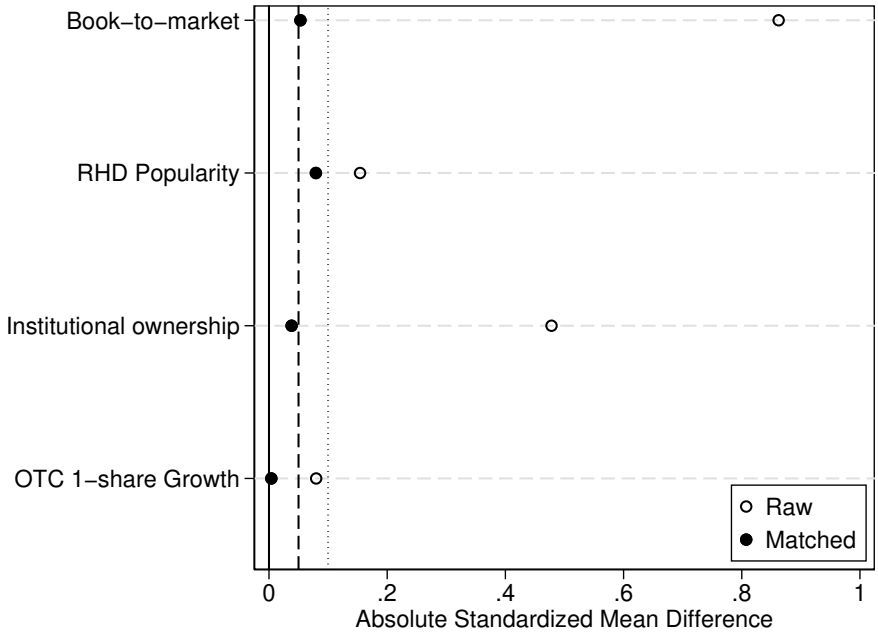
The algorithm is applied to OTC one-share trades: exchange code "D," (`EX='D'`) and trade size equal to one (`SIZE=1` before February 23; `SIZE`$\leq$`1` afterwards). Further, for Nasdaq TRF (`TRF in ('T','Q')`), the trades with latency (`TIME_M`$-$`PART_TIME`) between 135 and 300 milliseconds or greater than 20 milliseconds are classified as fractional trading. For NYSE TRF (`TRF in ('N')`), the trades with latency greater than 20 milliseconds are classified as fractional trading.

These criteria are based on the observation that fractional share trades from specific brokers exhibit distinctive latency patterns in the reporting chain, reflecting the additional processing steps involved in fractional share execution relative to standard whole-share trades. An implicit assumption of this detection approach is that the technology and routing infrastructure underlying these latency signatures did not change significantly between the algorithm's calibration period (approximately March 2022) and the study period. The original Bartlett, McCrary, and O'Hara (2024) algorithm only retains one-share trades with latency between 135 and 300 milliseconds for trade Nasdaq TRF to capture Robinhood fractional trading. The one-share trades with latency greather than 20 milliseconds for NYSE TRF was originally used to capture Drivewealth fractiona trading. After October 6, 2022, however, Drivewealth started to report fractional traing to Nasdaq TRF, though the latency pattern in NYSE TRF remains largely unchanged. Thus, I combine two latency conditions for Nasdaq TRF in my sample period, and retain the original condition for NYSE TRF.

A.2 Propensity Score Matching Details

The propensity-score-matched sample used in the difference-in-differences analysis of Section 4 is provided by Da, Fang, and Lin (2025). The matching procedure uses one-to-one nearest-neighbor matching without replacement. Treatment stocks are defined as stocks

Figure A.1. Test of Balance on Covariates



with prices above $100, and control stocks are those with prices below $100. The matching covariates are: the book-to-market ratio measured at the end of the 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 the growth in off-exchange one-share trades, defined as the cumulative daily count over the five-month period of June–October 2019 minus the cumulative daily count over the five-month period of January–May 2019. The matching procedure ensures balance on these covariates between treatment and control groups, supporting the parallel trends assumption required for causal interpretation of the DID estimates. Figure A.1 shows that the matching procedure ensures that treatment and control stocks are similar on observable characteristics.

B. Additional Empirical Results

B.1 Fractional Trading and Retail Trading

This section connects fractional share trading to the broader asset pricing literature by examining its relationship with existing measures of retail trading activity and its implications

for commonly used empirical measures.

B.1.1 Determinants of Fractional Trading

A growing literature in empirical finance seeks to measure retail investor trading activity using trade-level data from the consolidated tape. The most widely used approach is that of Boehmer et al. (2021) (hereafter BJZZ), who identify retail trades as off-exchange trades with prices at sub-penny increments, reflecting the price improvement typically offered to retail order flow by wholesale market makers. Barber et al. (2024) subsequently refined this measure. If fractional share trades are predominantly retail in origin, as suggested by the stylized facts in Section 2, then the newly observable fractional share data should be positively correlated with the BJZZ measure.

To formally examine the determinants of fractional share trading, I estimate the following panel regression:

$$FS_{i,t} = \beta \; BJZZ_{i,t} + \boldsymbol{\psi'} \boldsymbol{X_{i,t}} + \alpha_i + \gamma_t + \varepsilon_{i,t} \tag{B1}$$

where $FS_{i,t}$ is the natural logarithm of the number of fractional share trades for stock i on day t; $BJZZ_{i,t}$ is the natural logarithm of the number of BJZZ retail trades; $PRC_{i,t}$ is the natural logarithm of the closing price; $SIZE_i$ is the natural logarithm of market capitalization as of end-2025; $AGE_{i,t}$ is the natural logarithm of the number of calendar days since the stock's first trade in CRSP; $SPREAD_{i,t}$ is the natural logarithm of the bid-ask spread; $RANGE_{i,t}$ is the natural logarithm of the daily high-low price range; and $NYSE_i$ is an indicator equal to one for NYSE-listed stocks.

Table B.1 reports the results. In the cross-sectional specification without fixed effects (columns 3–4), the coefficient on $BJZZ_{i,t}$ is 0.516–0.518 and highly significant ($t > 50$), confirming the strong positive correlation between fractional share trading and the BJZZ retail trading measure. Stock price enters with a negative coefficient (-0.411 to -0.415), which may seem counterintuitive given that fractional trading is more prevalent for high-priced stocks. However, this coefficient is estimated conditional on firm size ($SIZE_i$), which enters with a large positive coefficient (0.267–0.268). The negative coefficient on price conditional

Table B.1
Determinants of Fractional Share Trading

This table reports OLS regression estimates of equation (B1). The dependent variable is the order imbalance of fractional trading (columns 1, 3–5) or the order imbalance of BJZZ retail trades (column 2). The robust standard errors clustered at the stock and day levels are show in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Oib^{FS}_{i,t}$	$Oib^{BJZZ}_{i,t}$	$Oib^{FS}_{i,t}$		
	(1)	(2)	(3)	(4)	(5)
$Oib^{BJZZ}_{i,t}$			0.014**	0.014**	0.005
			(0.01)	(0.01)	(0.01)
$Prc_{i,t}$	−0.081***	−0.019***	−0.082***	−0.083***	−0.062**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.03)
$Size_i$	0.035***	0.008***	0.035***	0.035***	−0.034
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
$Age_{i,t}$	−0.006***	0.002*	−0.006***	−0.006***	−0.020
	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)
$Spread_{i,t}$	0.005***	−0.006***	0.005***	0.005***	−0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Range_{i,t}$	0.050***	0.019***	0.051***	0.050***	0.037***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$NYSE_i$	−0.009*	0.014***	−0.008*	−0.009*	
	(0.00)	(0.00)	(0.00)	(0.00)	
α	0.025	−0.067***	0.024	0.025*	0.556
	(0.02)	(0.01)	(0.02)	(0.01)	(1.22)
Stock FE	No	No	No	No	Yes
Day FE	No	No	No	Yes	Yes
Observations	136,769	138,302	136,489	136,489	136,485
Adjusted R^2	0.016	0.004	0.017	0.021	0.121

on size reflects the fact that, holding market capitalization constant, higher-priced stocks have fewer shares outstanding and hence fewer trades overall. Firm age enters positively, the NYSE indicator enters negatively (consistent with greater retail trading on NASDAQ), and the price range enters positively (consistent with retail investors trading more actively in volatile stocks).

In the specification with stock and day fixed effects (column 5), the coefficient on $BJZZ_{i,t}$ remains positive and significant (0.274, $t = 9.13$), though smaller in magnitude, indicating that the positive association between fractional shares and retail trading persists

even after controlling for all time-invariant stock characteristics and all common daily shocks. The price coefficient flips to positive (0.603), reflecting the within-stock relationship: on days when a stock's price is higher, the same dollar-denominated order generates a smaller fractional share quantity, but more investors may be attracted to trade fractional shares in that stock.

B.1.2 Fractional Traders as Momentum Traders

To formally examine the determinants of fractional share trading, I estimate the following Fama and MacBeth (1973) regression:

$$Ret_{i,t} = \beta_1 \, Oib^{FS}_{i,t} + \beta_2 \, Oib^{BJZZ}_{i,t} + \boldsymbol{\gamma' X_{i,t}} + \alpha + \epsilon_{i,t}, \tag{B2}$$

The standard order imbalance measure is defined as:

$$Oib^{j}_{i,t} = \frac{BuyVolume^{j}_{i,t} - SellVolume^{j}_{i,t}}{BuyVolume^{j}_{i,t} + SellVolume^{j}_{i,t}}, \tag{B3}$$

where $BuyVolume_{i,t}$ and $SellVolume_{i,t}$ denote buyer-initiated and seller-initiated volume (in shares), respectively, for stock i on day t. j denotes the type of retail trading, either FS denoting fractional trading, or $BJZZ$ denoting BJZZ retail trades. $\boldsymbol{X_{i,t}}$ is a battery of control variables: $Inv_Prc_{i,t}$ is the inverse of closing price; $Size_i$ is the natural logarithm of market capitalization; $Age_{i,t}$ is the natural logarithm of the number of calendar days since the stock's first trade in CRSP; $Spread_{i,t}$ is the natural logarithm of the bid-ask spread; $Range_{i,t}$ is the natural logarithm of the daily high-low price range. The t-statistics are calculated using Newey and West (1987) with two lags.[21]

Table B.2 examines whether fractional trading and broader retail trading contain return-relevant information. Column (1) shows that fractional-trade order imbalance negatively predicts contemporaneous stock returns. The coefficient on $Oib^{FS}_{i,t}$ is -0.309 and statistically significant at the 1% level, indicating that stocks with more fractional buying relative to

[21] Following Greene (2011), we set the optimal lag as the integer part of $T^{1/4}$, where T is the number of trading days in our sample period. $0.75 * T^{1/3}$ generates the same optimal lag. Our results are robust with alternative lag, such as three.

Table B.2
Fractional Trading, Retail Order Imbalance, and Stock Returns

This table reports the Fama and MacBeth (1973) regressions of stock returns on order imbalance measures. $Oib_{i,t}^{FS}$ denotes order imbalance constructed from fractional trades, and $Oib_{i,t}^{BJZZ}$ denotes the retail order imbalance measure following Boehmer et al. (2021). Control variables include inverse stock price, size, age, bid–ask spread, intraday price range, and lagged return. The Newey and West (1987) t-statistics are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Ret_{i,t}$		
	(1)	(2)	(3)
$\boldsymbol{Oib_{i,t}^{FS}}$	**–0.309*** **		**–0.316*** **
	[–9.74]		**[–9.76]**
$\boldsymbol{Oib_{i,t}^{BJZZ}}$		**0.503*** **	**0.494*** **
		[9.26]	**[8.88]**
$Inv_Prc_{i,t}$	–2.258	–2.374*	–2.271
	[–1.66]	[–1.75]	[–1.67]
$Size_{i,t}$	–0.032**	–0.041***	–0.034***
	[–2.74]	[–3.53]	[–3.02]
$Age_{i,t}$	–0.029	–0.023	–0.029
	[–1.60]	[–1.23]	[–1.58]
$Spread_{i,t}$	–0.032	–0.028	–0.030
	[–1.67]	[–1.37]	[–1.58]
$Range_{i,t}$	–0.062	–0.075	–0.066
	[–0.82]	[–1.00]	[–0.88]
$Ret_{i,t-1}$	–0.055***	–0.056***	–0.054***
	[–3.99]	[–4.19]	[–3.96]
α	0.630***	0.698***	0.670***
	[5.85]	[6.70]	[6.23]
Observations	127,157	128,469	126,906
Adjusted R^2	0.143	0.143	0.146

selling earn lower returns. This result is consistent with the interpretation that fractional traders are liquidity-motivated or attention-driven investors who tend to trade on the wrong side of short-run price movements.

Column (2) provides a useful contrast using the retail order imbalance measure of Boehmer et al. (2021). The coefficient on $Oib_{i,t}^{BJZZ}$ is positive and highly significant, suggesting that the broader retail order imbalance measure contains positive return information. This finding is consistent with prior evidence that some retail order flow can be informative

and can predict short-run returns.

Column (3) includes both order imbalance measures simultaneously. The coefficient on $Oib_{i,t}^{FS}$ remains negative and significant, while the coefficient on $Oib_{i,t}^{BJZZ}$ remains positive and significant. The opposite signs indicate that fractional trading captures a distinct component of retail order flow rather than simply proxying for overall retail trading. In particular, fractional traders appear less informed than the broader retail investor population identified by Boehmer et al. (2021). Overall, the evidence suggests substantial heterogeneity within retail trading: while aggregate retail order imbalance may be informative, fractional-share order imbalance is associated with lower returns and weaker price discovery.

B.1.3 Bias in Order Imbalance from Rounded Fractional Shares

A key concern raised by the fractional share rounding convention is the potential for bias in commonly used measures of order imbalance. Under the pre-February 2026 rounding convention, a fractional buy of 0.99 shares and a fractional sell of 0.01 shares would both be reported as one-share trades. The rounding inflates both the numerator and the denominator of the order imbalance measure by different amounts, depending on the distribution of fractional trade sizes and the correlation between trade direction and fractional quantity. Consider a simple example: if true volumes are 0.99 (buy) + 101 (buy) = 101.99 buyer-initiated and 0.01 (sell) + 99 (sell) = 99.01 seller-initiated, the true order imbalance is $(101.99 - 99.01)/(101.99 + 99.01) \approx 1.48\%$. Under the rounding convention, reported volumes become 1 (buy) + 101 (buy) = 102 buyer-initiated and 1 (sell) + 99 (sell) = 100 seller-initiated, yielding an order imbalance of $(102 - 100)/(102 + 100) \approx 0.99\%$.

Table B.3 shows the formal analysis. The pre-rule reporting regime substantially distorted the measurement of fractional-trading order imbalance. Before February 23, 2026, fractional trades below one share were rounded up and reported as one-share trades, making the pre-rule proxy mechanically noisy. After fractional quantities became directly observable, both buy and sell volumes decline sharply across all size groups, indicating that the old one-share-based measure overstated the true magnitude of fractional trading activity.

The distortion is particularly severe for large firms. In the large-stock group, pre-rule buy and sell volumes are much larger than their post-rule counterparts, and the implied

Table B.3
Fractional Order Imbalance Before/After the New Reporting Rule

This table reports buy volume, sell volume, and fractional-trading order imbalance (Oib^{FS}) before and after the February 23, 2026 FINRA reporting rule. The sample is reported for all sample stocks and separately by firm-size groups. Stocks are assigned based on 30% and 70% NYSE breakpoints in June 2025. Pre and Post denote observations before and after fractional-share quantities became directly observable on the consolidated tape. Bias is defined as the percentage difference between the pre-rule and post-rule order-imbalance measures.

	Overall (1)	Large (2)	Medium (3)	Small (4)
Buy Volume (Pre)	696.6134	3907.1644	109.4450	26.5360
Buy Volume (Post)	66.8426	307.3374	34.8287	10.5958
Sell Volume (Pre)	288.1626	1491.5530	92.8163	24.4917
Sell Volume (Post)	57.4394	255.5148	33.0079	10.1346
Oib^{FS} (Pre)	0.0247	0.1743	0.0278	-0.0232
Oib^{FS} (Post)	−0.0399	0.0395	−0.0489	−0.0598
Bias (%)	−60.5548	−125.2981	−86.6583	−24.5195
N	139,268	23,215	38,977	77,076

order imbalance falls from 0.1743 before the rule to 0.0395 after the rule. The estimated bias is −125.3%, suggesting that the pre-rule proxy not only overstated fractional trading activity but also materially mismeasured the direction of net order flow. This pattern is consistent with fractional trading being most prevalent in large, high-priced stocks, where retail investors benefit most from dollar-based trading.

The bias is also economically meaningful for medium and small firms. For medium stocks, Oib^{FS} changes from 0.0278 before the rule to −0.0489 after the rule, implying a bias of −86.7%. For small stocks, the corresponding bias is smaller, at −24.5%, consistent with weaker fractional-trading intensity among lower-priced and smaller firms. Overall, the evidence highlights the importance of the February 2026 reporting reform: without direct reporting of fractional quantities, researchers may draw misleading conclusions about both the level and direction of fractional retail order imbalance.

The direction and magnitude of the bias depend on the joint distribution of fractional trade sizes and directions, and can vary across stocks and days. This bias is particularly

consequential in applications where order imbalance appears in the denominator, such as the estimation of price multipliers in demand-based asset pricing frameworks (Koijen and Yogo 2019). The price multiplier, often expressed as $(dp/p)/(dq/q)$, measures the price impact of a unit change in demand. If order imbalance used to proxy for dq/q is systematically biased, the resulting price multiplier estimates will also be biased, potentially leading to incorrect inferences about the effects of demand shocks on prices (Li and Lin 2026).