This Draft: July, 2026

# Crumbs on the Tape: Examining Fractional Trading

Michael Coccia*†
PhD Student
School of Business Administration
University of Mississippi
macoccia@olemiss.edu

Robert Van Ness*
Bruce Moore Scholar of Finance
School of Business Administration
University of Mississippi
rvanness@bus.olemiss.edu

Abstract

A February 2026 FINRA reporting change requires fractional-share trades in U.S. equities to print to the consolidated tape at their native size, making a slice of retail activity directly observable. We motivate fractional prints on the tape as a proxy for retail activity and assemble the first census of fractional trades reported to the consolidated tape. Fractional trades are executed by retail brokers, track Rule 605 wholesaler and BJZZ retail benchmarks across the cross-section and rise with r/wallstreetbets attention. Roughly 54% of common stock fractional trades are not identified by the BJZZ sub-penny classifier.

Keywords: Fractional Trading, Retail Trading, Market Microstructure, Rule 605

JEL Codes: G10, G23

* We acknowledge the Mississippi Center for Supercomputing Research (MCSR) at the University of Mississippi for providing the computing resources and technical support that contributed to the research results reported within this paper

† Corresponding Author

## 1. Introduction

Retail investors account for a large and growing share of U.S. equity trading, and research studies how they trade, what they know, and how their order flow moves prices.[1] Retail trades are not directly observable in public data. Retail marketable orders are routed off-exchange to wholesalers and internalized, they reach the consolidated tape without a retail label, and researchers must infer retail activity indirectly, from the sub-penny price improvement that wholesalers grant (Boehmer, Jones, Zhang, and Zhang 2021, hereafter BJZZ) or from broker-specific latency footprints (Bartlett, McCrary, and O'Hara 2024, hereafter BMO). Both approaches recover only fragments of the activity, and the accuracy of the sub-penny method in particular is contested (Barber, Huang, Jorion, Odean, and Schwarz 2024; Battalio, Jennings, Saglam, and Wu 2023). On February 23, 2026, a change to the FINRA trade-reporting specification lifted part of this veil. Fractional-share trades, previously rounded to whole shares before they print, now report to the consolidated tape at their native, non-integer size. For the first time, a large and identifiable component of retail activity is visible directly in TAQ, a fractional trade is simply a print whose reported share quantity is not an integer.

BMO conclude their study of fractional trading by calling for fractional trade reporting transparency; it has since arrived, and with it the ability to identify fractional trades by direct observation rather than by inference. Fractional trading is primarily a recent retail innovation. Although fractional positions have existed as the residue of stock splits, mergers, and dividend-reinvestment plans, deliberate fractional trading entered mainstream brokerage only in 2019, when SoFi, Square, Interactive Brokers, and Robinhood, followed by Fidelity and Schwab in 2020, began letting customers buy and sell fractions of a share, so that an investor could commit a fixed dollar amount to any stock regardless of its price. Before

[1] Barber and Odean (2000) investigate excessive trading habits; Barber Odean and Zhu (2008) assess whether retail trades move markets; Kaniel, Saar and Titman (2008) find retail traders provide liquidity; Kelley and Tetlock (2013) find that retail traders predict future stock returns with no evidence of reversals; Boehmer, Jones, Zhang and Zhang (2021) identify retail trades in public data and show retail traders may possess stock specific information; Eaton, Green, Roseman and Wu (2022) demonstrate causal evidence that retail trading influences on-exchange market quality; Welch (2022) examines Robinhood traders in the pandemic; Bryzgalova, Sikorskaya and Pavlova (2023) identify retail traders in options data and find their aggregate trading unprofitable; Bogousslavsky and Muravyev (2024) examine retail traders in option markets exhibit heterogeneity in their level of sophistication.

the reporting change, a broker executing a sub-one-share order reported it to the tape as a one-share trade, so these trades were not identified as fractional trades and inflated reported share volume (BMO). The native-size fractional prints now observable are not a complete population of fractional trading, since some fractional trades are internalized within omnibus accounts and never print as a separate customer trade, therefore the volume we observe on the consolidated tape is a lower bound. Although a lower bound, what we observe is direct. We study aggregate fractional activity in the tape and motivate its retail-based origin.

We show that fractional trades on the consolidated tape are a directly observable proxy for a distinct segment of retail traders and that it carries a signal complementary to, rather than redundant with, existing retail proxies. Over half of the fractional trades on the consolidated tape are unidentifiable by the BJZZ algorithm and would not be identified as retail. Despite the disjoint identification between the BJZZ algorithm and fractional trades, they agree strongly on which stocks attract retail interest, and fractional activity rises with retail attention as measured by r/wallstreetbets mentions. Our second contribution is descriptive. We provide the first direct characterization of the anatomy of fractional trading, its size, timing, concentration, and origin, separately for common stocks and exchange-traded funds (ETFs). The direct data also let us revisit two claims (an increase in volatility and a widening of spreads on the next trading day) from the latency-inference-based study (BMO).

Fractional trading is small and heavily concentrated. The typical fractional trade is tiny: a majority execute for under $5 and below one-tenth of a share. While the majority of trades are small, we do find that when measured in dollars, fractional trades show a pronounced round-dollar signature, which accumulates just under $1, $10, $25, and $50, fingerprints of investors placing orders in round dollar amounts. Fractional activity occurs more frequently in the morning in common stocks, and is absent from the closing auction. Fractional activity is concentrated: the top quartile of stocks, ranked by fractional activity, accounts for 98% of common-stock fractional dollar volume and 99% of ETF fractional dollar volume.

Da, Fang, and Lin (2025, hereafter DFL), show that fractional trading is a device for capital-constrained investors to reach high-price stocks they could not otherwise afford. The raw data appear to confirm that fractional dollar volume rises with share price, a log-log correlation of 0.53 in common stocks.

However, we find that high-price stocks are also high-activity stocks, so a positive raw relation confounds price with activity. Once we scale by a stock's total dollar volume, the relation reverses: conditional on size, volatility, turnover, and BJZZ activity, the fractional share of a common stock's volume falls with price. Contrary to the view that fractional traders reach for expensive stocks, we find they take tiny positions in stocks that happen, on average, to be expensive. The size distribution reinforces this finding: it is invariant to share price, as a reach-for-expensive-stocks mechanism would not be, and it is too concentrated near zero to be the split-off remainder of larger dollar-denominated orders, a null we confirm by simulation.

We present several lines of evidence to establish that the fractional trades are mostly retail. First, we identify thirteen brokers that execute fractional trades, using a break in the shares-to-trades ratio firms report to FINRA's OTC Transparency data around the reform. These span the retail-facing ecosystem: fintech-focused clearers, app-based brokerages, and traditional full-service firms alike. Together, these identified firms make up roughly 24% of the fractional trades we observe; the remaining trades are treated as coming from the same heterogeneous retail population. Second, fractional activity tracks two established retail benchmarks in the cross-section: the Rule 605 wholesaler execution reports that Dyhrberg, Shkilko, and Werner (2025) treat as the public record of marketable retail activity, and the BJZZ-identified retail volume, which has a stock-level rank correlation with fractional volume of 0.90 in common stocks and 0.83 in ETFs. Because the round-lot Rule 605 universe is disjoint from sub-share fractional trades by rule (only round-lots appear in 605 data), this agreement is a cross-population validation, not a mechanical relation. Not only is the agreement between fractional activity and 605 data informative, but the disagreement as well; we find that fractional traders overweight stocks with higher prices, higher market cap, and higher volatility than the 605 round-lot retail trader population.[2] Third, fractional activity responds to retail attention: a 1% rise in a stock's r/wallstreetbets mentions is associated with a 0.27% rise in its fractional trade count over the following two weeks in common stocks, 0.28% in ETFs, and the fractional share of

[2] We find that fractional participation in the cross-section is roughly price-invariant. A round-lot order's minimum notional trade size rises one-for-one with the share price as opposed to fractional trades which do not; this is the mechanism which causes aggregate fractional trading to not tilt towards high-price stocks but fractional trading to outpace round-lot 605 retail activity in high-priced stocks.

volume rises by more than total volume does, the pattern one would expect if fractional prints originate from attention-driven retail traders.

The population reveals a striking feature of fractional trades, the clustering of trade sizes at exact, often peculiar quantities: 7.9% of fractional trade common-stock prints are for exactly 0.003 shares, almost all of them in Nvidia. We show these are not the footprint of a sophisticated strategy, retail or institutional. Converted to dollars they are fixed sub-dollar amounts, signed overwhelmingly as buys (88% buyer-initiated), and contain no price impact. We attribute these trades to automated micro-investing, a small, fixed dollar amount invested repeatedly, with no underlying information.

We find that aggregate fractional activity bears no robust relation to next-day liquidity or volatility in common stocks at the daily frequency, contrary to BMO's finding that Robinhood and DriveWealth fractional trades predict next-day liquidity.[3] However, this study and the BMO study are not directly comparable. BMO isolate the fractional trades of two app-based brokers, whereas we observe all fractional trade prints during a time period four years later. With no robust relation to future market quality outcomes, coupled with trade level price impact that is statistically and economically zero, our evidence suggests fractional activity does not play a significant role in market quality or the price discovery process.

Our paper is closest to BMO, which infers the fractional trades of Robinhood and DriveWealth from latency footprints. Fractional trades reporting to the tape at their native size lets us observe the full population of fractional trades on the tape directly, revisit their high-price and market-quality findings, and measure the volume inflation they document, which our sample would have carried at roughly $1.36 billion per day. We build on DFL, whose introduction-date event study motivates the high-price interpretation we revise. Our methodological contribution speaks to the retail-identification literature, BJZZ and the critiques of it (Battalio, Jennings, Saglam, and Wu 2023; Barber, Huang, Jorion, Odean, and Schwarz 2024), by offering a directly observed retail signal that needs no sub-penny inference and captures trades the sub-penny filter misses. We also connect to the literature on retail attention and social media (Barber, Huang,

[3] We caveat this by stating we do not find a robust relation, we are able to recover BMO's findings with varying sample restrictions, as displayed in Table A3.

Odean, and Schwarz 2022; Eaton, Green, Roseman, and Wu 2022; Bryzgalova, Pavlova, and Sikorskaya 2023), for which fractional trades offer a new, high-frequency, directly observable proxy.

## 2. Data

### *2a. The Consolidated Tape*

The primary data source is the NYSE Trade and Quote (TAQ) files. We utilize the consolidated trade, consolidated national best bid or offer (NBBO), exchange best bid or offer (BBO) file, and the TAQ master security files. The sample runs from February 2 to June 18, 2026, and straddles the February 23, 2026, revision to the FINRA trade-reporting specification. Under the revised specification, fractional-share trades print to the consolidated tape at their native size with up to six decimal places of precision. Previously, a 0.5-share order printed as a one-share trade, and a 4.5-share order printed as a four-share trade and a one-share trade.[4] Most of our analysis uses post-revision data from February 23, 2026 to June 18, 2026. We retain pre-revision days to illustrate the reporting change as fractional trades that previously report as one-share trades now report at their true fractional size.

From the trade file we extract, for each trade, the symbol, trade price, trade volume, exchange, SIP timestamp, participant timestamp and trade-reporting facility code. From the NBBO file we extract the symbol, SIP timestamp, best bid and ask, and the best bid and ask exchanges. The NBBO file is augmented with the BBO file, following the data preparation instructions of Holden and Jacobsen (2014). We filter to regular trading hours (9:30-16:00 ET) unless otherwise stated, drop corrected and cancelled prints, and remove the official market opening and closing trade status messages. We further partition the sample into common stocks (security type code A), and exchange-traded funds (code ETF) using the master file. We partition fractional trades into sub-one-share (a fractional trade less than one share) and super-one-share trades (a trade for more than one share that also has a fractional component), we find the vast majority of fractional trades report as the former.

### *2b. Which Fractional Trades Are in the Consolidated Tape?*

[4] https://www.finra.org/rules-guidance/notices/trade-reporting-notice-20260114, accessed July 2026.

The native-size fractional prints we observe are a subset of all fractional trading, not a complete census of all fractional trades. Retail fractional activity may be internalized within broker or clearing-firm omnibus accounts and execute on a riskless-principal basis, and never print to the consolidated tape as a separate customer-size fractional trade (BMO). We do not claim to identify all fractional trades, we identify all fractional trades on the consolidated tape. We do identify all fractional trades which report to the consolidated tape. While we cannot rule out the possibility that our sample of fractional trades is systematically different from fractional trades not reported to the tape, there is no extant literature that suggests that this is the case as the latter is unobservable. The volume of fractional trading which we observe in the consolidated tape is therefore a lower bound on fractional trading activity. The focus of our paper is to identify all fractional trades which do print at their native size and characterize what that printed subset represents, where it originates and whether it is retail. For the rest of the paper when using the term fractional trading, we refer to the subset of observable fractional trades which report to the consolidated tape.

***2c. Supplementary Data***

We use three other sources of data to support our characterization of fractional trades, each is discussed in detail in the section where it is utilized, with a summary of the sources appearing here. The first data source is the FINRA OTC Transparency data, which contains data on the number of trades and shares which execute off exchange on a stock-week-broker level. Before the February 23, 2026 reporting change, brokers who execute fractional trades exclusively had a shares-to-trades ratio of approximately one (BMO), following the reporting change these brokers display a significant drop in the shares-to-trades ratio. We use this break to identify executors of fractional trades by name.

The second data source is Rule 605 execution quality reports. Every venue that executes stock orders, wholesalers and exchanges alike, must file a monthly report, mandated by SEC Rule 605, detailing the execution quality of the orders it handled. The reports filed by the large off-exchange wholesalers consist overwhelmingly of marketable retail orders and are regarded as a public record of how retail order flow is handled. Dyhrberg, Shkilko, and Werner (2025) provide a full description and analysis of these data. We use the monthly reports of the eight wholesalers identified in Dyhrberg, Shkilko, and Werner (2025), over the February-May 2026 period as a benchmark for the marketable retail volume a stock attracts. Importantly, because Rule 605 covers only ordinary market and marketable orders of at least one round lot, the reports exclude odd-lot, limit, and institutional not-held trades, and fractional trades. Rule 605 data provides a comparatively clean round-lot retail slice and allows us to test whether the sub-share fractional trades we observe on the tape track this independent round-lot retail benchmark.

The third data source we use is Reddit comments and submissions which we obtain from publicly available monthly data dumps.[5] We construct a retail attention measure on the stock-day level following Eaton, Green, Roseman and Wu (2022) and Bryzgalova, Pavlova and Sikorskaya (2023). We use this data to test the relation between retail chatter on social media and fractional trading observed on the tape. We also use reddit data to present anecdotal evidence of two specific meme-stock trading events; the shoe company Allbirds pivoting from selling shoes to selling cloud-based computing for AI on April 15, 2026, and the "Save Wendy's" r/wallstreetbets retail short squeeze on June 24, 2026.

***2d. Trade Signing and Sample***

Trades are signed using the Lee and Ready (1991) algorithm with the exchange-to-SIP latency correction of Holden, Pierson and Wu (2023). The latency adjustment shifts trade times to reflect the NBBO observed by the submitting exchange (participant) rather than the SIP-registered NBBO, improving the accuracy of trade signing. The quote rule signs each trade against the prevailing quoted midpoint, and the tick test resolves trades which execute at the midpoint. We also re-estimate regressions by excluding trades which execute at the midpoint to assess the degree to which the tick test may bias our results.

The initial descriptives section imposes no sample filter beyond the common-stock and ETF partition. In tests of liquidity and volatility we restrict the sample to stock-days where the median trade price is above five dollars. Results are robust to including the full sample without the five-dollar filter.

[5] The GitHub page for Project Arctic Shift can be found here https://github.com/ArthurHeitmann/arctic_shift.

Where we posit fractional activity may differ across asset classes, we further split ETFs into broad-market index and leveraged or inverse funds using the ETF name listed in the TAQ master files.

Stocks are partitioned into five price bins, under \$50, \$50-\$100, \$100-\$250, \$250-\$500, and over \$500, the price bins are assigned at the stock-day level from the stock's median trade price. Existing literature on fractional trading states that fractional trading is utilized by capital-constrained investors to enter positions in high-priced stocks which they could not normally afford (DFL). We use the price bins to examine whether fractional trading is concentrated in high priced stocks.

Several stock characteristics are utilized as controls and outcomes in Section 4. In the cross-sectional tests a stock's price is the time-series average of its daily median trade price over the sample, distinct from the stock-day median trade price used above to assign price bins. We measure firm size by market capitalization, defined as a stock's shares outstanding, taken from the TAQ master security file, multiplied by its daily median trade price, and summarized as the median of this daily value over the sample. Turnover is a stock's total dollar volume divided by its market capitalization. Daily realized variance is the sum of squared one-minute log midpoint returns within regular trading hours (defined formally in equation 15); in the cross-sectional regressions we use a stock's mean daily realized variance over the relevant window. The proportional effective spread of a trade is twice the distance between the price and the prevailing NBBO midpoint multiplied by the trade's direction, divided by the midpoint (equation 13), and a stock-day effective spread is the mean over that day's regular-hours trades. These characteristics enter the regressions in natural logarithms.

We report fractional volume in both dollars and shares and state which we use in each test. The fractional share of dollar volume is a stock's fractional dollar volume divided by its total dollar volume, where a trade's dollar volume is its price times its share quantity. Order imbalance is fractional dollar buy volume less fractional dollar sell volume divided by their sum, with each trade signed as a buy or sell by the Lee and Ready (1991) algorithm.

## 3. Descriptive Statistics

Following the February 23, 2026 FINRA reporting change, fractional trades print to the consolidated tape at their native size. This section documents the anatomy of the fractional activity; its magnitude, timing, size, and cross-sectional footprint, separately for common stocks and ETFs.

### *3a. Fractional Activity*

Figure 1 plots the daily time series of one-share and fractional-share trade counts on Exchange "D," the FINRA facility where off-exchange trades report. Panel A presents common stocks. Before the reporting change, one-share prints on Exchange "D" hover just under ten million per day. After the rule change on February 23, 2026, this count splits. Roughly four million former one-share prints now report at their true fractional size, while about six million remain one-share prints. The reform reveals activity that the old rounding convention had folded into the one-share count. Panel B shows the split is stable across the sample: fractional and one-share prints together account for roughly 20% of all Exchange "D" trade counts in common stocks, and fractional prints for just under 10%. Panel C presents ETFs. Aggregate counts are lower, but the fractional share is higher, fractional prints are just under 20% of Exchange "D" trade counts and, together with one-share prints, nearly 30%. If fractional prints represent retail interest, this is consistent with a larger retail role in ETF trading, potentially attributable to passive investing (Gempesaw, Henry, Xiao, 2024).

Table 1 separates fractional activity out by stock price. For each of five price bins, under \$50, \$50–\$100, \$100–\$250, \$250–\$500, and above \$500, we report the number of fractional prints, the split between sub- and super-one-share trades, and the fractional share of all Exchange "D" trades. Raw fractional counts rise with price, though not monotonically: they peak in the \$100–\$250 and \$250–\$500 bins and fall off above \$500. This invites the interpretation that fractional trading is a means of reaching otherwise-unaffordable high-price stocks (BMO; DFL). In section 4a we regress fractional activity on stock characteristics to test that interpretation. The price-bin profile differs by security type: common-stock fractional counts peak in the middle price bins (\$100–\$500), whereas ETF fractional counts are U-shaped, concentrated in the cheapest (<\$100) and most expensive (>\$500) bins with a trough in the middle. We note that Table 1 presents the statistics for fractional trades that occur on the tape inside and outside of regular trading hours (RTH). We find that approximately 5% of fractional activity occurs outside of RTH.

### *3b. Intraday Fractional Activity*

The microstructure literature documents a pronounced intraday U-shape pattern in volume and spreads, with activity concentrated at the open and again into the close (Wood, McInish, and Ord 1985; McInish and Wood 1992; Chung, Van Ness, and Van Ness 1999). We examine whether fractional trades follow this documented pattern. Figure 2 plots the count of fractional trades by five-minute intervals, with off-exchange one-share trades alongside for reference. Panel A presents common stocks. Fractional activity is overwhelmingly a morning phenomenon as the opening five-minute bar alone contains over 8% of the day's fractional prints, nearly four times the volume of any later bar, and almost three-quarters of fractional volume arrives before noon, tapering steadily through the late morning. One-share trades and fractional trades appear to loosely track one another in count throughout the day, with the exception of the market close. Off-exchange one-share trades exhibit the canonical closing spike, their final five-minute bar is the single busiest of the day, whereas fractional prints show no comparable surge into the close. The closing auction is the domain of institutions and sophisticated traders who engage in index rebalancing (Bogousslavsky and Muravyev, 2023) and pinging for liquidity with one-share trades (Davis, Roseman, Van Ness, and Van Ness, 2017). The absence of fractional activity at the closing auction, in tandem with the elevated morning trading profile, is the intraday signature one would expect of a dispersed retail population that places orders at the open (or overnight) as opposed to timing the close of the market. Panel B presents ETFs. The morning concentration is again pronounced, though less pronounced than in common stocks. Unlike common stocks, ETF fractional activity shows a modest increase into the close, but notably not at the close, in the 3:50–3:55 p.m. bar, and a smaller bump near 2:00 p.m. The intraday U-shape pattern of the seminal literature therefore holds qualitatively for ETF fractional trades but not for common-stock fractional trades, which lack the closing increase.

### *3c. Trade Size and Dollar Denomination*

A fractional print can arise from an order for less than one share (e.g., 0.5 shares) or from a dollar-denominated order that implies a non-integer share quantity (e.g., $200 of a $120 stock). Rather than adjudicate between the source of fractional trades in this subsection, we document the size distribution of share- and dollar-trade-sizes and return to the source of fractional trades in Section 4a. Two observations stand out, and both are suggestive of a micro-investing retail population.

First, we discover that the typical fractional trade is extremely tiny. Figure 3 plots the distribution of sub-one-share trade sizes; for both common stocks (Panel A) and ETFs (Panel B) the mass of the distribution lies below one-tenth of a share, 67% of sub-one-share common prints and 55% of ETF prints fall below 0.1 shares. The distribution is essentially unchanged across price bins (we plot the pooled histogram for brevity, the by-bin histograms are near-identical), so whatever process generates these small trades does not depend on share price, a point we return to in Section 4a. Super-one-share prints are correspondingly rare and grow rarer as price rises: from Table 1, trades with fractional components above one share fall from 16.1% of fractional prints in the under-$50 bin to 2.0% in the $250–$500 bin.

Second, measured in dollars rather than shares, a clear round-number signature emerges. Figure 4 plots the dollar-size distribution below $50 (larger sizes are sparse). The modal fractional trade is under one dollar, roughly a third of common-stock prints below $50 fall in the $0–$1 bin, yet distinct peaks appear just below $10, $20, $25, $30, $40, and $50 in both samples. The peaks sit under each round figure, exactly where a $10 or $50 trade lands once trading costs are netted out, and are the signature of investors placing orders in round dollar amounts. Table 2 confirms the pattern within every price bin: the $0–$1 bucket is the most populated dollar-size bin in every common-stock price bin except above $500, where it trails only $1–$2.

One caveat precedes our interpretation: retail brokers may sell the whole-share leg of a super-fractional-trade to a wholesaler for payment for order flow and internalize (or seek a different broker for execution) only the fractional remainder, so the tape can carry the fractional leg without its whole-share partner. Robinhood's disclosures are consistent with this: in the week of March 23, 2026 it reported 117,842 trades for 18,432.816273 aggregate shares, an average of 0.156 shares per trade. The tiny sizes we observe are partly attributable to the fractional and whole share component executing in two transactions.

***3d. Inflated Volume***

Prior to the February 2026 reporting change, fractional trades inflated reported dollar volume: a sub-one-share fill was rounded up to a full share, so the consolidated tape recorded volume that never transacted. BMO estimate that fractional trading inflated U.S. equity dollar volume by \$211–\$225 billion between March 2021 and March 2022, roughly \$0.79 billion per day. Direct identification lets us measure the inflation our sample would have carried under the old regime. For each fractional trade we compute the inflated volume as the trade's size rounded up to the next whole share, minus the trade's size, times the trade price, summed across all fractional prints:

$$\$inflated_k = (roundup(tradesize_k) - \ (tradesize_k)) * tradeprice_k \tag{1}$$

where $k$ is the kth trade and the total dollar inflation is,

$$Total\$Inflated = \sum_{k=1}^{K} \$inflated_k \, . \tag{2}$$

Table 3 reports the result by price bin, with common stocks in Panel A and ETFs in Panel B. Total hypothetical volume inflation over the sample is \$111.9 billion, with \$82.4 billion attributed to common stocks and \$29.4 billion to ETFs, or about \$1.36 billion per day across our 82 trading days. This exceeds the daily figure in BMO, unsurprisingly, since fractional trading has grown substantially since their 2021–2022 window. In relative terms, however, the distortion is small: inflated volume ranges from under one basis point of consolidated dollar volume in the lowest-price bins to 23 basis points in the above \$500 bin, concentrating in high-price stocks where rounding a partial share to a whole one adds the most notional volume. Fractional trading inflated the pre-reform tape substantially in absolute dollars but left aggregate volume economically almost undistorted.

***3e. Common Stocks vs. ETFs***

Up to this point we have partitioned our results between common stocks and ETFs, with little economic motivation provided. We predict that fractional trading in common stocks and ETFs should be fundamentally different, as fractional traders likely purchase ETFs in fractional components to slowly build market exposure whereas trading in common stocks is likely a component of a dynamic strategy. Additionally, leveraged ETFs may be used by investors in a fundamentally different manner (Cheng and Madhavan, 2009), along with the popularity of ETFs among retail traders (Gempesaw, Henry, and Xiao, 2024) we expect fractional activity in leveraged ETFs to be categorically different from that in broad index ETFs.[6] We split stocks into four security-types, common stocks, broad index ETFs, leveraged/inverse ETFs and other ETFs. We flag an ETF as leveraged/inverse when its fund name carries a leverage multiplier (*2X*, *3X*, *−1x*), a leverage word (*Ultra*, *Leveraged*), or a directional term (*Bull*, *Bear*, *Inverse*). These naming conventions are standard. We use the TAQ master files for stock names and flag 726 leveraged/inverse ETFs in the master file, 683 of which appear in our post-reform sample. We then assemble the broad-market index funds as a curated list of the 33 largest diversified equity funds (funds such as SPY, VOO, VTI, QQQ), and all other ETFs form a residual category.

We examine the different security-types on multiple characteristics. The characteristics are: mean order imbalance, as measured by the fractional buy volume less fractional sell volume divided by the sum; the fractional volume persistence, as measured by the lag-one autocorrelation of the fractional dollar volume share; and the degree of return chasing as measured by the correlation of daily fractional dollar share and the absolute value of the close-to-close return. We expect that broad market exposure ETFs should display a buy-side order-imbalance (OIB) tilt, persistent fractional activity and little return chasing, consistent with passive market exposure investing. Whereas leveraged ETFs should have a neutral OIB, low persistence and exhibit significant return chasing, consistent with strategic investing. We expect common stocks and general ETFs to fall somewhere in between the two, reflecting a mix of market exposure and strategic investing.

[6] Charupat and Miu (2011) find that leveraged and inverse ETFs are popular among retail investors; Ben-David, Franzoni, Kim and Moussawi (2023) document that specialized ETFs are often catered to attention-grabbing themes and retail traders are documented with chasing attention grabbing events (Barber, Huang, Odean and Schwarz, 2022).

We present statistics in Table 4. Table 4 is descriptive and we draw no formal inference from it. Our expectations for broad-index ETFs are met as they exhibit the highest mean order imbalance, highest persistence and lowest return chasing. We are met with a contradiction to our expectation for leveraged ETFs, as leveraged ETFs exhibit the second highest fractional order imbalance, and persistence. Common stocks are associated with a moderate buy-side order imbalance, roughly a third of broad-index ETFs (0.018 vs 0.048) and exhibit little persistence, more consistent with a mix of exposure-building and strategic trading. For all the groups the degree of return chasing is economically insignificant.

## 4. What do Fractional Trades Represent?

Section 3 presents the descriptive characteristics of fractional trades, high in count, tiny in size, higher volume in the morning, and more prevalent in ETFs. The fractional reporting reform provides a direct, inference-free view of retail trading. In this section we characterize the composition of fractional trades, identify the firms that execute it by brokerage name, and test if fractional trades are retail against two established benchmarks and an independent attention measure. We also show where fractional activity concentrates, popular rather than expensive stocks, and correlates with retail attention episodes.

### *4a. Fractional Share Concentration.*

Fractional activity is potentially a lower-bound proxy for retail interest, and we use it to ask which stocks fractional retail traders congregate in. The answer is a handful of popular names. Table 5 sorts stocks into quartiles within each sample by fractional dollar volume. In common stocks (Panel A), the bottom two quartiles are economically small, the most active stock in the second quartile transacts just \$165,229 of fractional volume over the sample, while the top quartile holds 98.29% of all common-stock fractional dollar volume, ranging from \$1.24 million at the bottom to \$3.79 billion at the top. ETFs are even more concentrated, at 99.53% of dollar volume. Figure 5 plots cumulative distribution functions of stock-level activity; in common stocks (Panel A) the fractional CDF lies below the CDF of overall activity, so fractional trading is more concentrated than non-fractional trading, and the log-log scatter of fractional against total trade counts (Panel B) is convex. While Table 5 suggests that ETF fractional activity is more concentrated than non-fractional trading, the cumulative distribution function of stock-level activity in Figure 5 (Panel

C) displays that the concentration in ETFs is similar to overall trading volume, corroborated by the linear log-log scatter (Panel D).[7]

Does this concentration reflect a reach for expensive stocks? DFL argue that fractional trading is a mechanism for capital-constrained investors to purchase high-price stocks they otherwise could not afford. Figure 6 is our initial inspection of this claim. Panels A and C plot stock-level fractional dollar volume against price on log scales; in common stocks the two are positively related (Pearson = 0.53 on logs), as they are in ETFs (Pearson = 0.39 on logs). This replicates the prior finding that fractional volume is higher in expensive stocks.

We contend that raw fractional volume is not the correct variable, as high-price stocks are also high-activity stocks that carry higher non-fractional volume as well, so a positive raw relation confounds price with activity. Panels B and D of Figure 6 normalize by total dollar volume: we plot the share of dollar volume attributable to fractional trades against price. In common stocks the relation reverses to −0.17. Measured as a proportion of the stock's own trading, fractional activity is lower in expensive stocks. In ETFs the correlation remains slightly positive at 0.14 but visually appears as noise. We test whether these relations persist after controlling for stock characteristics. Table 6 regresses the fractional share of dollar volume on log price, log market capitalization, log realized variance, log turnover, and the stock's BJZZ retail share (the total volume of BJZZ identified trades divided by the total volume). In Panel A the coefficient on log price is negative and significant for common stocks (−0.0176, $t = -5.84$), yet positive and significant for ETFs (0.0534, $t = 3.03$). Conditioning on size, volatility (realized variance), activity (turnover), and an independent retail measure, the fractional share of a common stock's volume does not rise with its price whereas the ETF coefficient points in the other direction. We also find that the BJZZ retail share is positively related to the fractional share of ETFs yet insignificant for common stocks. The insignificant relation in common stocks could be attributed to the misclassification of trades as retail under BJZZ (Barber, Huang, Jorion, Odean, and Schwarz 2024; Battalio, Jennings, Saglam, and Wu 2023),

[7] In Figures A1 and A2 we present the stocks with the highest fractional trade counts during the sample

fractional trading capturing a different segment of retail investors, or the relation between fractional trading and BJZZ volume share being fully subsumed by stock characteristics.

In Panel B of Table 6, we replace the dependent variable from the fractional share of dollar volume to the log-count of fractional trades. The results are consistent with Panel A, fractional counts fall with price in common stocks and rise with price in ETFs, conditioning on overall activity, volatility, and size. For common stocks this reinforces that higher-priced stocks have not only a lower share but a lower absolute count of fractional prints once a stock's trading characteristics are held fixed. We interpret the relation of fractional counts and price in ETFs carefully, as fractional activity is heavily concentrated (Table 5), and most ETFs trade fractionally in negligible amounts. We re-estimate both specifications on stocks ranked in the top fractional-dollar-volume quartile of each sample (Table A1) and find the common stock coefficients are essentially unchanged. For ETFs, however, the positive price coefficient in the dollar-share specification becomes insignificant among active stocks ($t = 1.35$). The full-sample ETF fractional-share result is driven by ETFs which have very thin fractional trading activity. The positive relation between the count of fractional trades and the price of the ETF remains in the top activity quartile specification. Therefore, in ETFs with the most fractional trading, we find a relation between the count and stock price, the kind of capital-constraint mechanism DFL describe. A 1% higher priced stock is associated with 0.54% more fractional trades. Notably, in our estimations on the top quartile of fractional activity the BJZZ retail share becomes a positive and significant predictor of the fractional share in both samples. The null result in the full sample appears to be a product of thinly traded securities, which may differ in their BJZZ and fractional population base.

We reconcile our divergence from DFL: our specification is fundamentally different, we control for stock activity (turnover), whereas their fractional-trading-introduction event study does not. High-price stocks in their sample possibly carried higher overall volume around the introduction regardless of fractional activity. While we do not refute the claim that high-price stocks had an increase in off-exchange one-share trades after the introduction of fractional trading, we show that the current fractional trader does not reach for high-price stocks in the cross-section. The difference in specification, together with a different sample period and our direct rather than one-share-inferred measurement of fractional counts, is a natural source of divergence.

The pattern that emerges is not one of capital-constrained investors reaching for expensive stocks, but of retail investors taking tiny positions in stocks that happen, on average, to be expensive. A skeptic may have reservations about our "crumb" interpretation, as fractional shares may execute in a manner which is unobserved on the tape (Apex Clearing) or what we see on the tape may be the fractional leg from mixed-order (super-fractional trade). We cannot speak to the first and therefore cannot rule out the possibility that unobserved fractional activity is fundamentally different from the fractional activity we observe on the tape, however, there is no extant empirical literature that suggests it is. Addressing the second, fractional shares which originate from a mixed-order and execute in a separate print are unlikely to account for a significant portion of tiny trades we observe in the data. Consider a buyer that purchases \$300 of a \$200 stock. If the fractional and whole leg are separated, this would produce a one-share trade and a 0.5-share trade; this mechanism occurring repeatedly across investors would produce a uniform sub-one-share fractional trade size distribution. The sub-one-share prints which we find are not evenly distributed. Of the 329 million common-stock trades below one share, 35.1% fall in the first hundredth of a share, 66.7% below a tenth, and 87.8% below a half. The mass of the distribution is towards zero and decays near monotonically (Figure 3), rather than spreading evenly as a split remainder would require. We confirm this directly in Appendix Figure A3, simulating the fractional legs of dollar-denominated-orders across the empirical price distribution, the null is flat, the data are not. While we cannot rule out the split-leg mechanism for any individual print, it seems unlikely to be the primary generating process for what we observe on the tape. The typical fractional trader we can identify on the tape does not appear to reach primarily for high-priced stocks or to place large fractional orders; rather, they buy crumbs at all price levels.

***4b. Sophisticated Fractional Trading?***

Our interpretation at this point suggests that fractional activity arises from retail traders making small purchases, we concede that the fractional trading we observe is a heterogeneous population that we necessarily pool. In this section we attempt to identify if fractional trading is used in sophisticated trading strategies. Fractional trades may arise from different mechanisms, as discussed above, and we are unable to attribute intent to any trade we observe on the tape. The data suggest, however, that fractional trading is used by retail traders to make minuscule trades in stocks. We note that fractional trading is not restricted to only retail traders, institutional traders could engage in fractional trading to ping for liquidity (Davis, Roseman, Van Ness, and Van Ness, 2017) or fractional trading could be a means of stealth trading at the finest possible grain.[8] Retail traders may also use fractional trading as a method for their own version of stealth trading, and given that retail traders will typically have lower capital than institutions, fractional trades may be necessary for sufficient order-splitting. Furthermore, practitioner studies argue that retail traders can earn alpha with relatively simple algorithmic strategies (Harke, Shishlenin, and Koppisetti, 2020) and algorithmic trading originating from retail traders is documented in the options market (Garcia-Ares, Amaya, Pearson, and Vasquez, 2026). We explore whether we can observe traces of fractional institutional activity, or fractional algorithmic retail trading in the consolidated tape.

Regulation, rather than inference, rules out fractional pinging as exchanges and ATSs accept only integer share quantities, so fractional prints cannot be pings to an exchange or ATS.[9] We next investigate whether we find the footprint of sophisticated trading strategies which execute by either institutional or retail investors. A striking feature of the observable fractional trades on the tape is the clustering of trade sizes. A large share of fractional prints land at exact, and often peculiar, quantities that recur across millions of trades. Table 7 presents the three modal fractional trade sizes ranked by trade count for both Nasdaq and NYSE common stocks.[10] In common stocks, 7.9% of all fractional prints are for exactly 0.003 shares, and 88.0% of those originate from Nvidia, where the 0.003 quantity alone accounts for 39.5% of the stock's

---

[8] Stealth trading literature documents that price-changing information content in trades can be predominantly traced to institutional traders using medium-sized trades (500-9900), as opposed to large trades (10,000 <) to conceal their information (Barclay and Warner, 1993; Chakravarty, 2001). While fractional trades are much smaller than the medium trades documented in previous studies, modern markets have gotten much smaller and odd-lot trades have become more prevalent (O'Hara, Yao and Ye, 2014). It is not unreasonable to suggest that institutions in modern markets could potentially move towards the smallest trade size available, which are fractional trades.

[9] https://www.federalregister.gov/documents/2024/09/09/2024-20170/self-regulatory-organizations-national-securities-clearing-corporation-notice-of-filing-and, accessed July 2026.

[10] We present at most one trade count per symbol, without this filter NVDA would be associated with the number one (0.003) and number two (0.002) trade size.

fractional trades. This phenomenon occurs across stocks: for example, 99.5% of all 0.0016-share prints are Tesla, and many of the high-profile stocks are effectively dominated by some discrete sub-share quantity. Odd fractions such as 0.003 shares, repeated identically across tens of millions of executions, are likely to be automated executions as opposed to orders entered by investors. We denote these clustered trade sizes as spikes and attempt to identify their origin.

Viewed in dollars rather than shares, a pattern emerges. While the trade size in share-terms across the most frequent trade sizes seems random, most fall in a tight sub-dollar band (~\$0.40-\$0.80) when viewed in dollars.[11] The mechanism is therefore a fixed dollar amount, divided by the stock's price and rounded to a coarse share grid. The seemingly strange fractional trade sizes of 0.003 shares of Nvidia (~\$200), 0.0016 shares of Tesla (~\$400), and 0.01 shares of Coca-Cola (~\$80) all work out to sub-dollar purchases. This is the signature of automated round-ups by fintech firms, not of size selection by a trader optimizing execution.[12]

Despite the small notional value of the trades, we cannot dismiss that this could be the footprint of a sophisticated trading strategy. For each stock we flag its recurring spike sizes, any exact quantity that accounts for at least $\tau$ of the stock's fractional prints, and we describe the trades that fall in them at thresholds of $\tau = \{5\%, 10\%, 15\%\}$, verifying robustness across thresholds.

Four features place these trades well outside anything a sophisticated trader would produce, presented in Table 8. First, they are economically negligible in terms of volume, spike trades make up 22.2% of all fractional trades but 0.12% of fractional dollars. On the median stock-day the total dollar volume in spike sizes is \$6.10, the 95$^{th}$ percentile is \$912 and the busiest spike day in the entire sample, NVDA on June 15, reaches only \$243,022, which is negligible against its multi-billion-dollar trading

[11] There are exceptions to this pattern, for example we find significant spikes in PLTR (~\$1.41) and SNDK (~\$0.93). Most significant spikes in sub-one-share fractional trades are for under \$1.00 in notional.
[12] Multiple different fintech firms offer a service where after a purchase, the price is rounded up to the nearest dollar and the remainder is transferred into an investment or savings account. For example: Revolut, https://help.revolut.com/en-US/help/app-features/vaults/how-do-spare-change-round-ups-work/, accessed July 2026; Acorns, https://www.acorns.com/round-ups/; and Cashapp, https://cash.app/help/us/en-us/10131-cash-card-round-ups/, accessed July 2026.

activity. It is hard to rationalize an institution's trading strategy that deploys so little capital. The small capital does not rule out retail traders deploying algorithms (Garcia-Ares, Amaya, Pearson, and Vasquez, 2026). Second, the average spike trade is worth \$0.73. Third and potentially most damaging to the notion of sophisticated fractional trading in these trade sizes, most trades are signed as buys, 88.3% of spike trades are buyer-initiated and 67.8% of stock-days carry a net buy imbalance. This is the footprint of a steady accumulation from a savings strategy rather than a two-sided trading strategy. The strong buy-side order imbalance is not a misclassification due to the tick test (Lee, Ready 1991), because only 0.26% of these trades print at the midpoint, the quote rule signs almost all of them. Fourth, the trades are uninformed, over the five minutes after a spike print the midpoint moves −0.06 basis points. To test whether spike-fractional trades differ in price impact from non-spike-fractional trades and from non-fractional trades, we estimate:

$$\overline{PI}_{i,t,c} = \beta_1 \text{Spike}_{i,t,c} + \beta_2 \text{NonSpikeFractional}_{i,t,c} + \alpha_{i,t} + \varepsilon_{i,t,c} \quad (3)$$

where the unit of observation is a stock-day-category cell. For each stock *i* and date *t* we group that day's trades into three categories *c*, spike-fractional, non-spike-fractional, and non-fractional. $\overline{PI}$ is the mean price impact of the trades in the cell, where a trade's price impact is its signed five-minute-forward midpoint return in basis points. *Spike* equals one for the spike-fractional cell, a fractional trade is a spike if its exact share size accounts for at least τ of a stock i's fractional prints over the sample, among stocks with at least 100 fractional prints. *NonSpikeFractional* indicates the remaining fractional trades, and non-fractional trades are the omitted category. Therefore, $\beta_1$ measures the difference in price impact between a stock's spike trades and its non-fractional trades on the same day, and $\beta_2$ measures the difference between its non-spike-fractional and non-fractional trades. The stock-by-date fixed effects $\alpha_{i,t}$ absorb each stock-day's average price impact, so both coefficients are identified within a single stock and date, we cluster standard errors by stock. To compare spike trades against non-spike-fractional trades directly, we re-estimate (3) on fractional trades alone, with non-spike-fractional as the omitted category, the coefficient on *Spike* is then the spike-versus-non-spike-fractional difference reported in Table 8.

We find that spike-fractional trades have a 7.58-basis-point lower price impact than an ordinary non-fractional trade in the same stock on the same day ($t = -14.2$), and spike trades are statistically indistinguishable from the rest of a stock's fractional trades. It is hard to rationalize a sophisticated investing strategy (institutional or retail) which, largely, places mostly buy orders, transacts in minuscule size, and carries virtually no information. A broader finding falls out of this subsection, fractional trades, spike or not, are uninformed as measured by price impact. This is evidenced as spike and non-spike fractional trades are statistically indistinguishable, while both fall far below non-fractional trades, ordinary fractional trades are equally uninformed. Tightening the threshold from 5% to 15% retains only the most concentrated sizes (fewer spike cells, higher within-stock share), and findings are consistent.

We do not present the results for brevity, but the statistics are similar in ETFs. The clustered trades are trivial in volume, 13.2% of fractional trades but 0.07% of fractional dollars, and uninformed, moving the midpoint 1.41 basis points less than non-fractional trades over the following five minutes ($t = -8.3$). Lastly, 80.4% of ETF spike trades are buyer-initiated. The programmatic fractional trading footprint is evident, but we interpret it as the regularity of a dispersed retail investor base. We attribute the spikes to automated micro-investing: a small, fixed dollar amount, invested repeatedly, in one direction, with no effect on price. This is in line with the crumb interpretation of Section 4a.

***4c. Who Executes Fractional Trades?***

If fractional prints are retail, the firms that execute these trades should be retail brokers. We identify a set of the brokers that execute fractional trades using the FINRA OTC data. Before the February 23, 2026 reporting change, a broker which executes a sub-one-share order reports it as a one-share trade, so a firm whose trades are fractional printed roughly one share for every trade it reported: a shares-to-trades ratio of approximately one (BMO). After the change, that same firm reports each trade at its true sub-share size, and its shares-to-trades ratio declines below one. A firm that executes whole-share trades, by contrast, reports many shares per trade and the shares-to-trades ratio does not decline. We use the FINRA OTC

Transparency data, which reports shares and trades that execute off-exchange at the firm-week level.[13] We measure this change for every off-exchange executor and identify by name the firms whose ratio drops.

We measure the change within NMS Tier 1, the S&P 500, Russell 1000, and major exchange-traded products, computing each firm's shares-to-trades ratio in the seven weeks before and the fourteen weeks after the reform. Restricting to Tier 1 is not for convenience: across every off-exchange executor in the sample, no firm clears the fractional threshold within NMS Tier 2 without also clearing it within Tier 1. We find that some firms do not clear the fractional threshold in their blended ratio (Tier 1 and Tier 2) but are clearly identified as fractional executors from their Tier 1 ratio, which is why we focus on the Tier 1 ratio. We classify a market participant as a fractional executor if its Tier-1 ratio falls below 0.90 post-reform, a threshold we set below the break point of one. The highest Tier-1 ratio among confirmed executors is 0.86 (Pershing), and the closest miss is 0.94 (DriveWealth's post-merger Tier-1 ratio, discussed below). As a cross-check, and because it is what FINRA publishes as the per-firm totals, we also compute the blended ratio, summed across all NMS tiers. Table 9 reports both NMS Tier 1 and the blended ratio, nine of the thirteen confirmed executors clear the threshold on both bases, for four executors, the two measures diverge. Table 9 lists the confirmed executors, ranked by post-reform Tier-1 trade count.

The first group is dedicated fractional-clearing firms: Alpaca Securities (34.5 million Tier-1 trades, ratio 1.00 to 0.27), Apex Clearing (post-ratio 0.68), Velox Clearing (post-ratio 0.27), and Green Pier Fintech (post-ratio 0.18). Apex is the omnibus clearer behind SoFi, Webull, and Tastytrade. Apex's trade count is low relative to its scale because a predominant share of its transactions never appear on the tape at all, reported instead through internal inventory allocation (BMO). Alpaca is a broker-dealer that supplies brokerage infrastructure, including fractional order handling, to other fintech applications under its own registration, reportedly serving several million accounts across dozens of countries.[14]

[13] The FINRA OTC data is publicly available and can be found here https://otctransparency.finra.org/otctransparency/OtcDownload, accessed July 2026.
[14] Information on Alpaca can be found here https://alpaca.markets/, accessed July 2026.

The second layer is retail brokerage apps clearing in their own name: Futu Clearing, Moomoo's clearer (2.1 million Tier-1 trades, 1.01 to 0.29), Robinhood Securities (1.8 million Tier-1 trades, 1.00 to 0.15), TradeUp Securities (0.14 post-ratio), and Albert Securities (post-ratio 0.24). Robinhood, the name most associated with fractional trading in the popular press, is neither the largest executor in this layer nor across the full list.[15] Note that Futu's (1.32) and Albert's (1.14) do not clear the threshold, their non-Tier-1 business is large enough to dilute it, a pattern that is shared by firms in the third category.

The third category is conventional-broker and clearing-firm entities that run fractional programs alongside a larger whole-share business. National Financial Services, Fidelity's clearing arm, reports 34.2 million Tier-1 trades at a ratio of 1.00 to 0.27, second in scale only to Alpaca across the entire list, while its blended, all-tier ratio of 1.73 gives no indication of a fractional program at all. The remaining conventional executors are Mirae Asset (0.77), Morgan Stanley's retail arm (0.42) - distinct from its wholesale entity, whose ratio remains in the thousands - Pershing (0.86), and Axos Clearing (0.31).

DriveWealth, the white-label clearer behind many brokerage apps, operated two registered entities before June 2025. DriveWealth Institutional, whose shares-to-trades ratio was higher (between 33 and 94), indicative of whole-share institutional trades, and DriveWealth, LLC, whose ratio was exactly 1.00 in every week, the fractional arm studied by BMO. The two entities consolidated in June 2025, before our sample window begins, which is why DriveWealth's 2026 ratio no longer dips below the threshold. Its post-reform Tier-1 ratio of the now combined entity, 0.94, is the closest miss in our sample, consistent with, not contradicting, its fractional status. However, we do not include it in this list as it is unclear the count of trades which can be reasonably attributed to fractional executions.

Summing Tier-1 trade counts across all thirteen confirmed fractional executors yields roughly 83 million trades over the fourteen post-reform weeks, over this same time period we observe 350 million sub-

[15] We posit that Robinhood likely altered how it services fractional customers. BMO document that Robinhood executed approximately 50 million trades from November 1 2021 to March 21 2022. We go farther back in the OTC data and find that Robinhood was reporting 5 million trades a week in early 2024, but the count of trades dropped near monotonically, in 2025 Robinhood began executing less than half a million trades a week, moderately higher than the ~0.15 million / week we observe in our sample. We found no explicit evidence of Robinhood altering their fractional clearing process, nor do we find evidence of their total notional volume decreasing.

one-share fractional trades on the tape.[16] Executors we can name account for about 24% of the sub-one-share fractional trades we observe. We report this share as the identified portion rather than extrapolating a broker-level footprint across the remainder. Identified firms span dedicated fractional clearers, retail app-based brokers, and traditional brokers. We treat the unidentified remainder as belonging to this same heterogeneous population, not a distinct one. BMO were able to match fractional trades on the tape to broker identities using a latency footprint and estimate market quality effects from only the app-based brokers they chose to identify. We do not proceed with a direct identification of our own using latencies for two reasons. First, the purpose of our paper is to study fractional trading on the tape as a whole. Second, full identification would require repeatedly executing test trades to re-derive latency footprints as execution patterns drift. We attempt to use the BMO identification method for Robinhood and DriveWealth in Appendix A, and find that in the current market regime, both firms are unidentifiable with the previous latency-based methodology. We therefore treat fractional trading on the tape as a heterogeneous group.

***4d. Is Fractional Trading a Proxy for Retail Traders?***

We have argued that fractional activity can be attributed to retail traders through its trading characteristics: small, uninformed trades in high-profile stocks. Section 4c corroborated this point, as we were able to identify a handful of market participants who execute fractional trades; these participants are retail brokers or retail broker clearing houses. We are able to attribute only 24% of the fractional trades we observe on the tape to these identified participants. In this section we ask whether all fractional activity on the tape correlates with retail activity. We use two sources to measure overall retail activity: the BJZZ (2021) sub-penny method, whose accuracy is widely debated (Barber, Huang, Jorion, Odean, Schwarz, 2024; Battalio, Jennings, Saglam, and Wu, 2023), and Rule 605 reports. We follow Dyhrberg, Shkilko, and Werner (2025) in treating the monthly execution-quality reports that wholesalers file under Rule 605 as the most comprehensive public record of retail activity. The rationale is institutional, retail brokers route the large

[16] This count reflects common stocks and ETFs combined, during regular trading hours, over the fourteen post-reform weeks (2026-02-23 through 2026-05-31) that coincides with the FINRA OTC data which is available. Using the full trading session as opposed to filtering to just the RTH, the count increases to 388 million for all fractional prints.

majority of their customers' marketable orders not to exchanges but to a small set of wholesalers, who internalize these trades and return part of the bid-ask spread to the customer as price improvement. Rule 605 requires every wholesaler to report stock-month statistics of execution quality of all orders it handles, so the filings aggregate to a near-complete census of the marketable retail orders routed off-exchange. Industry consensus and the regulatory record hold that these wholesaler reports contain predominantly retail orders and cover virtually all of them (Dyhrberg, Shkilko, and Werner 2025).

There are two features which make rule 605 data a useful retail benchmark for our question. First, it covers only held, liquidity-demanding orders of 100 to 9,999 shares. Held orders require immediate execution and are the signature of self-directed retail, whereas the not-held and special-handling orders typical of institutional trading are excluded by rule, so wholesaler 605 volume nets out the institutional side even at firms that operate both a retail and an institutional book. Second, the round-lot floor means 605 excludes fractional and odd-lot trades entirely. The retail activity that 605 measures is therefore, by construction, disjoint from the sub-share fractional activity we study. Any agreement between the two is a cross-population test of whether fractional trades and overall retail trades concentrate in the same securities.

We build the 605 measure from the February through May 2026 filings of the eight wholesalers identified by Dyhrberg, Shkilko, and Werner (2025). We further partition the eight into six payment-for-order-flow wholesalers, Citadel Securities, Virtu, G1 Execution (Susquehanna), Jane Street, Two Sigma, and UBS, and the two banks that internalize their own trades, Morgan Stanley and Merrill Lynch. For each stock-month we sum executed share volume on marketable orders across the six PFOF wholesalers, then separately across all eight, and scale by the stock's total share volume to form its wholesaler share. We keep the two captive internalizing banks separate, because if fractional trading tracks the PFOF wholesalers but not the bank captives, that difference is informative about which kind of retail activity fractional trading represents.

BJZZ identifies retail trades as off-exchange (Exchange "D") prints on a sub-penny price grid, and signs them from the sub-penny fraction. A trade priced just below a round penny is a retail buy, just above is a retail sell. The method therefore requires two things of a trade, that it print off-exchange, and that its price carry a sub-penny increment in a signable band. Fractional trades satisfy the first by construction, since they all print off-exchange, so we can measure exactly how much of the fractional tape BJZZ would identify. Table 10 shows that, of the 335 million common-stock fractional trades, 26.0% print at an exact penny with no sub-penny improvement and 28.0% print at the midpoint or within the midpoint band (0.4 to 0.6). Therefore, BJZZ assigns a retail direction to 46.0%. ETFs are nearly identical (44.7% signable, 28.2% round-penny, 27.1% unsigned). A researcher relying on BJZZ to measure retail activity would identify under half of the fractional trades as retail. We also find that the trades which are missed are systematically different: round-penny trades carry a much larger median dollar size ($15.00 versus $1.56 for signable common-stock trades), so BJZZ systematically drops the larger fractional retail prints.

In Table 6 we find that the BJZZ volume share is positively correlated with fractional counts for both common stocks and ETFs.[17,18] We now examine the relation between the fractional trades we observe on the tape and the retail 605 data. Because the Rule 605 marketable universe and the fractional population sit on incomparable scales (605 share volume is larger by orders of magnitude) we test for rank agreement rather than a level relation, conditioning on the firm characteristics that drive both measures independently of retail intent. For stock $i$ in month $t$, define the fractional (F) and PFOF-wholesaler (W) shares of total share volume,

$$F_{i,t} = \frac{\text{FracVol}_{i,t}}{\text{Vol}_{i,t}},\; W_{i,t} = \frac{\text{WholeVol}_{i,t}}{\text{Vol}_{i,t}}, \tag{4}$$

where $\text{FracVol}_{i,t}$ is fractional share volume, $\text{WholeVol}_{i,t}$ is the executed share volume of the six PFOF wholesalers, and $\text{Vol}_{i,t}$ is total share volume, measured as the total volume in the TAQ consolidated feed. We construct a set of firm characteristics with which retail activity may be correlated, $X_{i,t} =$

[17] In the full cross-section the relation between fractional volume shares and BJZZ volume shares is insignificant for common stocks but significant for ETFs. In Table A2 when restricting the sample to only the top quartile ranked by fractional activity, we estimate a significant relation between fractional volume shares and BJZZ volume shares.

[18] In unreported results we find that stock-month correlations between BJZZ-identified and fractional volume in common stocks is 0.90 (Spearman; and 0.87 Pearson in logs); for ETFs it is 0.83 (Spearman; 0.81 in logs). The correlation between the fractional order imbalance and the BJZZ order imbalance is essentially zero (Pearson 0.02 for common stocks, near zero and slightly negative for ETFs).

$(\ln \text{Price}_{i,t}, \ \ln \text{MktCap}_{i,t}, \ \ln \text{Vol}_{i,t})'$ (price, market capitalization, and total volume). We then compute residuals, orthogonal by construction to these characteristics, by estimating the following regressions,

$$F_{i,t} = \alpha_F + \beta_F' X_{i,t} + \delta_t^F + \varepsilon_{i,t}^F, \tag{5}$$

$$W_{i,t} = \alpha_W + \beta_W' X_{i,t} + \delta_t^W + \varepsilon_{i,t}^W, \tag{6}$$

where $\delta_t$ are month fixed effects, and we finally measure the conditioned agreement as the Spearman rank correlation of the residuals,

$$\rho_{conditional} = \rho_{spearman}\left(\varepsilon_{i,t}^F, \varepsilon_{i,t}^W\right). \tag{7}$$

We also estimate the raw agreement $\rho_{\text{raw}} = \rho_{spearman}(F_{i,t}, W_{i,t})$ which applies the same rank correlation to the shares directly, without the first-stage residualization; the gap between $\rho_{\text{raw}}$ and $\rho_{conditional}$ can be interpreted as how much of the co-movement is merely shared exposure to size, price, and volume.

Table 11 presents the correlations for different windows. Recall that fractional trades began reporting to the tape on February 23, 2026, and our correlation in February is therefore estimated with an incomplete fractional tape for the month. For common stocks, conditioned agreement is $\rho_c = 0.36$, compared to the raw $\rho_{\text{raw}} = 0.41$. ETFs agree weakly ($\rho_c = 0.18$). The agreement is consistent, and higher across March-May as we have a full panel of fractional activity. We also find that the correlation is stronger when restricting our volume-share measures to just the six PFOF wholesalers as opposed to Morgan Stanley and Merrill Lynch, who execute their own order flow; PFOF6, $\rho_c = 0.36$; MS/ML $\rho_c = 0.29$.

We also estimate an identical framework against the BJZZ volume share as opposed to the wholesaler volume shares. When estimating the correlations between the proportions of volume, in Table 11, we find that $\rho_c = 0.12$ ($\rho_{\text{raw}} = 0.35$) for common stocks and $\rho_c = 0.20$ ($\rho_{\text{raw}} = 0.16$) for ETFs. In common stocks, the overall BJZZ and fractional activity are highly correlated but the share of volume attributable to both attenuates to 0.12 when conditioning on firm characteristics. In ETFs, by contrast, the correlation between BJZZ and fractional volume shares increases when residualized and is higher than the relation of 605 and fractional volume shares.

We note that BJZZ and wholesaler trades overlap substantially, with a population rank agreement of 0.58 for common stocks and 0.69 for ETFs (Table A2), higher than the fractional trading agreement with either benchmark. This is expected and does not conflict with Battalio, Jennings, Saglam, and Wu (2023), who show BJZZ to be an unreliable retail classifier at the trade level.[19] Their critique concerns which trades BJZZ labels whereas a cross-sectional rank agreement is a coarser object that identifies which stocks the measures both share activity in. The overlap is also partly mechanical: BJZZ and 605 are both round-lot, off-exchange constructions drawn from the same population of trades, whereas fractional prints are disjoint from 605 by rule. If BJZZ carries any retail signal, it is not surprising its identified trades track 605 more closely than it tracks fractional trades, which is why we treat 605 as the primary benchmark and read BJZZ as corroboration rather than an independent second source.

Two ratios that share a denominator can correlate spuriously (Pearson, 1897; Kronmal, 1993). We therefore perform a simple robustness check to confirm the agreement is not an artifact of the shared $1/\mathrm{Vol}_{i,t}$ denominator in $F$ and $W$. First, in Table 12, we re-estimate the conditioned agreement within each decile $d$ of total volume and report the average,

$$\bar{\rho}_{conditional} = \sum_{d=1}^{10} \frac{1}{10} \rho_c^{(d)}, \tag{8}$$

which equals 0.37 for common stocks and 0.23 for ETFs. The count-weighted decile correlations are slightly higher than the pooled figures, so the co-movement survives where the common denominator is held to a tighter band than in the whole sample. The decile agreement for common stocks peaks in deciles 6 and 7, and deciles 1 and 10 display the weakest relation. In ETFs the relation is strongest in decile 10 and roughly equivalent in deciles 2-8, decile 1 has a particularly weak relation as it is populated with thinly traded funds.

Having established that fractional and wholesaler trades agree on where retail concentrates, we now examine which stock characteristics drive the places where they diverge. We do not use a conditioned

[19]Battalio, Jennings, Saglam, and Wu (2023) find that it identifies under a third of known retail trades and misclassifies an economically large volume of non-retail off-exchange prints as retail.

correlation in this step, as we wish to observe the degree of deviation related to each stock characteristic. For each stock-month, we define the gap as the difference in percentile ranks of the fractional and PFOF-wholesaler shares, $(F_{i,t}, W_{i,t})$

$$\text{gap}_{i,t} = P\left(F_{i,t}\right) - P\left(W_{i,t}\right), \tag{9}$$

so that gap $> 0$ when fractional trades rank a stock higher than wholesaler flow and gap < 0 when fractional trades rank a stock lower than wholesaler trades.[20] We regress the gap on log price, log market capitalization, log realized variance, the modal-size concentration (the percentage of a stock's fractional prints occurring at its single most common exact share size, computed over stocks with at least 100 fractional prints), and retail attention measured as the log of the stock's monthly r/wallstreetbets mentions, entering the regressors one at a time, then jointly (column 6), and clustering standard errors by stock.[21] Because the two samples behave differently, we estimate the regression separately for common stocks and ETFs, ranking each stock within its own sample.

Table 13 reports the specifications, estimated separately for the two samples. In common stocks the gap rises with price (0.045, t = 15.4), market capitalization (0.044, t = 19.1), and realized variance (0.020, t = 8.0). Relative to the round-lot 605 population, fractional activity tilts toward large, volatile, and high-priced names. The gap declines with modal-size concentration (−0.0035, t = −10.0) and, in the full specification, with social-media attention (−0.0042, t = −2.0). Stocks whose fractional activity is dominated by a single recurring size (round-up signature), and are high-attention (social media), rank relatively lower in fractional activity than in retail wholesaler activity. Attention enters positively on its own but turns marginally negative once price, size, and variance are held fixed, so high-attention names are overweighted by fractional traders (relative to wholesalers) only through their size, price, and volatility profile. In ETFs we find similar results, fractional shares exceed retail shares in high priced, large, and volatile stocks. The

[20] Because the gap differences two ranks that carry the same total-volume denominator, that denominator nets out of the construction, and the shared-denominator concern addressed above does not arise here.
[21] Section 4e details the methodology for r/wallstreetbets extensively, we closely follow Eaton, Green, Roseman and Wu (2022) and Bryzgalova, Pavlova, Sikorskaya (2023).

differences between ETFs and common stocks are that we do not find a significant estimation on the coefficient for modal-size concentration in ETFs, but we do find that the fractional shares overweight ETF shares which have been discussed on r/wallstreetbets that month.

The positive price coefficient may appear to conflict with Section 4a, where the fractional share of a common stock's volume falls with price. The two results answer different questions against different benchmarks. Table 6 benchmarks fractional activity against all trading in a stock and asks whether fractional trading tilts toward expensive stocks. Table 13 benchmarks fractional activity against round-lot marketable retail flow, and a positive price coefficient there requires only that the wholesaler share decline with price faster than the fractional share does. A marketable order in the 605 universe is at least one round lot, so its minimum ticket rises one-for-one with the share price, while a fractional order's dollar-denominated ticket is invariant to price. The share-price barrier that DFL argue fractional trading was designed to remove is visible in Table 13, binding on the round-lot retail benchmark not on fractional traders. Fractional trading democratizes access to high-price stocks without producing an aggregate tilt toward them (Table 6). The price-invariant size distribution of Section 3c is informative, dollar-denominated crumbs are blind to the share price.

Taken together, the section answers its question with a bounded yes. Fractional trades concentrate in the same securities that two retail benchmarks identify. Fractional trades track the Rule 605 wholesaler census across the cross-section after being residualized on price, size, and volume and tracks BJZZ-identified retail dollar volume. We have demonstrated that fractional trades possess the characteristics of retail trades, as well as highly correlate with a known retail benchmark. While fractional trades miss a significant portion of retail volume, where fractional trades occur, is correlated with overall retail activity. We conclude that fractional trading is a complementary retail variable which has an independent signal from BJZZ, and, as Section 4b argues, is unlikely to originate from institutions; fractional trading is an independent retail proxy.

***4e. Does Fractional Activity Respond to Retail Attention Signals?***

If fractional prints are overwhelmingly app-based retail, as the trade-size and routing evidence indicates, then fractional activity in a stock should rise and fall with retail attention to that stock. We use the volume of mentions a stock receives on the Reddit forum r/wallstreetbets as an external retail-attention proxy. While other social media platforms are geared towards retail investors such as Stocktwits (Cookson, Niessner, 2020) or SeekingAlpha (Chen, De, Hu, and Hwang, 2014), we focus on r/wallstreetbets as it is one of the largest investing communities with almost 15 million members, and it is tied to the 2021 GameStop episode.[22] r/wallstreetbets is where the self-directed, app-based retail traders congregate, and we use the mention counts as a proxy for attention.[23] We expect attention and fractional trading to co-move, and fractional activity to respond to attention by more than total trading volume does.

There are established methods in the literature for using r/wallstreetbets data (Bryzgalova Pavlova, and Sikorskaya, 2023; Eaton, Green, Roseman and Wu, 2022), and we closely follow Eaton, Green, Roseman, and Wu (2022). For each stock we build a token set from its ticker, its cash-tag ($ + ticker), and its company name and name-variants, dropping tokens that collide with common English or finance vocabulary and requiring each surviving token to map to a single stock. A stock-day's attention is the count of r/wallstreetbets mentions of any of its tokens, taken from the public monthly Reddit comment archives for February through May 2026. Non-trading-day mentions are attributed forward to the next trading day, so weekend discussion loads onto Monday's session. Let $M_{i,t}$ be stock $i$'s mention count on trading day $t$ and $A_{i,t} = \ln\left(1 + M_{i,t}\right)$ the attention measure.

In the data, fractional activity is heavily right-skewed, spikes multiplicatively on attention days and is often delayed in response to r/wallstreetbets activity so we model it in logs and estimate the response with a distributed lag. Let $Y_{i,t} = \ln\left(1 + \mathrm{FracTrades}_{i,t}\right)$ be log fractional trade count. We estimate

$$Y_{i,t} = \alpha_i + \delta_t + \sum_{k=0}^{K} \beta_k \, A_{i,t-k} + \gamma' X_{i,t} + \varepsilon_{i,t}, \tag{10}$$

[22] https://www.reddit.com/r/wallstreetbets/, accessed July 2026.
[23] Our analysis is directed at correlating attention and fractional activity, we do not attempt to assign a sentiment score and relate the sentiment to a signed imbalance of fractional activity.

with $K = 10$ trading days of lags, stock fixed effects $\alpha_i$, day fixed effects $\delta_t$, and standard errors clustered by stock. The lags are built on the trading-day index, so lag $k$ is $k$ sessions back regardless of weekends and holidays. The object of interest is the cumulative response,

$$B = \sum_{k=0}^{K} \beta_k , \tag{11}$$

the total effect on fractional activity after a rise in attention accumulated over the following two trading weeks (ten trading days). The control vector $X_{i,t}$ comprises log price, log total trade count, the lagged absolute daily return ($| r_{i,t-1} |$), the lagged realized variance ($\mathrm{RV}_{i,t-1}$), and the lagged effective spread ($\mathrm{Spread}_{i,t-1}$).

Log fractional trade count rises with retail attention, in both ETFs and common stocks. In the full specification (Table 14), net of price, volume, volatility and liquidity, the cumulative two-week response to a 1% rise in the mentions of a ticker's name is associated with a 0.27% increase in fractional trade counts ($B = 0.266$; $t = 13.9$) for common stocks (column 1) and a 0.28% increase in fractional trade counts ($B = 0.284$; $t = 7.1$) for ETFs (column 4). We re-estimate the specification in columns (2) and (5) using the log count of the mentions of only the firm's cash-tag ($AAPL) as opposed to aggregating counts of the ticker as well as company names. We find the results are nearly identical in sign and significance.

It is possible that fractional trade counts as well as overall trade counts both increase following r/wallstreetbets mentions. To determine whether fractional activity experiences a larger increase, we replace the outcome in equation (10) with the log fractional share of dollar volume,

$$\ln \left(\frac{\mathrm{FracVol}_{i,t}}{\mathrm{Vol}_{i,t}}\right) = \alpha_i + \delta_t + \sum_{k=0}^{K} \theta_k \; A_{i,t-k} + \gamma' Z_{i,t} + u_{i,t}, \tag{12}$$

and we find that cumulative $\Theta = \sum_k \theta_k = +0.226$ ($t = 7.9$) for common stocks (column 3) and $+0.309$ ($t = 5.3$) for ETFs (column 6). Controlling for a stock's daily trading characteristics we find that the fractional trade counts and fractional volume shares increase following r/wallstreetbets mentions, consistent with fractional trading activity responding to retail signals and further supporting the notion that fractional trades are representative of retail attention.

While the panel regression suggests that fractional traders are influenced by social media activity and trade on the attention, to provide visual corroborating evidence we inspect two social media events which occurred since fractional trading was reported to the tape (Figure 7). On 2026-04-15, Allbirds (BIRD), a failing shoe company, announced a pivot to AI and its shares ran from about $2.50 to as high as $24. r/wallstreetbets mentions of Allbirds went from essentially zero to a same-day spike, and fractional trading intensified. Fractional activity (along with all volume) increased on the event date, the fractional share of volume remains elevated into the post-window, suggesting retail attention persisted after other participants left.[24] While the Allbirds event is not unequivocally a "meme" event, it was interpreted as such.[25] The second event was in Wendy's. Late on 2026-06-23, a reddit user on r/wallstreetbets posted that "We need to save Wendy's," the post has since garnered 23,000 upvotes and over 4,000 comments.[26][27] This was a textbook meme event, the campaign drove $WEN mentions from a few hundred a day to over five thousand in a day, trades from roughly 30,000 to over 500,000, and a price increase of 28%, its fractional activity and fractional dollar share spiked in response (the spike of mentions, trades and price occurred on the following day 2026-06-24). Similar to the Allbirds event, the volume share of fractional trading remains elevated after the initial activity spike, implying that fractional intensity persists longer than the overall volume spike. These anecdotes are illustrative, not inferential; we present them to display the relation the panel estimates in individual examples, not as independent evidence.

---

[24]Welch (2022) finds that Robinhood traders add to their positions following market volatility four days post, suggesting they await bank transfers. Our first anecdotal event is consistent with a delayed response in activity to news as the fractional share of volume remains elevated long after the event.

[25] https://www.spglobal.com/market-intelligence/en/news-insights/research/2026/04/is-allbirds-bird-the-latest-meme-stock, accessed July 2026.

[26] The original post can be found here, https://www.reddit.com/r/wallstreetbets/comments/1udygxi/we_need_to_save_wendys/, accessed July 2026. Users on r/wallstreetbets often make comments that after losing all their money trading they will need to work at Wendy's and thus if the company were to fail, they would be unemployed, direct quote: "We need to save Wendy's before it's too late. If this company goes bankrupt, we'll all be out of a job!".

[27] Our reddit data for all activity concludes in May, the Wendy's event lies outside of our sample and therefore panel regression. We complete a separate data pull using a targeted web scrape to create the Wendy's figure.

Taken together, the evidence in this section establishes that fractional trading tracks retail attention. Fractional trade counts rise with r/wallstreetbets mentions in both common stocks and ETFs, and intensifies to a higher degree than total trading does. The Allbirds and Wendy's episodes illustrate the retail-attention-to-fractional-trading channel.[28] This is what we would expect if fractional prints are composed of retail activity, and it lets fractional trades serve as a proxy for retail attention, one visible directly in TAQ.

***4f. Do Fractional Trades Predict Next-Day Liquidity and Volatility?***

Section 4d shows that fractional trades and the standard retail proxies agree cross-sectionally on where retail concentrates. However, the correlation is not perfect between 605 nor BJZZ identified retail, recall that fractional volume shares tracked 605 volume shares more closely than BJZZ. We test in this section whether aggregate fractional activity contains a different signal from the BJZZ-identified retail trades. If the two measures were interchangeable, a researcher who already computes BJZZ would learn little from fractional prints. We run a regression replicating BMO, a "horserace" in which the two retail measures compete to predict a stock's next-day liquidity and volatility.

Before moving on we note a significant deviation in our test versus BMO's specification, their fractional activity variable is all fractional trades from Robinhood and DriveWealth whereas we use all fractional trades visible on the tape. Robinhood and DriveWealth are selected by BMO as they can identify their specific fractional trades on the tape, and the two sets of trades can be linked to app-based retail traders. Our results are not directly comparable to theirs; Robinhood and DriveWealth do not capture all app-based retail traders fractional trades, as evidenced from section 4c there are other app-based retail brokers or clearinghouses besides Robinhood and DriveWealth that execute significant fractional activity, therefore BMO's estimated coefficients may not reflect the true relation of app-based fractional activity with future market quality outcomes; we aggregate all fractional activity, meaning that we have app-based fractional trades, as well as fractional trades which arise from traditional retail brokers; our sample period is approximately four years after BMO's sample ends. While re-estimating BMO's regression with identically

[28] We note that the Wendy's event sits outside the stated sample window, it would therefore not be encapsulated by the panel regression but we present it nonetheless as a retail attention event.

identified fractional trades would make for a more comparable analysis, we cannot do so as the latency-based methodologies for Robinhood and DriveWealth both fail during our sample period, as discussed in Appendix A. Since we use all fractional trades and cannot replicate the BMO counts of fractional trades, we interpret our results as the estimated liquidity and volatility effects of all fractional trades, rather than the effects from app-based fractional trades.

Following BMO, we use two stock-level measures of market quality for each trade k in stock i on day t, first, the proportional effective spread is the,

$$\mathrm{ES_k} = \frac{2 * \mathrm{D(P_k - M_k)}}{\mathrm{M_k}} \,. \tag{13}$$

where $\mathrm{P_k}$ is the trade price, $\mathrm{M_k}$ the NBBO midpoint at the trade and $D_k$ is the trade's direction, with a buy being +1 and a sell being -1. We then take the average over the $\mathrm{N_{i,t}}$ trades in the 09:30–16:00 window,

$$\mathrm{ESpread_{i,t}} = \frac{1}{\mathrm{N_{i,t}}} \sum_{k=1}^{N_{i,t}} ES_k \tag{14}$$

The volatility measure is the day's realized variance built from one-minute midpoint returns,

$$\mathrm{RV_{i,t}} = \sum_{\mathrm{m}} \mathrm{r^2_{i,t,m}}\,,\ \mathrm{r_{i,t,m}} = \ln \mathrm{M_{i,t,m}} - \ln \mathrm{M_{i,t,m-1}}\,, \tag{15}$$

the $\mathrm{r_{i,t,m}}$ being successive one-minute log changes in the midpoint within the trading day. Both enter the regressions in logs.

We estimate the horse race between the two predictors: BJZZ, the log(1 + count of BJZZ trades) on day t for stock i, and Frac, the log(1 + count of fractional trades) on day t for stock i. The specification is as follows: for each outcome Y ∈ {ESpread, RV} we estimate

$$\begin{aligned} \ln \mathrm{Y_{i,t+1}} = \beta_1\, \mathrm{BJZZ_{i,t}} + \beta_2\, \mathrm{Frac_{i,t}} + \beta_3\big(\mathrm{Top100_i} \cdot \mathrm{BJZZ_{i,t}}\big) + \beta_4\big(\mathrm{Top100_i} \cdot \mathrm{Frac_{i,t}}\big) \\ +\gamma' \mathrm{X_{i,t}} + \phi\, \ln \mathrm{Y_{i,t}} + \alpha_i + \tau_t + \varepsilon_{i,t}, \end{aligned} \tag{16}$$

with stock fixed effects $\alpha_i$, date fixed effects $\tau_t$, and standard errors double-clustered by stock and by day. The control vector $\mathrm{X_{i,t}}$ is BMO's: log share volume, log trade count, prior-day, prior-week, and prior-month midpoint returns, log market capitalization, turnover, and prior-month return volatility. The lagged dependent variable $\ln Y_{i,t}$ absorbs any persistence in spreads and volatility. The $Top100_i$ flags the hundred stocks with the most fractional trades over the sample. Because its level is time-invariant and absorbed by $\alpha_i$, it enters only through interactions with the two retail variables. We estimate the regression using our samples of common stocks and ETFs, and assess robustness to sample restrictions in Appendix Table A3.

Table 15 reports the results for the common stock sample, in Panel A the BJZZ proxy is a robust negative predictor of the next day's effective spread ($\beta_1 = -0.0368$, $t = -10.1$) implying that a day of heavier sub-penny retail activity forecasts a tighter, more liquid market the following day. The fractional-trade count does not appear to add an additional signal net of the BJZZ coefficient as when Frac enters alone it carries only a weak negative association ($\beta_2 = -0.0091$, $t = -2.8$). The Frac association is entirely shared with BJZZ: in the joint column it collapses to zero ($\beta_2 = +0.0007$, $t = 0.2$) while the BJZZ coefficient is unchanged ($\beta_1 = -0.0369$, $t = -10.4$). The interaction for Top-100 fractional trading stocks is insignificant for both Frac and BJZZ.

In Panel B of Table 15 we present the results for volatility as the dependent variable and both measures predict higher next-day realized volatility on their own ($\beta_1 = 0.0534$, $t = 9.4$; $\beta_2 = 0.0733$, $t = 14.5$). When both enter the regression simultaneously both retain their significance and relative magnitude with Frac totaling ($\beta_2 = 0.064$, $t = 12.6$) and BJZZ totaling shrinks by about a quarter ($\beta_1 = 0.039$, $t = 6.9$). The fractional tape carries predictive content about next-day volatility that the BJZZ retail proxy does not subsume, while BJZZ retail trades retain a distinct signal. We again find no significant coefficients for the Top-100 indicator variable interacted with BJZZ and Frac.

Results for ETFs (Table 16) are similar to the common stock results. We find that only BJZZ carries a significant relation to liquidity when entered alone ($\beta_1 = -0.0160$, $t = -3.0$), or with Frac present as a covariate (($\beta_1 = -0.0154$, $t = -2.8$). Frac on the other hand is estimated with no significant relation to forward liquidity when entered alone ($\beta_2 = -0.0076$, $t = -1.4$), with BJZZ present as a covariate ($\beta_2 = -0.0036$, $t = -0.6$). In Panel B, as was the case with common stocks, we find both BJZZ and Frac appear to be predictive of elevated future volatility in ETFs ($\beta_1 = 0.0126$, $t = 2.37$; $\beta_2 = 0.0340$, $t = 4.28$).

When including the Top-100 indicator variable interactions, the coefficient on BJZZ decreases slightly in magnitude with the interaction coefficient loading positive ($\beta_3 = 0.1573$, $t = 3.0$), indicating that in ETFs with heavy fractional activity, the BJZZ-volatility relation intensifies.

We investigate the robustness of the results, summarize our conclusions and reconcile our results with BMO. In Table A3 we re-estimate the full specification with varying sample restrictions, presenting only the coefficients on $\beta_1$ and $\beta_2$. We first filter to stocks with a median daily trade price of at least \$5.00; second, we filter to stocks which are in the top quartile of fractional activity (Table 5); and lastly, we apply both the \$5.00 filter and the top quartile filter simultaneously. In common stocks when liquidity is the outcome variable, we find that the coefficient on BJZZ is robust to the different specifications, retaining its significance and size. The coefficient on Frac when liquidity is the outcome variable is sensitive, it becomes significant with a positive sign (wider spreads) when restricting to only the top quartile of active stocks, yet insignificant when we include the \$5.00 filter as well as the top quartile of active stocks. When the outcome variable is future volatility, BJZZ retains its sign and magnitude across the sample splits in common stocks. Frac is sensitive to the sample, it loses significance when restricted to the top quartile of stocks ranked by fractional activity.

In ETFs, we find that the coefficient on Frac with liquidity as the outcome variable remains insignificant when altering the sample the regression is estimated on (Table A3). The coefficient for BJZZ with liquidity as the dependent variable loses its significance when restricting to the most active fractional stocks. This suggests that in the most heavily retail-traded stocks, neither BJZZ identified retail trades nor fractional trades carry incremental predictive content for future liquidity. In Panel B, both BJZZ and Frac retain their significance when predicting future volatility outcomes in ETFs.

We restate that our test differs from BMO in its timeframe and fractional trades captured; therefore, the results are not directly comparable. BMO find that app-based fractional trading predicts higher volatility and worsened liquidity in common stocks, especially in the most active fractionally-traded stocks. We find that aggregate fractional trading identified on the tape does not have a robust relation to either future volatility or liquidity in common stocks, but does appear to predict higher future volatility in ETFs. It is possible that our estimations differ from BMO as they capture fractional trades that may not arise from the typical app-based retail trader, or that we capture a larger swath of app-based trades which originate from brokers other than Robinhood and DriveWealth. We refrain from interpretations pertaining to the estimation of BJZZ and future market quality outcomes, besides noting that in our specifications we estimate that BJZZ retail activity predicts tighter future spreads in common stocks, opposite to BMO's estimated relation. Whether the divergence is caused by misidentifications (Battalio, Jennings, Saglam and Wu, 2023) or a different sample period used, we cannot determine.

**5. Conclusion**

The February 2026 FINRA reporting change requires fractional-share trades to print to the consolidated tape at their native size, making fractional activity directly identifiable in TAQ for the first time. We use it to examine if fractional trades are a directly observable proxy for retail activity and provide the first direct analysis of fractional trades on the consolidated tape.

We document that fractional trading is tiny in size and heavily concentrated in high-retail-interest stocks. The typical fractional trade executes for under $5, below one-tenth of a share, and the top quartile of fractional volume accounts for 98% of fractional dollar volume in common stocks and 99% in ETFs. Raw fractional volume rises with share price, but the relation reverses once we normalize by total dollar volume. Fractional traders do not appear to use fractional trading to reach high-price stocks they could not otherwise buy, but take tiny, price-invariant positions in stocks. The clustered sizes that dominate high-profile stocks are the signature of automated, fixed-dollar micro-investing, not of a sophisticated strategy.

Fractional trades display the characteristics of uninformed retail traders. Fractional trades are executed by retail brokers and their clearing firms, track the Rule 605 wholesaler census and BJZZ-identified retail volume in the cross-section, and rise with r/wallstreetbets mentions. While fractional trading activity tracks the 605 data, fractional traders rank high-price, large, and volatile stocks higher than the round-lot 605 population does. Over half of fractional trades are invisible to the standard sub-penny BJZZ classifier, so the fractional tape is a complementary retail signal rather than a substitute for existing proxies, one visible directly in TAQ. We also measure the information content of fractional trades. We find that fractional activity predicts elevated future volatility net of BJZZ, in common stocks and ETFs. While we estimate relations between fractional activity and future market outcomes, the coefficients are sensitive to sample restrictions. We also find that fractional prints at the trade level carry no price impact.

For researchers, the fractional tape offers a retail-attention proxy that is directly observable, requires no sub-penny inference, and captures a slice of retail trades the leading classifier misses; it could be useful for attention-based asset pricing and for the kind of event studies our Allbirds and Wendy's episodes illustrate. The census we conduct on all fractional trades has its limits. We observe only fractional trades that print to the tape, a lower bound on all fractional activity; and we can only name the executors behind roughly a fifth of the trades. Fractional trades are crumbs on the tape, tiny in size and negligible in price impact, yet indicative of retail attention, and correlated with the Rule 605 retail benchmark across the cross-section.

## References


Barber, B., Huang, X., Jorion, P., Odean, T., & Schwarz, C. (2024). A (sub) penny for your thoughts: Tracking retail investor activity in TAQ. *The Journal of Finance*, *79*(4), 2403-2427.

Barber, B., Huang X., Odean T., & Schwarz C. (2022). Attention-Induced Trading and Returns: Evidence from Robinhood Users. *Journal of Finance*, 77, 3141-3190.

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance *of* individual investors. *The journal of Finance*, 55(2), 773-806.

Barber, B. M., Odean, T., & Zhu, N. (2008). Do retail trades move markets?. *The Review of Financial Studies*, 22(1), 151-186.

Barclay, M. J., & Warner, J. B. (1993). Stealth trading and volatility: Which trades move prices?. *Journal of Financial Economics*, *34*(3), 281-305.

Bartlett, R. P., McCrary, J., & O'Hara, M. (2024). Tiny trades, big questions: Fractional shares. *Journal of Financial Economics*, *157*, 103836.

Battalio, R. H., Jennings, R. H., Saglam, M., & Wu, J. (2023). Difficulties in obtaining a representative sample of retail trades from public data sources. *Available at SSRN 4579159*.

Ben-David, I., Franzoni F., Kim B., and Moussawi R. (2023). Competition for Attention in the ETF Space. *The Review of Financial Studies*, 36, 987-1042.

Boehmer, E., Jones, C. M., Zhang, X., & Zhang, X. (2021). Tracking retail investor activity. *The Journal of Finance*, *76*(5), 2249-2305.

Bogousslavsky, V., & Muravyev, D. (2023). Who trades at the close? Implications for price discovery and liquidity. *Journal of Financial Markets*, *66*, 100852.

Bogousslavsky, V., & Muravyev, D. (2024). An anatomy of retail option trading. Available at SSRN 4682388.

Bryzgalova, S., Pavlova, A., & Sikorskaya, T. (2023). Retail trading in options and the rise of the big three wholesalers. *The Journal of Finance,* 78(6), 3465-3514.

Chakravarty, S. (2001). Stealth-trading: Which traders' trades move stock prices?. *Journal of Financial Economics*, *61*(2), 289-307.

Charupat, N., & Miu, P. (2011). The pricing and performance of leveraged exchange-traded funds. *Journal of Banking & Finance*, *35*(4), 966-977.

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

Cheng, M., & Madhavan, A. (2009). The dynamics of leveraged and inverse exchange-traded funds. *Journal of Investment Management*, 16(4), 43.

Chung, K. H., Van Ness, B. F., & Van Ness, R. A. (1999). Limit orders and the bid–ask spread. *Journal of Financial Economics*, 53(2), 255-287.
Cookson, J. A., & Niessner, M. (2020). Why don't we agree? Evidence from a social network of investors. *The Journal of Finance*, 75(1), 173-228.

Da, Z., Fang, V. W., & Lin, W. (2025). Fractional trading. *The Review of Financial Studies*, 38(3), 623-660.

Davis, R. L., Roseman, B. S., Van Ness, B. F., & Van Ness, R. (2017). 1-share orders and trades. *Journal of Banking & Finance*, 75, 109-117.

Dyhrberg, A. H., Shkilko, A., & Werner, I. M. (2025). The retail execution quality landscape. *Journal of Financial Economics*, 168, 104051.

Eaton, G. W., Green, T. C., Roseman, B. S., & Wu, Y. (2022). Retail trader sophistication and stock market quality: Evidence from brokerage outages. *Journal of Financial Economics*, 146(2), 502-528.

Garcia-Ares, P. A., Amaya, D., Pearson, N. D., & Vasquez, A. (2026). The Rise of Algorithmic Retail Option Traders. Available at SSRN 6480379.

Gempesaw, D., Henry, J. J., & Xiao, H. (2024). Retail ETF investing. *European Financial Management*, 30(4), 2305-2342.

Harke, G., Shishlenin, M., & Koppisetti, S. (2020). Application of algorithmic trading strategies for retail investors. Available at SSRN 3904097.

Holden, C. W., & Jacobsen, S. (2014). Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions. *The Journal of Finance*, 69(4), 1747-1785.

Holden, C. W., Pierson, M., and Wu, J. (2023). In the blink of an eye: Exchange-to-sip latency and trade classification accuracy. Available at SSRN 4441422.

Kaniel, R., Saar, G., & Titman, S. (2008). Individual investor trading and stock returns. *The Journal of finance*, 63(1), 273-310.

Kelley, E. K., & Tetlock, P. C. (2013). How wise are crowds? Insights from retail orders and stock returns. *The Journal of Finance*, 68(3), 1229-1265

Kronmal, R. A. (1993). Spurious correlation and the fallacy of the ratio standard revisited. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 156(3), 379-392.

Lee, C. M. and Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, 46(2):733–746.

McInish, T. H., & Wood, R. A. (1992). An analysis of intraday patterns in bid/ask spreads for NYSE stocks. *The Journal of Finance*, 47(2), 753-764.

O'Hara, M., Yao, C., & Ye, M. (2014). What's not there: Odd lots and market data. *The Journal of Finance*, 69(5), 2199-2236.

Pearson, K. (1897). Mathematical contributions to the theory of evolution.—On a form of spurious correlation which may arise when indices are used in the measurement of organs. Proceedings of the royal society of London, 60(359-367), 489-498.

Welch, I. (2022). The wisdom of the Robinhood crowd. *The Journal of Finance*, 77(3), 1489-1527.

Wood, R. A., McInish, T. H., & Ord, J. K. (1985). An investigation of transactions data for NYSE stocks. *The Journal of Finance*, 40(3), 723-739.

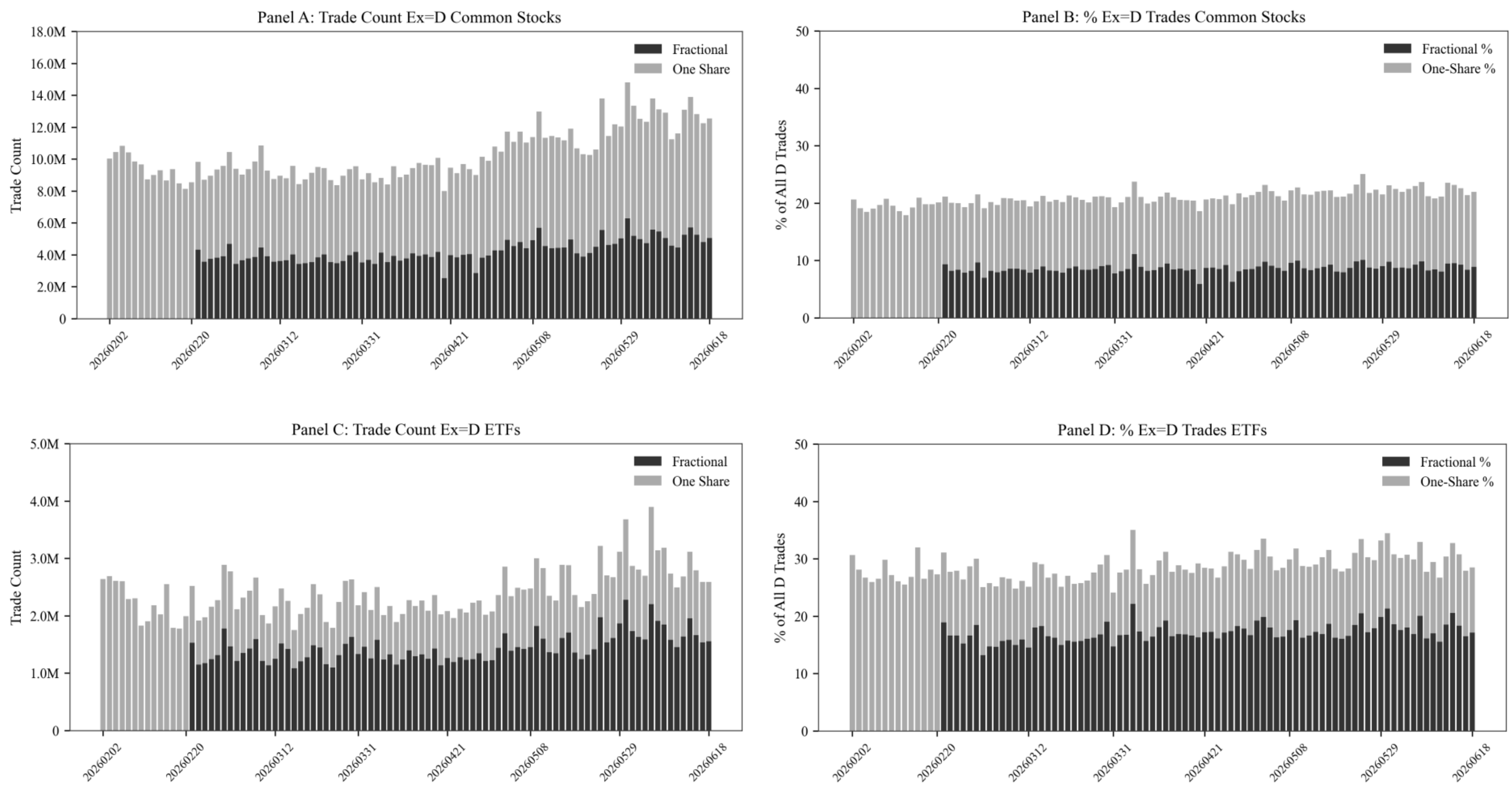


**Figure 1: Daily fractional and one-share trade counts and % on Exchange D.** The figure plots, for each trading day in the sample, the total number of fractional trades (non-integer share volume trades) and one-share trades executed off-exchange (Exchange D) for common stocks in panel A and ETFs in panel C, pooled across all stocks in the respective security types. The figure also plots the daily share of exchange "D" trades that are fractional as well as one-share for common stocks in Panel B and ETFs in Panel D. Fractional counts before February 23, 2026, are mechanically zero because sub-one-share trades were rounded to one. The sample used is February 2, 2026, to June 18, 2026.

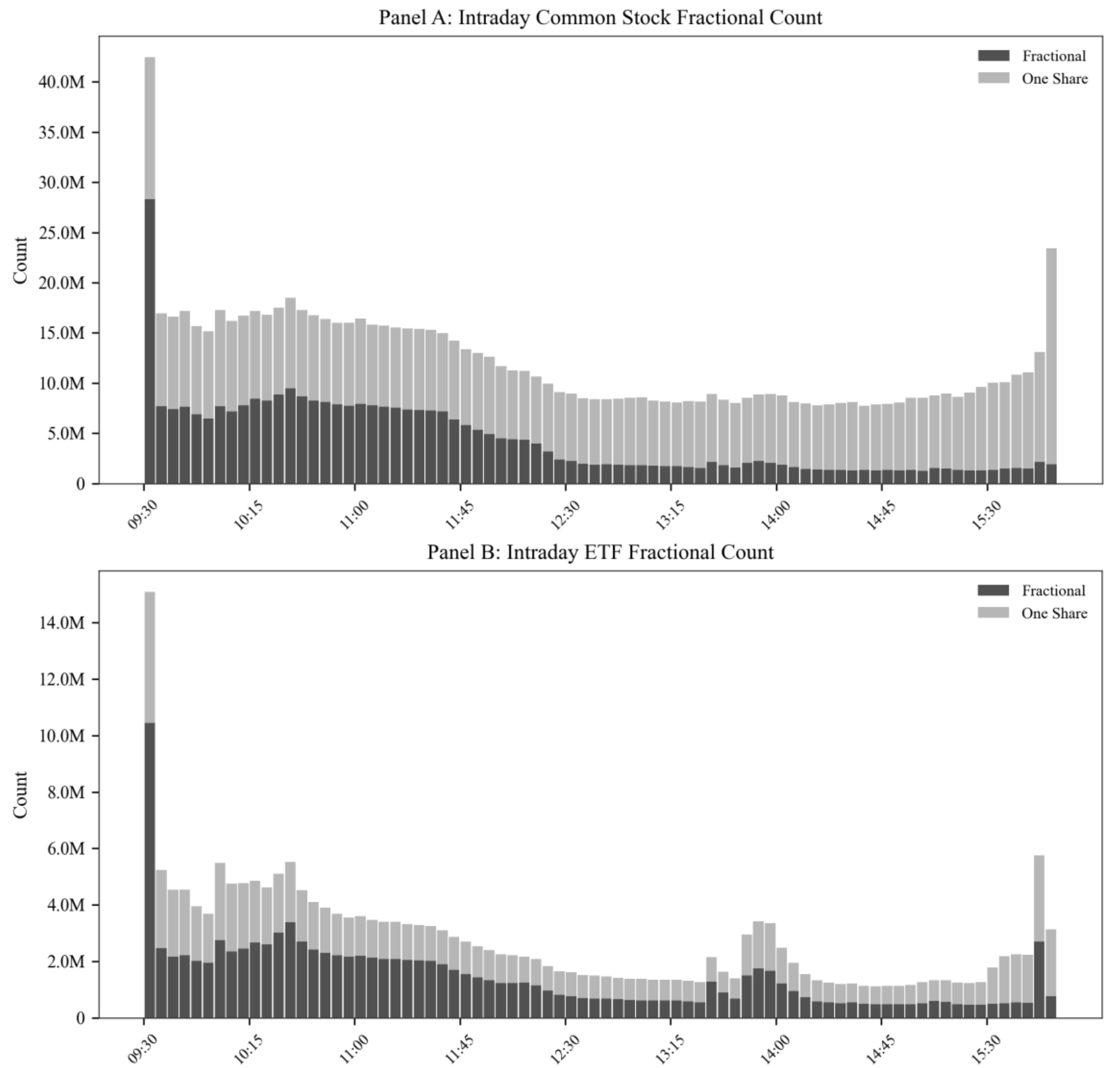


**Figure 2: Intraday Profile of Fractional and One-Share trade Counts.** For each 5-minute bin of the regular hours trading day (09:30–16:00) the figure plots the pooled per-minute count of fractional trades (non-integer share volume trades) and one-share trades on Exchange D. Panel A presents the data for common stocks and panel B ETFs. The sample used is from February 23, 2026 to June 18, 2026.

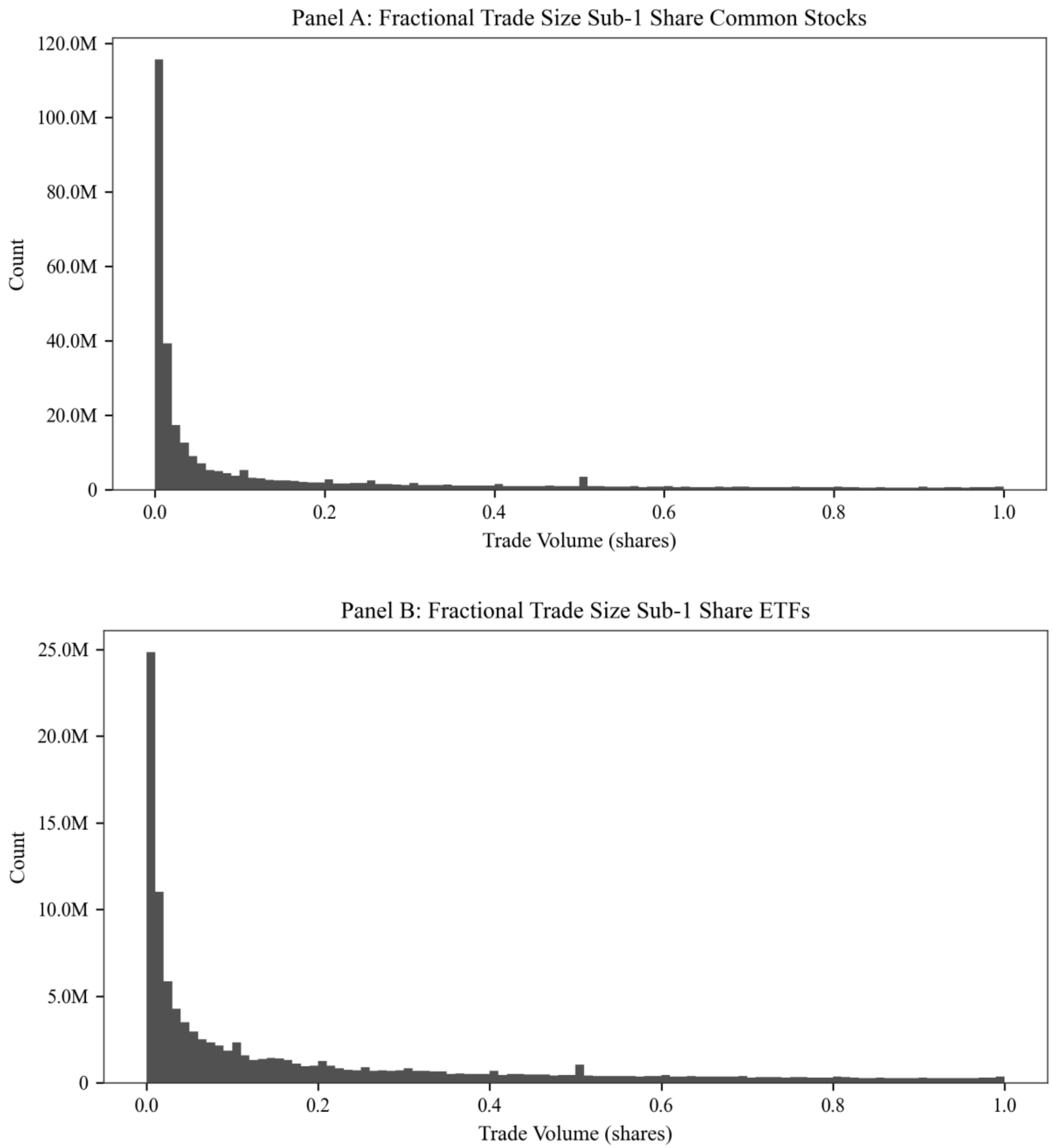


**Figure 3: Trade Size Distribution of fractional trades < 1.** The figure above presents a histogram of fractional trade sizes restricted to fractional trades with volume < 1 share, pooled across all stock-days. Bin width is 0.01 shares. Common stocks are presented in Panel A and ETFs are presented in Panel B. The sample used is from February 23, 2026 to June 18, 2026.

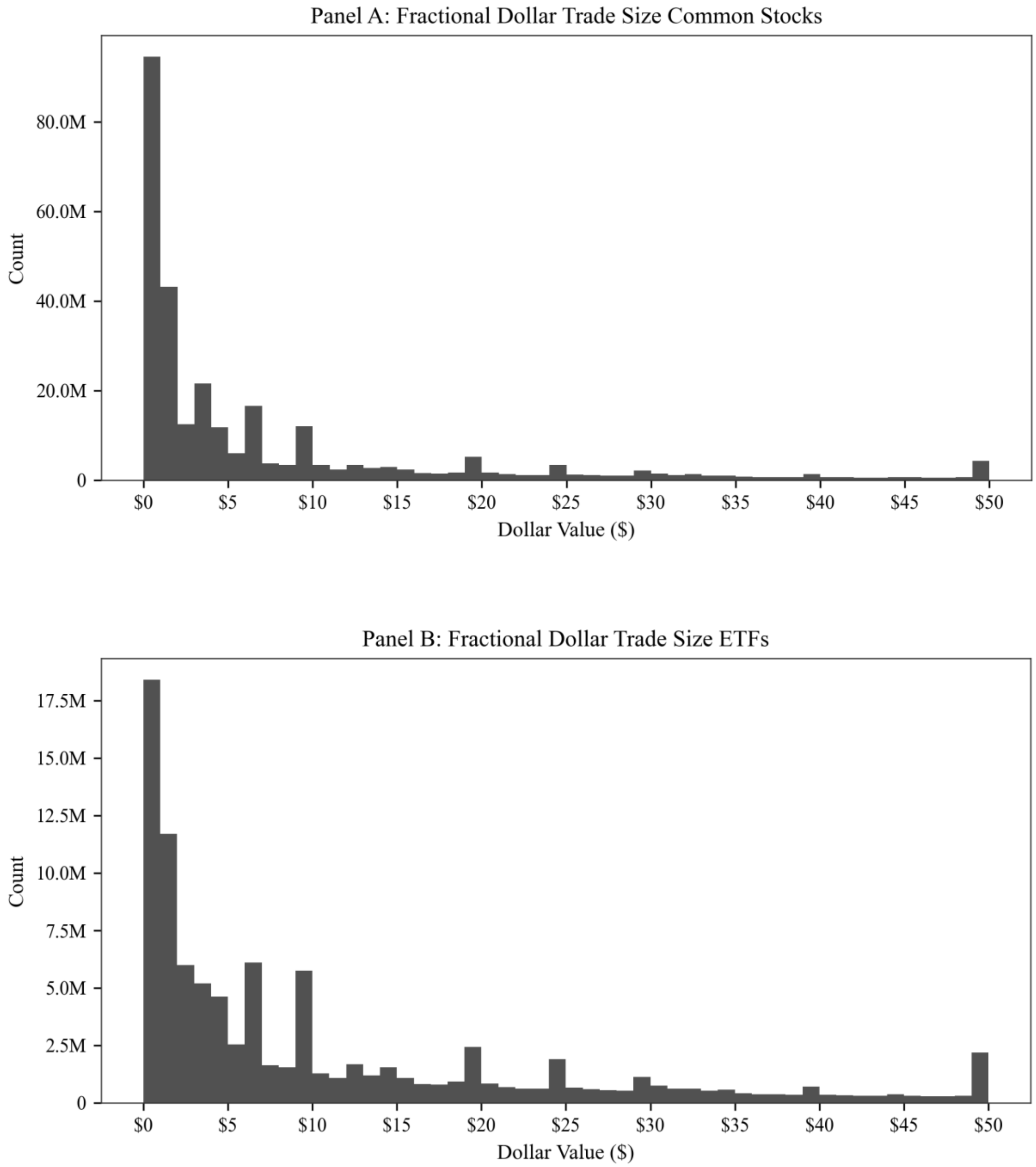


**Figure 4: Dollar Size Distribution of Fractional Trades < $50.** The figure above presents a histogram of the dollar trade size (Trade Price × Trade Volume) for all fractional trades with a dollar trade size below $50, pooled across stocks and days. Bin width is $1. Common stocks are presented in Panel A and ETFs are presented in Panel B. The sample used is from February 23, 2026 to June 18, 2026.

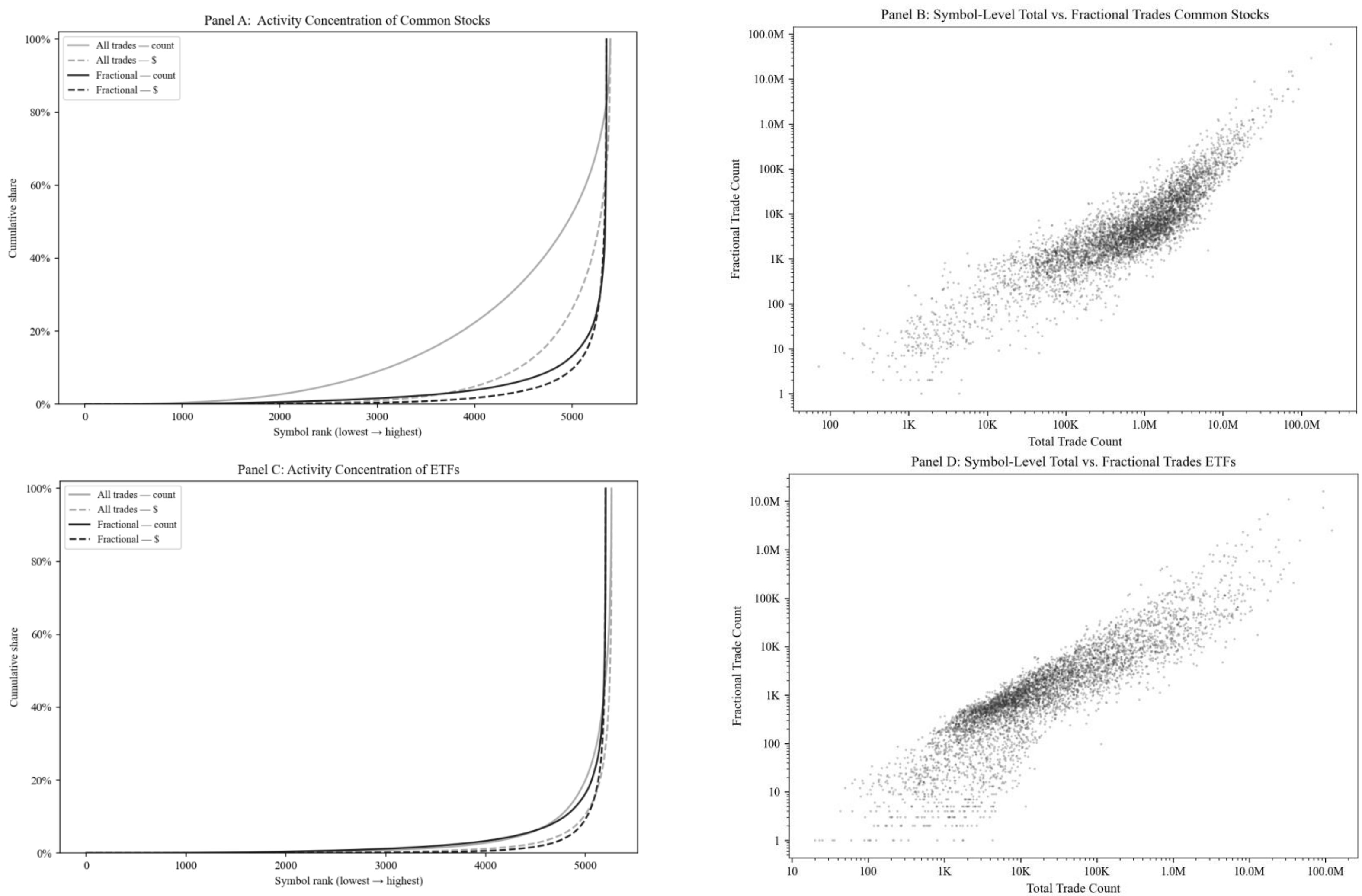


**Figure 5: Stock-Level CDF of Fractional Trade Concentration and Log-Log Scatter Plot:** The figure above presents the Cumulative distribution function across stocks: the x-axis ranks stocks in descending order of post-event fractional and total trade count, and the y-axis reports the cumulative share of the fractional trade count, total trade count, fractional dollar volume and total dollar volume up to that rank for common stocks in Panel A and ETFs in panel C. The figure also presents a Log-Log scatter plot where each dot is one stock in the post-event window. The x-axis is log-total trade count; the y-axis is log fractional trade count. The sample used is from February 23, 2026 to June 18, 2026.

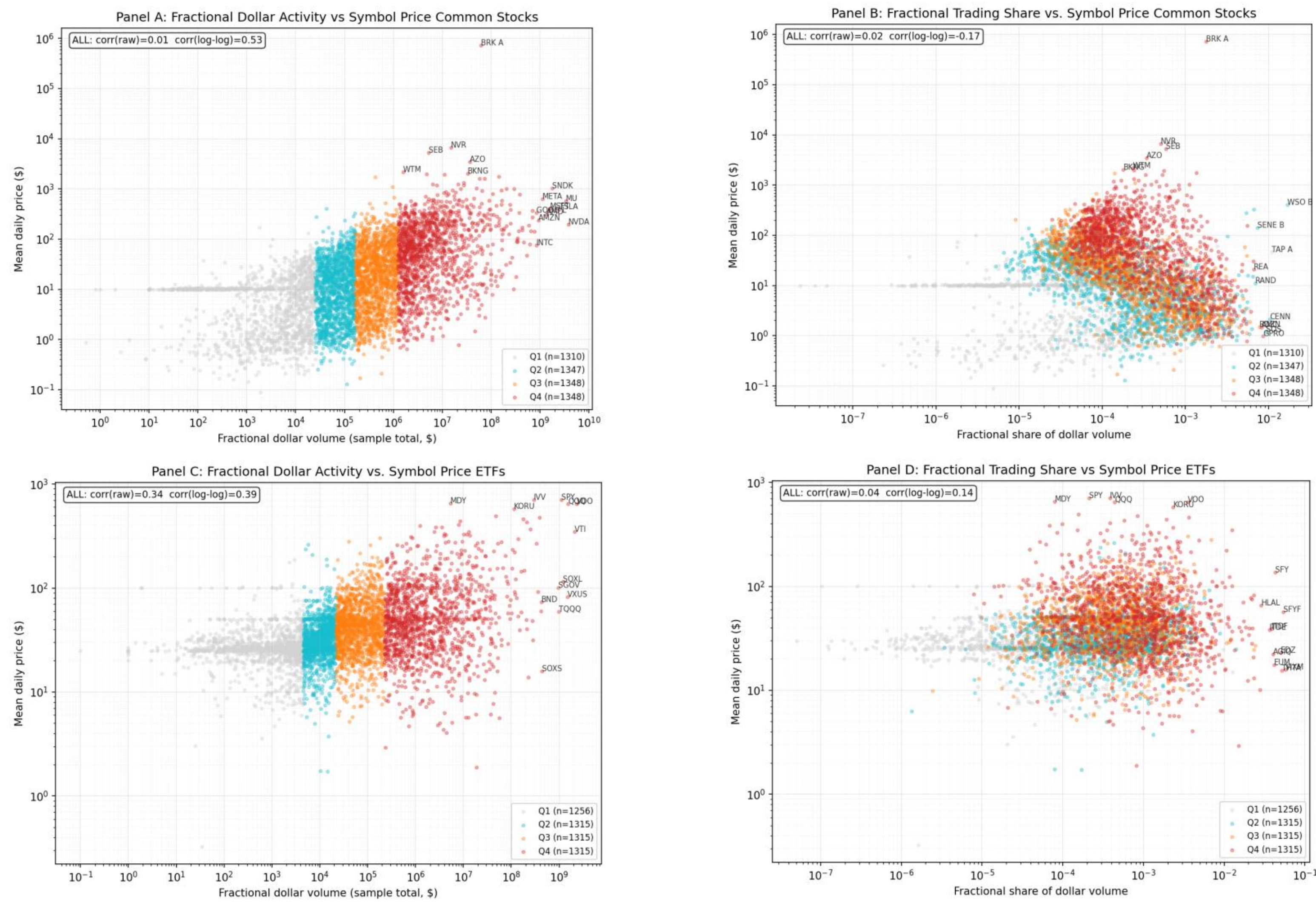


**Figure 6: Stock Level Log-Log Correlations of Fractional Dollar Activity.** The above figure presents scatter plots of log fractional dollar volume versus stock price over the sample period in Panel A and the log share of fractional dollar volume of total volume versus stock price over the sample period in Panel B. ETFs are presented in Panels C and D. The figure also presents the Pearson correlation of the raw variables as well as the log transformed variables in all panels. Stocks within each type (common stock, ETFs) are ranked into quartiles based on their fractional dollar volume, Q1 is gray, Q2 is blue, Q3 is orange and Q4 is red. The sample used is from February 23, 2026 to June 18, 2026.

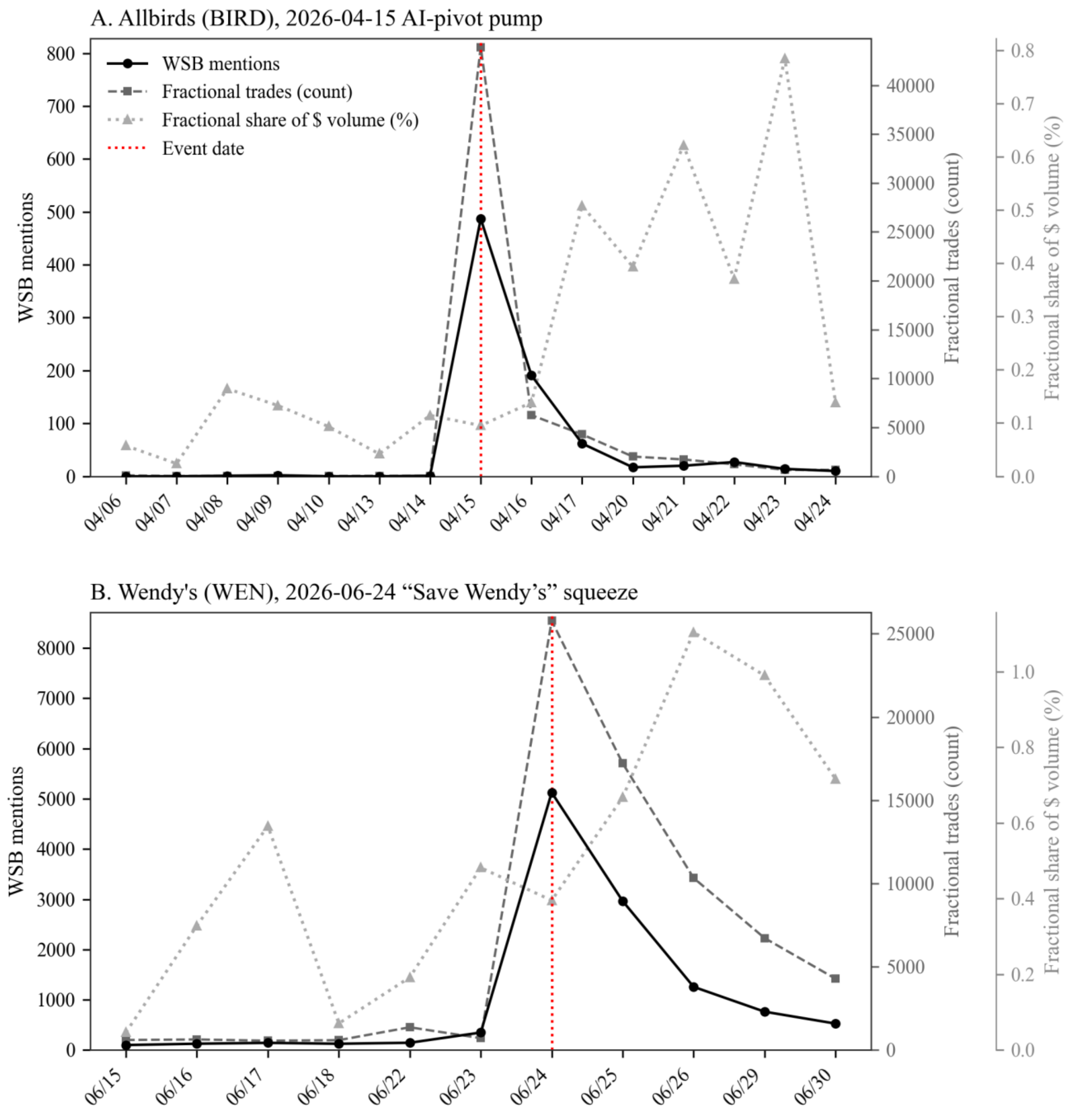


**Figure 7: Anecdotal Events.** Each panel overlays three daily series for one stock across a two-week window bracketing its event day (red dotted line). The first series is r/wallstreetbets mentions (left axis, solid), fractional trade count (right inner axis, dashed), and fractional share of dollar volume (right outer axis, dotted). Panel A, Allbirds (BIRD), 2026-04-15 AI-pivot pump; Panel B, Wendy's (WEN), 2026-06-24 "Save Wendy's" squeeze. We note that the Wendy’s event is outside of the data which compromises our panel regression. We execute a separate data pull for the Wendy’s r/wallstreetbets mentions.

**Table 1: Fractional Trade Counts by Price Bin.** This table reports, for each price bin, the total count of fractional trades and the decomposition into trades with volume < 1 share and volume > 1 share, and within-bin percentages (%). Fractional % of all exchange "D" is the proportion that fractional trades contribute to all trades reported to exchange D. Price bins are assigned at the stock-day level using the stock's median trade price. Panel A presents common stocks and Panel B presents ETFs. The sample is February 23, 2026 through June 18, 2026.

**Panel A – Common Stocks**

| Price Bin | Fractional Trades | Fractional Trades < 1 (N) | Fractional Trades > 1 (N) | Fractional Trades < 1 (%) | Fractional Trades > 1 (%) | Fractional % of all D |
|---|---|---|---|---|---|---|
| < $50 | 54,575,334 | 45,773,769 | 8,801,565 | 83.9 | 16.1 | 2.5 |
| $50 - $100 | 39,947,666 | 37,358,238 | 2,589,428 | 93.5 | 6.5 | 5.3 |
| $100 - $250 | 121,785,270 | 117,926,371 | 3,858,899 | 96.8 | 3.2 | 12.5 |
| $250 - $500 | 104,124,071 | 102,074,497 | 2,049,574 | 98.0 | 2.0 | 18.7 |
| > $500 | 26,792,333 | 26,089,302 | 703,031 | 97.4 | 2.6 | 15.1 |

**Panel B - ETFs**

| Price Bin | Fractional Trades | Fractional Trades < 1 (N) | Fractional Trades > 1 (N) | Fractional Trades < 1 (%) | Fractional Trades > 1 (%) | Fractional % of all D |
|---|---|---|---|---|---|---|
| < $50 | 26,342,977 | 23,508,377 | 2,834,600 | 89.2 | 10.8 | 9.3 |
| $50 - $100 | 28,724,436 | 26,650,238 | 2,074,198 | 92.8 | 7.2 | 12.5 |
| $100 - $250 | 15,897,485 | 14,979,820 | 917,665 | 94.2 | 5.8 | 11.9 |
| $250 - $500 | 9,519,835 | 9,254,526 | 265,309 | 97.2 | 2.8 | 20.9 |
| > $500 | 38,056,517 | 37,544,394 | 512,123 | 98.7 | 1.3 | 34.5 |

**Table 2: Notional size distribution of sub-$10 fractional trades.** Fractional trades with a trade size below $10 are assigned to ten one-dollar buckets ($0–$1, $1–$2, …, $9–$10) and summed across price bins. Price bins are assigned at the stock-day level using the median trade price. Cells report trade counts; the Total column sums each dollar bucket across all five price bins. Panel A presents common stocks and Panel B presents ETFs. The sample is February 23, 2026 through June 18, 2026.

**Panel A – Common Stocks**

| **Dollar Bin** | **<$50** | **$50 - $100** | **$100 - $250** | **$250 - $500** | **>$500** | **Total** |
|---|---|---|---|---|---|---|
| 0 - $1 | 10,896,330 | 10,154,965 | 38,740,861 | 32,361,037 | 2,386,876 | 94,540,069 |
| $1 - $2 | 6,690,834 | 4,015,849 | 16,908,036 | 12,603,469 | 2,932,441 | 43,150,629 |
| $2 - $3 | 3,656,713 | 1,666,215 | 3,349,279 | 2,970,114 | 841,635 | 12,483,956 |
| $3 - $4 | 3,252,314 | 2,061,716 | 7,992,735 | 7,441,343 | 791,986 | 21,540,094 |
| $4 - $5 | 3,318,446 | 1,447,708 | 3,157,201 | 2,899,653 | 965,754 | 11,788,762 |
| $5 - $6 | 2,015,360 | 818,203 | 1,616,570 | 1,019,229 | 481,748 | 5,951,110 |
| $6 - $7 | 2,364,959 | 1,558,251 | 5,619,879 | 6,096,074 | 938,708 | 16,577,871 |
| $7 - $8 | 1,413,877 | 460,598 | 894,625 | 739,079 | 243,387 | 3,751,566 |
| $8 - $9 | 1,282,375 | 438,267 | 760,073 | 634,698 | 263,656 | 3,379,069 |
| $9 - $10 | 2,396,696 | 1,481,057 | 3,461,114 | 3,394,545 | 1,253,566 | 11,986,978 |

**Panel B - ETFs**

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 - $1 | 3,997,817 | 3,949,190 | 1,172,338 | 875,239 | 8,425,704 | 18,420,288 |
| $1 - $2 | 2,592,394 | 3,072,328 | 1,804,240 | 571,469 | 3,657,413 | 11,697,844 |
| $2 - $3 | 1,367,709 | 1,236,033 | 418,842 | 257,999 | 2,703,454 | 5,984,037 |
| $3 - $4 | 1,504,416 | 1,084,645 | 458,641 | 358,335 | 1,788,586 | 5,194,623 |
| $4 - $5 | 1,424,172 | 1,147,818 | 595,032 | 371,844 | 1,078,412 | 4,617,278 |
| $5 - $6 | 783,001 | 612,509 | 239,681 | 120,383 | 797,240 | 2,552,814 |
| $6 - $7 | 1,582,055 | 1,422,906 | 650,503 | 493,593 | 1,948,871 | 6,097,928 |
| $7 - $8 | 654,569 | 423,088 | 190,427 | 98,480 | 266,606 | 1,633,170 |
| $8 - $9 | 619,148 | 433,624 | 211,945 | 98,722 | 178,568 | 1,542,007 |
| $9 - $10 | 1,418,570 | 1,447,723 | 931,018 | 536,233 | 1,426,411 | 5,759,955 |

**Table 3: Dollar-volume inflation from fractional prints.** For each price bin the table reports total consolidated dollar volume (Total Dollar Volume), the Inflated Dollar Volume and the corresponding % Inflated. The inflated dollar volume is computed as $\$\boldsymbol{inflated_k} = \boldsymbol{r}(\boldsymbol{oundup}(\boldsymbol{tradesize_k}) - (\boldsymbol{tradesize_k})) * \boldsymbol{tradeprice_k}$ and is subsequently summed over all trades within a price bin. Price bins are assigned at the stock-day level using the stock's median trade price. Panel A presents common stocks and Panel B presents ETFs. The sample is February 23, 2026 through June 18, 2026.

**Panel A – Common Stocks**

| Price Bin | Total Dollar Volume | Inflated Dollar Volume | % Inflated |
|---|---|---|---|
| < $50 | 14,790,907,148,385 | 759,445,375 | 0.01 |
| $50 - $100 | 14,107,233,865,564 | 2,379,892,085 | 0.02 |
| $100 - $250 | 29,644,392,104,577 | 19,595,288,877 | 0.07 |
| $250 - $500 | 23,630,094,813,323 | 33,868,566,855 | 0.14 |
| > $500 | 11,033,596,465,664 | 25,825,635,879 | 0.23 |

**Panel B - ETFs**

| | | | |
|---|---|---|---|
| < $50 | 5,319,104,249,926 | 536,207,497 | 0.01 |
| $50 - $100 | 7,593,559,953,045 | 1,531,114,354 | 0.02 |
| $100 - $250 | 5,652,919,265,579 | 1,876,286,029 | 0.03 |
| $250 - $500 | 2,290,993,741,821 | 2,612,815,007 | 0.11 |
| > $500 | 10,813,339,151,443 | 22,867,840,769 | 0.21 |

**Table 4: Fractional trades across ETFs and common stocks.** For each security category the table reports three per-stock measures of fractional trading, averaged within the category. Order imbalance is the mean (buy − sell) / (buy + sell) of fractional dollar volume. Persistence is the daily AR(1) autocorrelation of the fractional dollar share. Return-chasing is the correlation of the daily fractional dollar share with the absolute value of the daily return. Persistence and return-chasing require at least ten stock-days per stock, order imbalance is measured on days with at least twenty-five fractional trades. Exchange-traded funds are split into a curated list of broad-market index funds, leveraged/inverse funds classified by the fund name listed in the TAQ master files and all remaining funds in a residual category. The sample is February 23, 2026 through June 18, 2026.

| Category | Stocks | Mean order imbalance | Persistence | Return-chasing |
|---|---|---|---|---|
| Broad-index ETFs | 33 | 0.048 | 0.24 | -0.08 |
| Other ETFs | 4,522 | 0.008 | 0.06 | -0.03 |
| Common stocks | 5,389 | 0.018 | 0.09 | +0.02 |
| Leveraged / inverse ETFs | 683 | 0.035 | 0.12 | +0.03 |

**Table 5: Concentration of Fractional Dollar Volume Across Stocks.** Stocks are ranked within each security sample by total post-event fractional dollar volume and assigned to quartiles Q1–Q4. For each quartile the table reports the number of stocks, the minimum and maximum fractional dollar volume in the quartile, the total fractional dollar volume in the quartile, and the quartile's share of sample-wide fractional dollar volume. Panel A presents common stocks. Panel B presents ETFs. The sample is February 23, 2026 through June 18, 2026.

**Panel A – Common Stocks**

| Quartile | Stock Count | Fractional Dollar Volume Min | Fractional Dollar Volume Max | Total Fractional Dollar Volume | Fractional Dollar Volume Share |
|---|---|---|---|---|---|
| Q1 | 1,349 | 0 | 25,123 | 9,681,089 | 0.0002 |
| Q2 | 1,348 | 25,132 | 165,229 | 104,431,954 | 0.0022 |
| Q3 | 1,348 | 165,485 | 1,234,769 | 702,594,499 | 0.0147 |
| Q4 | 1,348 | 1,236,076 | 3,790,901,855 | 46,886,562,120 | 0.9829 |

**Panel B – ETFs**

| Quartile | Stock Count | Fractional Dollar Volume Min | Fractional Dollar Volume Max | Total Fractional Dollar Volume | Fractional Dollar Volume Share |
|---|---|---|---|---|---|
| Q1 | 1,315 | 0 | 4,504 | 1,861,691 | 0.0001 |
| Q2 | 1,315 | 4,506 | 21,834 | 14,147,324 | 0.0006 |
| Q3 | 1,315 | 21,851 | 223,415 | 103,999,428 | 0.0041 |
| Q4 | 1,315 | 223,839 | 2,306,294,259 | 25,267,009,912 | 0.9953 |

**Table 6: Cross-sectional determinants of fractional activity.** Panel A regresses the fractional share of dollar volume (100 × fractional $ / total $) on the stock characteristics log price, log market cap, log realized variance, log turnover, retail share and when applicable an ETF dummy. Price is the mean of the daily median trade price, market cap is the median of the daily median trade price multiplied by shares outstanding, realized variance is the mean of the realized variance computed as the summed one minute returns squared, turnover is the total dollar volume divided by market capitalization and retail share is the BJZZ identified volume divided by the total volume. Panel B regresses log(1 + fractional trade count) on the same characteristics with a count-based retail control. The sample is February 23 – June 18, 2026. We use robust standard errors. t-statistics in square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels.

**Panel A: Fractional share of dollar volume**

Dependent Variable = 100 × (fractional $ / total $)

| | **All** | **Common Stocks** | **ETFs** |
|---|---|---|---|
| | **(1)** | **(2)** | **(3)** |
| Log Price | 0.0117** | -0.0176*** | 0.0534*** |
| | [2.03] | [-5.84] | [3.03] |
| Log Market Cap | -0.0032 | 0.0061*** | -0.0088** |
| | [-1.16] | [4.34] | [-2.12] |
| Log Realized Variance | 0.0145*** | 0.0210*** | 0.0149*** |
| | [6.51] | [12.57] | [4.82] |
| Log Turnover | -0.0166*** | -0.0079*** | -0.0174** |
| | [-3.46] | [-2.85] | [-2.18] |
| Retail Share | 0.4438*** | -0.0358 | 0.8295*** |
| | [6.23] | [-1.05] | [6.84] |
| ETF Dummy | 0.0669*** | | |
| | [6.46] | | |
| Intercept | 0.3385*** | 0.3386*** | 0.2527** |
| | [5.02] | [7.45] | [2.38] |
| Num. Obs. | 10,603 | 5,359 | 5,244 |

**Panel B: Fractional trade count**

Dependent Variable = log(1 + fractional trade count)

| | **All** | **Common Stocks** | **ETFs** |
|---|---|---|---|
| | **(1)** | **(2)** | **(3)** |
| Log Price | 0.2161*** | -0.0375** | 0.5720*** |
| | [20.50] | [-2.16] | [30.01] |
| Log Market Cap | 0.0505*** | 0.4989*** | -0.2704*** |
| | [4.35] | [20.02] | [-18.13] |
| Log Realized Variance | 0.1025*** | 0.2669*** | 0.0490*** |
| | [16.26] | [20.66] | [7.07] |
| Log Turnover | -0.0527*** | 0.3779*** | -0.3370*** |
| | [-4.00] | [16.13] | [-19.49] |
| Retail Share | 0.8125*** | 0.3743*** | 1.1796*** |
| | [66.31] | [16.75] | [66.50] |
| ETF Dummy | 1.3127*** | | |
| | [43.80] | | |
| Intercept | -0.0479 | -2.3173*** | 2.1201*** |
| | [-0.36] | [-11.12] | [10.68] |
| Num. Obs. | 10,603 | 5,359 | 5,244 |

**Table 7: Name-specific fractional size spikes in common stocks.** The table lists the three highest occurring fractional counts within Nasdaq and NYSE stocks within common stocks, ranked by trade count (filtering to only one trade size per stock, without this filter NVDA would be the number one and number two trade count with 0.003 and 0.002). % of stock's fractional trades is the share of the stock's own fractional prints executed at that exact size; % of all prints at this size is the stock's share of every print at that size market-wide across all common stocks. Implied $ is the exact size multiplied by the stock's median daily share price, where the daily share price is the median of trade prices within the day. The sample is February 23 – June 18, 2026.

| **Stock** | **Size (shares)** | **Trades (millions)** | **% of stock's fractional trades** | **% of all prints at this size** | **Implied $** |
|---|---|---|---|---|---|
| NVDA (Nasdaq) | 0.0030 | 23.4 | 39.5% | 88.0% | $0.60 |
| KO (NYSE) | 0.0100 | 5.0 | 57.1% | 41.8% | $0.78 |
| TSLA (Nasdaq) | 0.0016 | 5.0 | 17.2% | 99.5% | $0.64 |
| MSFT (Nasdaq) | 0.0010 | 2.9 | 24.9% | 32.8% | $0.40 |
| JNJ (NYSE) | 0.0020 | 1.3 | 37.3% | 11.4% | $0.47 |
| IONQ (NYSE) | 0.0100 | 0.9 | 20.1% | 7.6% | $0.44 |

**Table 8: Clustered fractional trades Characteristics in Common Stocks.** This table characterizes "spike" fractional trades, trades executed at an exact sub-share size that appear on the tape for a given stock repeatedly (for example, NVDA at 0.003 shares). Formally, a spike cell is a (stock, exact share-size) pair in which that single size accounts for at least τ of the stock's fractional prints, we restrict attention to stocks with at least 100 fractional prints and report every statistic at spike thresholds τ = 5%, 10%, and 15%. The share of fractional trades is the trade-weighted share of fractional trades at a spike share denominated trade size. The share of fractional dollars is the dollar-weighted share of fractional dollar trading volume attributable to spike trade sizes. The median spike-$/day percentiles are taken across stock-days and are the sum of dollar volume at the spike fractional trade size within a stock-day. The mean trade notional is the equally weighted average trade size in dollar terms. Buyer-initiated trades is the percentage of all spike fractional trades which are classified as a buy, using the Lee Ready (1991) quote test, we do not rely on the tick test here as a fallback and trades at midpoint represents the percentage of all spike fractional trades that are priced at the prevailing midpoint. Stock-days with buy tilt is the equally weighted percent of stock-days where the order imbalance computed from spike fractional trades is on the buy side. Price impact is the signed five-minute-forward mid-quote return in basis points, averaged across all spike trades, non-spike-fractional trades and non-fractional trades. We then estimate a regression on the cell-level where each observation is a stock x date x trade-category, where the three categories are Spike trades, Non-spike-fractional trades and Non-fractional trades. The dependent variable of the regression is the cell's mean price impact, we include stock x day fixed effects and cluster errors by stock. Formally the regression takes the form $\overline{PI}_{i,t,c} = \beta_1 \text{Spike}_{i,t,c} + \beta_2 \text{NonSpikeFractional}_{i,t,c} + \alpha_{i,t} + \varepsilon_{i,t,c}$ where the non-fractional cell is the omitted category. Price-impact estimates are computed on stock-days with price ≥ $5 and regular hours excluding the first and last 30 minutes; the coverage and notional rows use all regular-hours trades. Significance: * p < 0.1, ** p < 0.05, *** p < 0.01. The sample is all common stocks from February 23 through June 18, 2026.

| | **τ = 5%** | **τ = 10%** | **τ = 15%** |
|---|---|---|---|
| **Coverage** | | | |
| Spike cells (stock × size) | 1,396 | 546 | 311 |
| Stocks | 942 | 467 | 282 |
| **Proportion of Activity** | | | |
| Share of fractional trades | 22.2% | 15.9% | 14.0% |
| Share of fractional dollars | 0.12% | 0.07% | 0.06% |
| Median spike, $/day | $6.10 | $4.00 | $3.00 |
| 95th-percentile spike, $/day | $912 | $1,674 | $2,473 |
| Maximum spike, $/day | $243,022 | $242,943 | $242,943 |
| **Fixed notional** | | | |
| Mean trade notional | $0.73 | $0.64 | $0.62 |
| **One-directional accumulation** | | | |
| Buyer-initiated trades | 88.3% | 87.5% | 87.0% |
| Stock-days with buy tilt | 67.8% | 66.5% | 62.5% |
| Trades at midpoint | 0.26% | 0.16% | 0.12% |
| **Price impact (5-min, bp)** | | | |
| Spike trades | −0.06 | −0.63 | −1.02 |
| Non-spike-fractional trades | 0.05 | 0.05 | 0.05 |
| Non-fractional trades | 6.93 | 6.93 | 6.93 |
| Spike − non-fractional | −7.58*** | −8.95*** | −10.70*** |
| t-statistic | (−14.2) | (−8.7) | (−6.4) |
| Spike − other-fractional | −0.37 | −0.70 | −1.47 |
| t-statistic | (−1.0) | (−0.9) | (−1.2) |

**Table 9: Fractional executors identified via the OTC ratio break.** For each firm, the table reports the shares-to-trades ratio computed from FINRA OTC Transparency weekly firm-level data (OTC_W_FIRM), in the seven weeks before and the fourteen weeks after the February 23, 2026 native-fractional reporting reform. Blended columns sum shares and trades across all NMS tiers; Tier 1 columns restrict to NMS Tier 1 (the S&P 500, Russell 1000, and major exchange-traded products). A firm is classified as a fractional executor, and listed in the table, if its post-reform shares-to-trades ratio, blended, or within any single reporting tier, falls below 0.90 (pre-reform ratios shown for reference). Trade counts are post-reform totals on each basis. Panel A presents dedicated fractional-clearing firms, Panel B presents retail brokerage apps, and Panel C presents conventional brokers and mixed clearers whose fractional business is a slice of a larger whole-share operation. We manually classify the firms into these three groups. Firms are ranked within each panel by post-reform Tier 1 trade count. The pre-reform period is January 5, 2026 through February 16, 2026; the post-reform period is February 23, 2026 through May 31, 2026.

**Panel A – Dedicated Fractional Clearers**

| Firm | Blended Pre-Ratio | Blended Post-Ratio | Blended Trades | Tier 1 Pre-Ratio | Tier 1 Post-Ratio | Tier 1 Trades |
|---|---|---|---|---|---|---|
| Alpaca Securities | 1.01 | 0.34 | 45,587,602 | 1.00 | 0.27 | 34,499,386 |
| Apex Clearing | 1.00 | 0.68 | 37,096 | 1.00 | 0.67 | 32,889 |
| Velox Clearing | 1.00 | 0.33 | 44,769 | 1.00 | 0.27 | 29,550 |
| Green Pier Fintech | 1.00 | 0.23 | 17,175 | 1.00 | 0.18 | 11,107 |
| **Panel B – Retail Brokerage Apps** | | | | | | |
| Futu Clearing (Moomoo) | 1.41 | 1.32 | 2,372,617 | 1.01 | 0.29 | 2,084,458 |
| Robinhood Securities | 1.01 | 0.17 | 1,982,396 | 1.00 | 0.15 | 1,795,026 |
| TradeUp Securities | 1.04 | 0.15 | 726,399 | 1.03 | 0.14 | 675,415 |
| Albert Securities | 1.78 | 1.16 | 113,543 | 1.14 | 0.24 | 109,695 |
| **Panel C – Conventional / Mixed Brokers** | | | | | | |
| National Financial Services (Fidelity) | 2.38 | 1.73 | 42,764,059 | 1.00 | 0.27 | 34,180,945 |
| Mirae Asset (USA) | 1.30 | 0.87 | 8,527,068 | 1.25 | 0.77 | 7,605,952 |
| Morgan Stanley (retail arm) | 1.00 | 0.43 | 1,453,091 | 1.00 | 0.42 | 1,236,122 |
| Pershing | 1.07 | 0.83 | 351,256 | 1.02 | 0.86 | 317,160 |
| Axos Clearing | 480.00 | 528.23 | 43,581 | 1.00 | 0.31 | 37,857 |

**Table 10: BJZZ coverage of the fractional tape.** Every fractional print is an off-exchange (Exchange "D") trade, so the BJZZ (Boehmer, Jones, Zhang and Zhang 2021) sub-penny method is applied to the entire fractional tape and each trade is classified by its sub-penny fraction z: signable (z in 0.0-0.4 or 0.6-1.0, assigned a retail buy/sell direction), round penny (exact penny, no price improvement), or midpoint (z in 0.4-0.6, left unsigned by BJZZ). Only the signable share is recovered as directed retail trades. Median $ is the median trade notional in the category. The sample is every fractional print on the tape in RTH with a spread that is not locked or crossed. Panel A presents common stocks, Panel B ETFs. The sample is February 23 through June 18, 2026.

**Panel A – Common Stocks**

| Category | Trades (N) | % of Trades | Median $ | Dollar Vol. ($bn) |
|---|---|---|---|---|
| Signable (sub-penny, 0.0-0.4 / 0.6-1.0) | 154,032,418 | 46.0 | 1.56 | 6.38 |
| Round penny (no sub-penny improvement) | 87,100,868 | 26.0 | 15.00 | 25.90 |
| Midpoint (0.4-0.6 band, unsigned) | 93,582,664 | 28.0 | 3.91 | 14.23 |
| Total | 334,715,950 | 100.0 | | 46.51 |

**Panel B – ETFs**

| Category | Trades (N) | % of Trades | Median $ | Dollar Vol. ($bn) |
|---|---|---|---|---|
| Signable (sub-penny, 0.0-0.4 / 0.6-1.0) | 51,424,503 | 44.7 | 3.25 | 4.46 |
| Round penny (no sub-penny improvement) | 32,405,021 | 28.2 | 19.43 | 11.91 |
| Midpoint (0.4-0.6 band, unsigned) | 31,232,620 | 27.1 | 15.67 | 9.33 |
| Total | 115,062,144 | 100.0 | | 25.69 |

**Table 11: Cross-sectional rank agreement with retail benchmarks.** Spearman rank correlation across stocks between the fractional share of volume and each retail benchmark's share of volume: the six PFOF wholesalers (PFOF-6), all eight wholesalers (All-8), the two bank-captive internalizers (Morgan Stanley and Merrill), and BJZZ. Each cell reports the conditioned correlation with the raw correlation in parentheses; conditioning residualizes both shares on log price, log market capitalization, and log total volume (plus month dummies when pooling months) before ranking. The sample is stock-months with a non-missing fractional share, wholesaler/BJZZ share (39,837 pooled: 20,576 common + 19,261 ETF). Fractional and wholesaler shares are share-volume; the BJZZ benchmark is dollar-volume. All entries are rank correlations, so the mixed basis does not affect the ranking. Panel A presents common stocks, Panel B ETFs. N is the number of stock-months. The sample is February through May 2026 (Rule 605 filing months 202602-202605).

**Panel A – Common Stocks**

| Sample | N | PFOF-6 | All-8 | Captive (MS/ML) | BJZZ |
|---|---|---|---|---|---|
| Pooled (Feb–May) | 20,576 | 0.36 (0.41) | 0.36 (0.41) | 0.29 (0.29) | 0.12 (0.35) |
| March–May | 15,443 | 0.40 (0.49) | 0.41 (0.49) | 0.32 (0.32) | 0.17 (0.43) |
| February | 5,133 | 0.26 (0.30) | 0.27 (0.30) | 0.30 (0.36) | 0.15 (0.28) |
| March | 5,138 | 0.42 (0.53) | 0.42 (0.53) | 0.31 (0.29) | 0.20 (0.48) |
| April | 5,147 | 0.40 (0.49) | 0.40 (0.49) | 0.32 (0.31) | 0.15 (0.42) |
| May | 5,158 | 0.40 (0.44) | 0.40 (0.45) | 0.33 (0.36) | 0.15 (0.39) |

**Panel B – ETFs**

| Sample | N | PFOF-6 | All-8 | Captive (MS/ML) | BJZZ |
|---|---|---|---|---|---|
| Pooled (Feb–May) | 19,261 | 0.18 (0.20) | 0.18 (0.20) | 0.11 (0.17) | 0.20 (0.16) |
| March–May | 14,530 | 0.22 (0.23) | 0.22 (0.24) | 0.15 (0.19) | 0.24 (0.23) |
| February | 4,731 | 0.16 (0.16) | 0.16 (0.16) | 0.16 (0.17) | 0.18 (0.17) |
| March | 4,777 | 0.20 (0.22) | 0.21 (0.22) | 0.13 (0.18) | 0.24 (0.23) |
| April | 4,827 | 0.25 (0.24) | 0.25 (0.24) | 0.17 (0.20) | 0.27 (0.24) |
| May | 4,926 | 0.23 (0.23) | 0.23 (0.23) | 0.14 (0.19) | 0.25 (0.23) |

**Table 12: Rank agreement within total-volume deciles (PFOF-6).** Conditioned rank agreement between the fractional share and the PFOF-6 wholesaler share, re-estimated within each of ten total-volume deciles. The conditioned correlation is presented with the raw correlation in parentheses; conditioning residualizes both shares on log price, log market capitalization, and log total volume (plus month dummies) before ranking. The final row is the average across deciles. The sample is 39,837 stock-months sorted into deciles within each sample based on the total volume. The sample is February through May 2026 (Rule 605 filing months 202602-202605).

| Total-volume decile | Common Stocks | ETFs |
|---|---|---|
| 1 | 0.22 (0.37) | 0.09 (0.08) |
| 2 | 0.29 (0.41) | 0.21 (0.22) |
| 3 | 0.32 (0.42) | 0.23 (0.27) |
| 4 | 0.36 (0.39) | 0.20 (0.26) |
| 5 | 0.41 (0.40) | 0.24 (0.31) |
| 6 | 0.48 (0.48) | 0.23 (0.28) |
| 7 | 0.50 (0.53) | 0.26 (0.28) |
| 8 | 0.43 (0.51) | 0.20 (0.20) |
| 9 | 0.43 (0.54) | 0.31 (0.20) |
| 10 | 0.25 (0.32) | 0.37 (0.27) |
| Average (all deciles) | 0.37 (0.44) | 0.23 (0.24) |

**Table 13: Fractional–wholesaler rank-gap regression.** OLS of the raw within-sample rank gap (a stock's fractional-share rank minus its PFOF-6 wholesaler-share rank, so a positive gap means fractional ranks the name higher than wholesaler trades does and a negative gap means it ranks the name lower) on stock characteristics. Columns (1)-(5) enter each characteristic univariate (one regressor at a time); column (6) is the full specification with all of them. Price is the average of the daily median trade price, market cap is the average of the daily median stock price multiplied by the shares outstanding, realized variance is the mean of the daily summed one minute returns squared, modal-size share is the proportion of all fractional trades which occur at its single most common fractional trade size and WSB mentions is log(1 + monthly cashtag mentions). All specifications include month fixed effects; standard errors are clustered by stock, with t-statistics in parentheses. Panel A is common stocks, Panel B ETFs, each ranked within its own sample. Significance: * 10%, ** 5%, *** 1%. The sample is February through May 2026 (Rule 605 filing months 202602-202605).

**Panel A – Common Stocks**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Log price | 0.0971*** | | | | | 0.0449*** |
| | (60.3) | | | | | (15.4) |
| Log market cap | | 0.0670*** | | | | 0.0435*** |
| | | (59.4) | | | | (19.1) |
| Log realized variance | | | -0.0366*** | | | 0.0202*** |
| | | | (-15.5) | | | (8.0) |
| Modal-size share | | | | -0.0086*** | | -0.0035*** |
| | | | | (-18.4) | | (-10.0) |
| WSB mentions (log) | | | | | 0.0515*** | -0.0042** |
| | | | | | (23.9) | (-2.0) |
| Num. obs. | 20,578 | 20,576 | 20,575 | 19,524 | 20,578 | 19,520 |
| $R^2$ | 0.438 | 0.463 | 0.182 | 0.211 | 0.176 | 0.504 |

**Panel B – ETFs**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Log price | 0.1167*** | | | | | 0.0874*** |
| | (18.5) | | | | | (13.4) |
| Log market cap | | 0.0274*** | | | | 0.0224*** |
| | | (18.5) | | | | (10.9) |
| Log realized variance | | | 0.0290*** | | | 0.0368*** |
| | | | (14.2) | | | (16.9) |
| Modal-size share | | | | -0.0031*** | | 0.0001 |
| | | | | (-9.0) | | (0.2) |
| WSB mentions (log) | | | | | 0.1037*** | 0.0635*** |
| | | | | | (15.9) | (11.9) |
| Num. obs. | 19,305 | 19,261 | 19,296 | 16,752 | 19,305 | 16,719 |
| $R^2$ | 0.124 | 0.115 | 0.110 | 0.109 | 0.114 | 0.224 |

**Table 14: WSB attention and fractional trading, by instrument and specification.** Full-specification panel regressions of fractional trading on r/wallstreetbets attention, common stocks in columns (1)–(3) and ETFs in (4)–(6), over the whole sample from the native-fractional reporting reform. Within each sample, columns (1) and (4) regress log fractional trade count, ln(1 + fractional trades), on the name-inclusive attention measure; (2) and (5) use the ticker-only measure (cash-tag and bare ticker, no company name); (3) and (6) regress the log fractional share of dollar volume on the name-inclusive measure. Attention is the log count of mentions by the Eaton, Green, Roseman and Wu (2022) token method, entered at lags 0 through 10 trading days; the reported coefficient is the cumulative response B = sum_k beta_k, the total effect over the two-week window, with its stock-clustered t-statistic in square brackets. Every column includes the full control set and stock and day fixed effects. Price is the average of the daily median trade price, total trade count is the count of all trades, lagged return is the absolute value of the previous days close-to-close return, volatility is the mean of the daily summed one minute returns squared, lagged effective spread is the previous days mean effective spread. *** p<0.01, ** p<0.05, * p<0.10.

| | **Common Stocks** | | | **ETFs** | | |
|---|---|---|---|---|---|---|
| | **WSB name (1)** | **WSB ticker (2)** | **Log $-share (3)** | **WSB name (4)** | **WSB ticker (5)** | **Log $-share (6)** |
| WSB attention | 0.266*** | 0.273*** | 0.226*** | 0.284*** | 0.289*** | 0.309*** |
| | [13.9] | [13.3] | [7.9] | [7.1] | [7.1] | [5.3] |
| Log price | Yes | Yes | Yes | Yes | Yes | Yes |
| Log total volume | Yes | Yes | Yes | Yes | Yes | Yes |
| Lagged \|ret\| | Yes | Yes | Yes | Yes | Yes | Yes |
| Volatility | Yes | Yes | Yes | Yes | Yes | Yes |
| Lagged effective spread | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock & day FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Num. obs. | 290,411 | 290,411 | 279,912 | 265,355 | 265,355 | 247,492 |
| Within $R^2$ | 0.343 | 0.343 | 0.062 | 0.130 | 0.130 | 0.139 |

**Table 15: Predicting next-day liquidity and volatility (Common Stocks).** A re-estimation of the BMO Table 7 horserace on the post-reform native-fractional tape: does a stock's day-t retail activity forecast its next-day (t+1) execution quality, and does the fractional-trade count add forecasting content beyond the BJZZ (Boehmer, Jones, Zhang and Zhang 2021) sub-penny proxy? Panel A's dependent variable is the log mean proportional effective spread, 2*D*(P−M)/M averaged over all trades in RTH, Panel B's is the log intraday realized variance built from the sum of one-minute midpoint returns squared. Both retail measures are dated at day t: BJZZ is log(1 + count of sub-penny-signed retail trades) and Fractional is log(1 + fractional-trade count). The Top-100 indicator flags the hundred stocks with the most fractional trades. Every column also includes controls: log dollar volume, log trade count, prior-day, prior-week and prior-month returns, log market capitalization, turnover, prior-month return volatility, and the lagged dependent variable along with stock and date fixed effects. t-statistics in brackets are computed from standard errors double-clustered by stock and by date. Significance: * 10%, ** 5%, *** 1%. The sample is February 23 through June 18, 2026.

| | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| **Panel A: ln effective spread (t+1)** | | | | |
| BJZZ retail | -0.0368*** | | -0.0369*** | -0.0369*** |
| | [-10.13] | | [-10.38] | [-10.37] |
| Fractional trades | | -0.0091*** | 0.0007 | 0.0006 |
| | | [-2.78] | [0.24] | [0.19] |
| BJZZ x Top-100 | | | | -0.0417 |
| | | | | [-1.10] |
| Frac x Top-100 | | | | 0.0462 |
| | | | | [1.56] |
| Controls + lagged DV | Yes | Yes | Yes | Yes |
| Num. Obs. | 410,579 | 410,579 | 410,579 | 410,579 |
| Within $R^2$ | 0.0706 | 0.0696 | 0.0706 | 0.0707 |
| **Panel B: ln intraday volatility (t+1)** | | | | |
| BJZZ retail | 0.0534*** | | 0.0393*** | 0.0392*** |
| | [9.43] | | [6.93] | [6.90] |
| Fractional trades | | 0.0733*** | 0.0637*** | 0.0632*** |
| | | [14.45] | [12.62] | [12.49] |
| BJZZ x Top-100 | | | | 0.0824 |
| | | | | [1.61] |
| Frac x Top-100 | | | | 0.0256 |
| | | | | [0.59] |
| Controls + lagged DV | Yes | Yes | Yes | Yes |
| Num. Obs. | 404,700 | 404,700 | 404,700 | 404,700 |
| Within $R^2$ | 0.1687 | 0.1693 | 0.1697 | 0.1698 |

**Table 16: Predicting next-day liquidity and volatility (ETFs).** A re-estimation of the BMO Table 7 horserace on the post-reform native-fractional tape: does a stock's day-t retail activity forecast its next-day (t+1) execution quality, and does the fractional-trade count add forecasting content beyond the BJZZ (Boehmer, Jones, Zhang and Zhang 2021) sub-penny proxy? Panel A's dependent variable is the log mean proportional effective spread, 2*D*(P−M)/M averaged over all trades in RTH, Panel B's is the log intraday realized variance built from the sum of one-minute midpoint returns squared. Both retail measures are dated at day t: BJZZ is log(1 + count of sub-penny-signed retail trades) and Fractional is log(1 + fractional-trade count). The Top-100 indicator flags the hundred stocks with the most fractional trades. Every column also includes controls: log dollar volume, log trade count, prior-day, prior-week and prior-month returns, log market capitalization, turnover, prior-month return volatility, and the lagged dependent variable along with stock and date fixed effects. t-statistics in brackets are computed from standard errors double-clustered by stock and by date. Significance: * 10%, ** 5%, *** 1%. The sample is February 23 through June 18, 2026.

| | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| **Panel A: ln effective spread (t+1)** | | | | |
| BJZZ retail | -0.0160*** | | -0.0154*** | -0.0152*** |
| | [-3.02] | | [-2.84] | [-2.81] |
| Fractional trades | | -0.0076 | -0.0036 | -0.0030 |
| | | [-1.41] | [-0.65] | [-0.56] |
| x Top-100 (BJZZ) | | | | -0.0105 |
| | | | | [-0.14] |
| x Top-100 (Frac.) | | | | -0.0179 |
| | | | | [-0.31] |
| Controls + lagged DV | Yes | Yes | Yes | Yes |
| Num. Obs. | 377,189 | 377,189 | 377,189 | 377,189 |
| Within $R^2$ | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| **Panel B: ln intraday volatility (t+1)** | | | | |
| BJZZ retail | 0.0200*** | | 0.0135** | 0.0126** |
| | [3.47] | | [2.53] | [2.37] |
| Fractional trades | | 0.0399*** | 0.0363*** | 0.0340*** |
| | | [4.74] | [4.51] | [4.28] |
| x Top-100 (BJZZ) | | | | 0.1573*** |
| | | | | [2.96] |
| x Top-100 (Frac.) | | | | -0.0088 |
| | | | | [-0.18] |
| Controls + lagged DV | Yes | Yes | Yes | Yes |
| Num. Obs. | 378,780 | 378,780 | 378,780 | 378,780 |
| Within $R^2$ | 0.0692 | 0.0694 | 0.0694 | 0.0695 |

## APPENDIX A – Bartlett, McCrary and O'Hara (2024) Latency Measure

BMO attribute individual off-exchange fractional prints to specific brokers using two fields carried on the trade tape: the trade-reporting facility through which the print clears, and its reporting latency, the gap between the exchange timestamp and the broker's own participant timestamp. A single-share off-exchange trade is assigned to DriveWealth if it clears the NYSE Trade Reporting Facility with a latency above twenty milliseconds, and to Robinhood if it clears the Nasdaq Trade Reporting Facility with a latency between 135 and 300 milliseconds. The rule works because, in their 2021–22 sample, each broker occupies a distinct (facility, latency) cell, which they validate with the FINRA OTC data. Because native fractional trades no longer print as one share after the reform, we re-point the rule at native fractional prints rather than one-share prints. The authors themselves warn of and document potential for drift. We note that identifying Robinhood and DriveWealth trades suffers from more than drift in their latency signatures.

The DriveWealth signature is gone: the rule keys DriveWealth to the NYSE facility, but DriveWealth moved its fractional reporting to the Nasdaq facility in October 2022, a change BMO flag in their own robustness work. A larger issue pertaining to DriveWealth exists. DriveWealth LLC, the fractional arm, and DriveWealth Institutional, the institutional arm, merge together in 2025. This merger forces the share/trade ratio calculated from the FINRA OTC data to ingest both fractional and institutional trades, and the fractional signal is no longer interpretable.

The Robinhood band is badly calibrated for 2026. The 135-to-300-millisecond window was fit to Robinhood's 2021–22 infrastructure and in our data we identify 73.75 million Robinhood fractional trades using the latency measure, against the 1.89 million trades Robinhood reports to FINRA over the same window. Benchmarked against that ground truth, the latency band over-attributes Robinhood by nearly forty-fold in trade count. A further issue is that Robinhood has likely off-loaded a sizable portion of its fractional clearing as the weekly trade counts reported to FINRA have declined from 5 million per week in mid-2024 to 0.15 million per week in early 2026.

BMO are explicit that firm signatures drift with technology and must be re-validated against OTC disclosures each period. We do not place our own trades and therefore make no latency-based broker attribution. We identify fractional executors instead from the OTC Transparency ratio break in Section 4c.

# APPENDIX B – Additional Tables and Figures

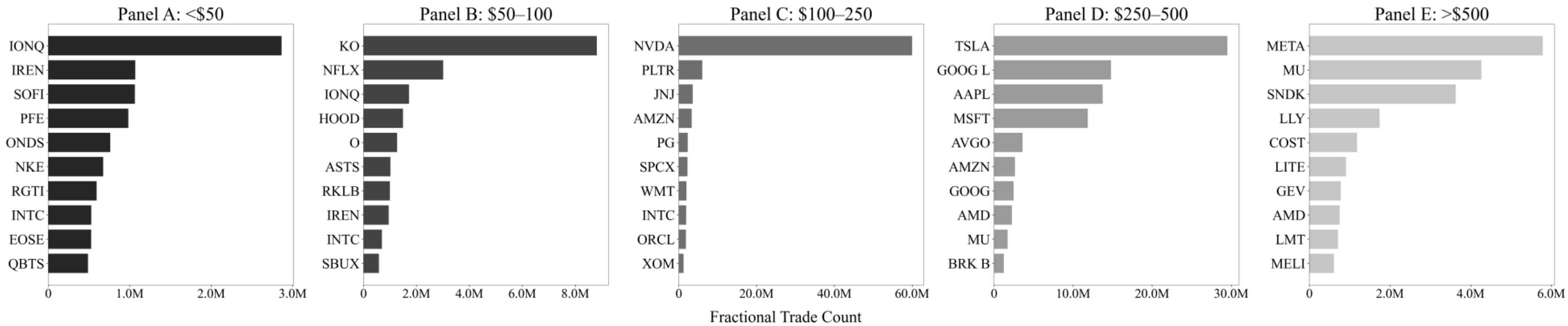


**Figure A1: Top Stocks.** This figure presents the top ten stocks partitioned by stock price bin. Stock price bins are assigned on the stock-day level using the median trade price. Stocks are ranked by the count of fractional trades over the sample period which is from February 23, 2026 to June 18, 2026. Only Common stocks are included.

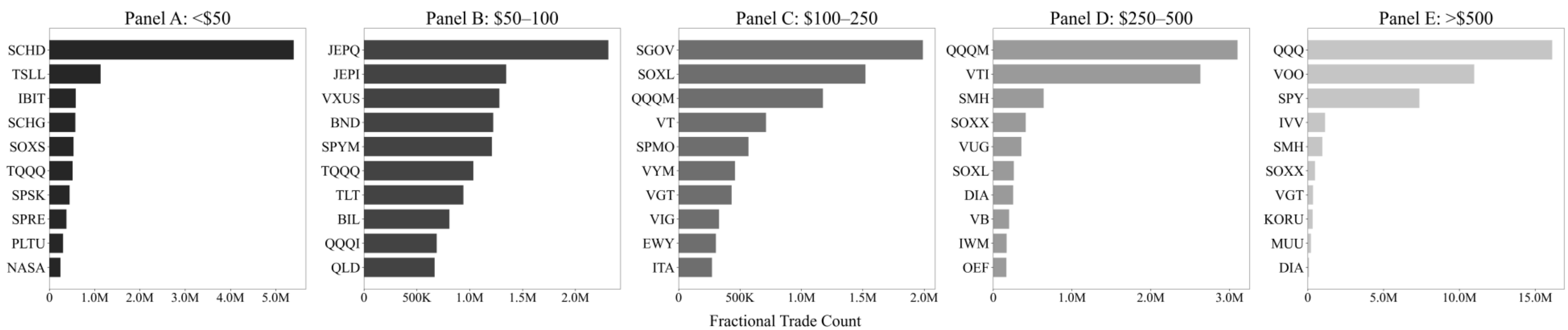


**Figure A2: Top Stocks.** This figure presents the top ten stocks partitioned by stock price bin. Stock price bins are assigned on the stock-day level using the median trade price. Stocks are ranked by the count of fractional trades over the sample period which is from February 23, 2026 to June 18, 2026. Only ETFs are included.

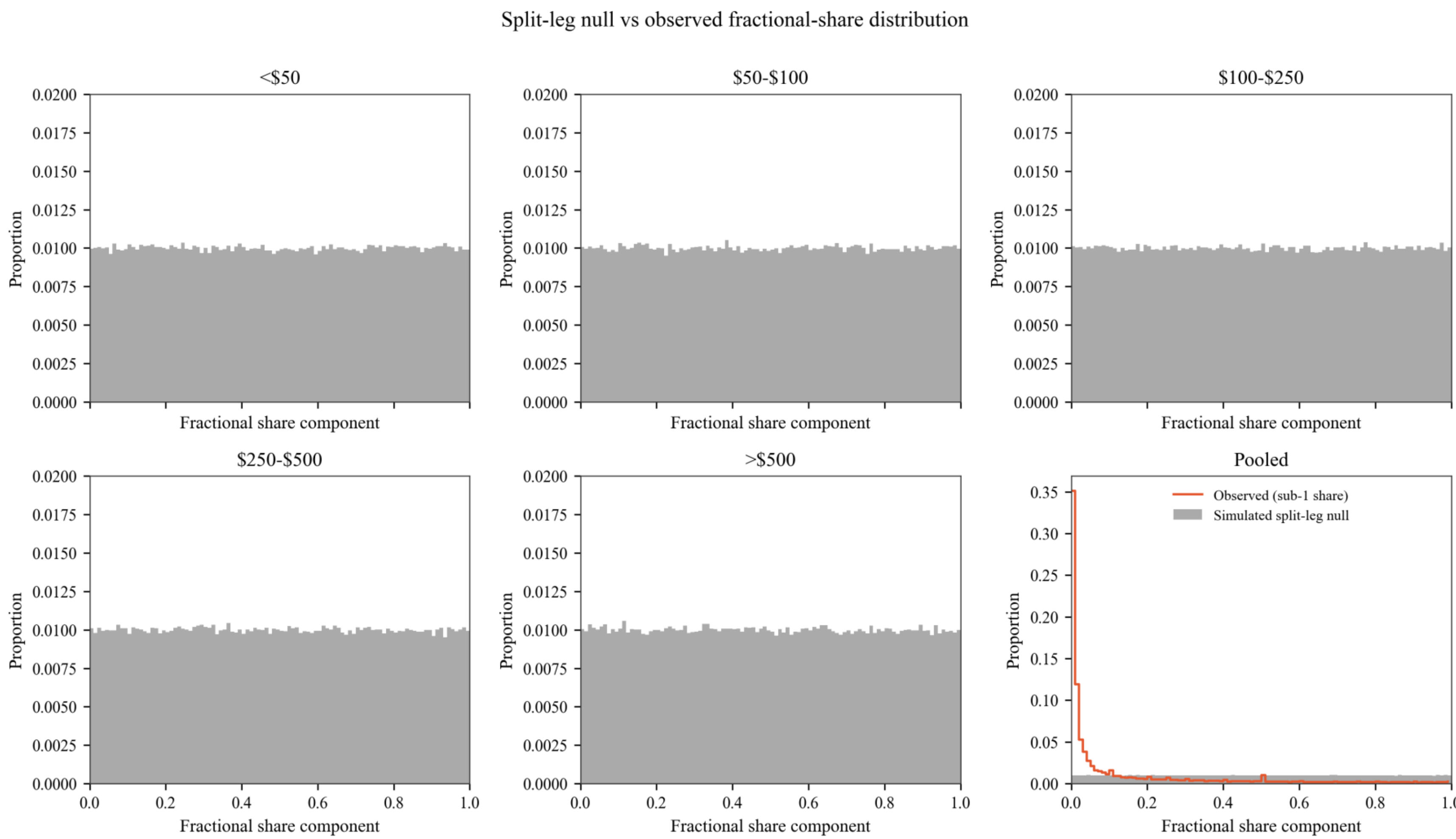


**Figure A3. Simulated Dollar-Denominated Trades in Common Stocks.** Each panel plots the fractional-share component mod((dollar trade size / price),1) of simulated dollar orders. Prices are drawn from the per-stock daily median price of the common sample, sampled equal-weight. Each order draws a dollar amount D ~ U($1, $100,000) and we retain only orders large enough to buy at least one whole share (D > P). The pooled panel (lower right) overlays the observed distribution of common-stock prints below one share (red). The simulation uses 400,000 draws per panel.

**Table A1: Cross-sectional determinants of fractional activity.** Panel A regresses the fractional share of dollar volume (100 × fractional $ / total $) on the stock characteristics log price, log market cap, log realized variance, log turnover, retail share and when applicable an ETF dummy. Price is the mean of the daily median trade price, market cap is the median of the daily median trade price multiplied by shares outstanding, realized variance is the mean of the realized variance computed as the summed one minute returns squared, turnover is the total dollar volume divided by market capitalization and retail share is the BJZZ identified volume divided by the total volume. Panel B regresses log(1 + fractional trade count) on the same characteristics with a count-based retail control. The sample is February 23 – June 18, 2026 only including stocks which rank in the top quartile of fractional trades within each stock sample. We use robust standard errors. t-statistics in square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels.

**Panel A: Fractional share of dollar volume**

Dependent Variable = 100 × (fractional $ / total $)

| | **All** | **Common Stocks** | **ETFs** |
|---|---|---|---|
| | **(1)** | **(2)** | **(3)** |
| Log Price | 0.0311*** | -0.0116*** | 0.0273 |
| | [3.67] | [-3.05] | [1.35] |
| Log Market Cap | -0.0736*** | -0.0038 | -0.0997*** |
| | [-6.56] | [-1.21] | [-6.37] |
| Log Realized Variance | 0.0154*** | 0.0494*** | 0.0082 |
| | [2.86] | [8.23] | [1.26] |
| Log Turnover | -0.0686*** | -0.0300*** | -0.0788*** |
| | [-5.95] | [-3.85] | [-5.62] |
| Retail Share | 1.6197*** | 1.0495*** | 1.5193*** |
| | [7.45] | [5.58] | [5.06] |
| ETF Dummy | 0.0339 | | |
| | [1.60] | | |
| Intercept | 1.5595*** | 0.8533*** | 1.8825*** |
| | [6.93] | [5.65] | [6.42] |
| Num. Obs. | 2,663 | 1,347 | 1,316 |

**Panel B: Fractional trade count**

Dependent Variable = log(1 + fractional trade count)

| | **All** | **Common Stocks** | **ETFs** |
|---|---|---|---|
| | **(1)** | **(2)** | **(3)** |
| Log Price | 0.2674*** | -0.0951** | 0.5425*** |
| | [14.20] | [-2.26] | [22.24] |
| Log Market Cap | -0.1970*** | 0.5844*** | -0.4403*** |
| | [-8.56] | [7.91] | [-20.22] |
| Log Realized Variance | 0.0680*** | 0.3508*** | 0.0074 |
| | [6.88] | [9.59] | [0.82] |
| Log Turnover | -0.3322*** | 0.4030*** | -0.5498*** |
| | [-13.06] | [4.53] | [-23.61] |
| Retail Share | 1.1974*** | 0.5752*** | 1.3904*** |
| | [40.70] | [5.39] | [52.35] |
| ETF Dummy | 1.7169*** | | |
| | [31.36] | | |
| Intercept | 1.2605*** | -4.6974*** | 4.1980*** |
| | [4.19] | [-5.97] | [14.04] |
| Num. Obs. | 2,663 | 1,347 | 1,316 |

**Table A2: Cross-benchmark agreement: BJZZ vs wholesaler.** Rank agreement between the BJZZ share and the PFOF-6 wholesaler share with the same conditioning as Table 11. The sample is the same as the Table 11 baseline (39,837 stock-months); N is stock-months. The sample is February through May 2026 (Rule 605 filing months 202602-202605).

| **Sample** | **N** | **Raw Spearman** | **Conditioned Spearman** |
|---|---|---|---|
| Common Stocks | 20,576 | 0.81 | 0.58 |
| ETFs | 19,261 | 0.67 | 0.69 |
| All | 39,837 | 0.75 | 0.69 |

**Table A3: Predicting next-day liquidity and volatility (Robustness).** The joint specification from column 3 of Tables 15 and 16: BJZZ and Fractional entered together is re-estimated under four sample screens, separately for common stocks and ETFs. Each cell is the same regression, BMO's eight controls, the lagged dependent variable, stock and calendar-day fixed effects, and standard errors double-clustered by stock and by day. Only the two retail coefficients are shown (the Top-100 interactions, controls, and fit statistics are suppressed). The first row is the BMO exact specification with the full sample and no minimum-price screen. Each subsequent row adds a screen: a $5 day-median-price floor, the top fractional-activity quartile, and both together. N is stock-days, t-statistics in brackets. Significance: * 10%, ** 5%, *** 1%. The sample window is February 23 through June 18, 2026 (the post-reform native-fractional sample).

| | Common Stocks | | | ETFs | | |
|---|---|---|---|---|---|---|
| **Sample screen** | **BJZZ** | **Fractional** | **N** | **BJZZ** | **Fractional** | **N** |
| **Panel A: ln effective spread (t+1)** | | | | | | |
| Full sample | -0.0369*** | 0.0007 | 410,579 | -0.0154*** | -0.0036 | 377,189 |
| | [-10.4] | [0.2] | | [-2.8] | [-0.7] | |
| $5 minimum-price | -0.0252*** | 0.0066 | 290,926 | -0.0177*** | -0.0077 | 374,278 |
| | [-6.1] | [1.6] | | [-3.3] | [-1.4] | |
| Top-quartile (Q4) | -0.0383*** | 0.0111** | 107,834 | 0.0102 | 0.0103* | 104,875 |
| activity | [-4.3] | [2.0] | | [1.4] | [1.8] | |
| Q4 and $5 screens | 0.0035 | 0.0090 | 97,714 | -0.0015 | 0.0064 | 103,241 |
| | [0.5] | [1.6] | | [-0.2] | [1.2] | |
| **Panel B: ln intraday volatility (t+1)** | | | | | | |
| Full sample | 0.0393*** | 0.0637*** | 404,700 | 0.0135** | 0.0363*** | 378,780 |
| | [6.9] | [12.6] | | [2.5] | [4.5] | |
| $5 minimum-price | 0.0299*** | 0.0515*** | 285,563 | 0.0110** | 0.0329*** | 375,869 |
| | [4.3] | [7.0] | | [2.1] | [4.2] | |
| Top-quartile (Q4) | 0.0467*** | 0.0176 | 107,745 | 0.0555*** | 0.0295*** | 102,576 |
| activity | [4.2] | [1.4] | | [4.6] | [2.8] | |
| Q4 and $5 screens | 0.0403*** | -0.0000 | 97,629 | 0.0478*** | 0.0230** | 100,942 |
| | [2.8] | [-0.0] | | [3.9] | [2.2] | |