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Are Fractional Share Trades Informative?

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Abstract. Recent literature suggests coordinated fractional share trading impacts stock prices. We provide evidence that at least one retail broker systematically executes fractional share orders in batches on a daily basis between 2023 and 2024. For example, during a 5000-millisecond time interval on March 7, 2024, over 65,000 inferred fractional share trades execute in Tesla. We construct a methodology to systematically identify these 'bursts' of inferred fractional share trades and use them to investigate whether the batched execution of fractional share orders has price impact. Despite the fact that over 93% of the inferred fractional share trades in bursts are buyer-initiated, both univariate and multivariate analyses indicate that bursts of inferred fractional share trades do not impact underlying security prices.

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I. Introduction

On January 2nd, 2024, Apple (AAPL) had an influx of off-exchange one-share (OEOS) trades. For the first forty-one minutes of the day, which was before the influx, OEOS trades as a percentage of all trades in Apple were around 20%. Starting at 10:11 a.m., the percentage of OEOS in Apple rose sharply to 58% and this elevated activity persisted until 11:06 a.m. Following the influx the proportion of OEOS trades in Apple returned to around 20% for the remainder of the trading day. During the fifty-five minutes of elevated OEOS trade reporting, OEOS trades as a percentage of consolidated trading in Apple exceeded 60% in most minutes and peaked at 76%. What makes the activity more intriguing is that Apple is not the only stock that displays this intensity of OEOS trades, which we refer to as "bursts." The same anomalous intense reporting of one-share trades is identified in other stocks such as Tesla (TSLA), Amazon (AMZN), Microsoft (MSFT) and Nvidia (NVDA) in synchronization, as illustrated in Figure 1.[1]

[Insert Figure 1 about here.]

To investigate if these bursts (Figure 1) generalize beyond these five stocks during one day in January 2024, we construct a methodology to identify minutes in which there is an abnormal spike in OEOS trading and we define a 'burst' of OEOS trading as an interval of at least five consecutive minutes of abnormal OEOS trades within a stock. We identify over 49,700 bursts in 1,437 stocks from 2021-2024. The average (median) burst is 20 (13) minutes long and contains 7,175 (1,685) OEOS trades. We find OEOS trades comprise 11.4% (45.6%) of a stock's consolidated trades outside of (during) a burst. As seen in Figure 1, the bursts in the five stocks start and stop at the same time. While we detect some bursts and instances of synchronized bursting before March 15, 2023, Figure 2 reveals there is an abrupt and dramatic change in the frequency

[1] The same pattern is not observed in any other small trade sizes such as 2-share trades which can be seen in Figure A1.

and degree of synchronization of bursts across stocks beginning on March 15, 2023. The burst activity we document, which is concentrated in the first few hours of the trading day, stops suddenly on November 8th, 2024. Given the compelling logic in Easley and O'Hara (1987), it is difficult to imagine what type of informational events would lead to this increase in OEOS trades but would not lead to an increase in trades of other sizes.[2]

[Insert Figure 2 about here.]

Bartlett et al. (2024) place marketable orders for either $10.00 or $1.00 in different securities with two brokers: Robinhood and DriveWealth (DW). Because DW does not offer a brokerage platform to retail investors but rather executes orders for other introducing brokers, the authors place orders with Cash App, who uses DW to execute its orders.[3] In Appendix A, the authors locate the trades generated by their marketable orders they placed with Cash App and DW in the NYSE's TAQ data. The authors present the raw data associated with the prints and we notice that Cash App executions have a participant timestamp that is rounded to millisecond precision. In our data, the OEOS trades within a burst overwhelmingly print with participant timestamps that are rounded to the millisecond.[4] Using the participant timestamp as a classifier, and weekly reports filed with FINRA, we present compelling evidence that the fractional shares DW executes are responsible for a large amount of synchronized OEOS bursts documented in this paper.

DriveWealth (2022) states that it had more than 100 introducing brokers and over 15 million customers around the world in 2021. Given the dispersion of customers across time-zones, it is likely that many of the fractional share orders are placed with DW's introducing brokers

[2] We do not detect bursts of other trade sizes. As anecdotal evidence in Figure A1 we present the proportion of trades in other trade sizes of the same five stocks on January 2, 2024 from Figure 1.
[3] Bartlett et al. (2024) note that "through its customizable suite of API's, DW is the brokerage firm behind 'micro-investing' platforms such as Revolut and Cash App that allow their customers to trade in fractional shares and/or invest their 'spare change' in fractional shares."
[4] In our analysis we find that OEOS trades associated with a burst have a rounded participant timestamp and execute with trade prices that are either a round-penny or sub-penny pricing with sub-penny component as x.xx88.

outside of U.S. trading hours. Consistent with this conjecture, DW's fractional share disclosure states that "unless eligible for extended market trading sessions, market orders received after the close of the previous regular trading session will be retained for execution in the next regular trading session if not cancelled." The disclosure also states that "orders placed prior to market open may not be executed directly at the open and orders placed close in timing to the close of the market will not be guaranteed to be processed that same day." All orders placed with DW are marked "Not Held," which gives DW the discretion to execute the orders whenever it chooses.[5] Our evidence is consistent with assertion that fractional share orders are batched and execute in bursts by DW. As it is unlikely that the market conditions prevailing when the fractional orders are executed motivated the placement of the fractional orders (e.g., the trades do not represent real-time trading interests), our sample of bursts is an ideal setting to evaluate the price impact of fractional share trades that are not motivated by real-time information.

Jacklin et al. (1992) construct a multiperiod Glosten and Milgrom (1985) model to examine market crashes and show that if the market underestimates the use of dynamic hedging strategies such as portfolio insurance, the trades generated by these strategies will have greater price impact than they would have had market participants known the motivation for these trades. In our setting, if fractional share orders contain value relevant information and market participants are unaware that DW is executing fractional share orders in batches these fractional share trades should collectively have an outsized price impact. Moreover, the size of the price impact should be positively correlated to the intensity of fractional trading within a burst. If information pertaining

[5] Regulators do not use the order-receipt time quotes to evaluate the execution quality given to not-held orders. In contrast, most orders placed with Fidelity, Schwab, and Robinhood are "Held" and the execution quality of these orders is evaluated against the quotes prevailing when the orders are received by the brokers.

to the origin of the order flow which compromises bursts were to be revealed to all market participants, then any existing price response should be dampened.

O'Hara et al. (2014) investigate odd lot trades in US equity markets and find that while the median percentage of odd lot trades in a stock is 24%, they contribute 35% to the discovery of equity prices. This may be because the size of a trade is determined by the liquidity provider when the order is larger than the number of shares offered at the best quote. Using Nasdaq order book data, Davis et al. (2017) find that 34.89% of all one-share Nasdaq trades in 2012 are intentional and not the source of a broken order. They further provide evidence that one-share trades are disproportionately aggressive and more likely to execute against hidden liquidity. Bartlett et al. (2025) find odd-lot quotes (e.g., orders for less than 100 shares) that improve upon but are not displayed in the National Best Bid and Offer (NBBO) are predictive of future NBBO midpoints, suggesting they play a role in discovering asset prices. Bartlett et al. (2024) develop a latency-based method for identifying a large sample of fractional share trades and present evidence that fractional share trades are predictive of value relevant data such as future liquidity and volatility.

Lin (2024) leverages the OTC data provided by FINRA, in conjunction with the Bartlett, McCrary, O'Hara (2024) algorithm for identifying fractional trades, finds results consistent with Da, Fang and Lin (2025) that fractional trades do induce price pressure. Specifically, Lin analyzes unanticipated 8-K filings and finds that in the post fractional trading period, stocks which are identified as "high fractional" are associated with stronger price responses to 8-K filings than stocks which are "low fractional". The price action is typically followed by a reversal. Lin finds that informed traders are adept to the price reactions induced by retail traders as they appear to profit from the volatility and mispricing caused by retail traders. Da et al. (2025) study fractional share trades and find that "these tiny trades, when coordinated during attention-grabbing events, are forceful enough to exert large price pressure on high-priced stocks." We contribute to this literature by investigating whether the batched execution of inferred fractional share trades that are likely not motivated by real time information events impact underlying asset prices.

In this paper we examine the market's response to OEOS trades during and after bursts that occur between March 15, 2023 and November 8, 2024. We begin our analysis by introducing a methodology to systematically identify bursts of intense OEOS trading volume within stocks and by providing several pieces of evidence that suggest that the OEOS trades which execute during bursts are likely generated by batched fractional share orders. We argue that bursts provide us with a unique opportunity to examine the impact of fractional shares on market prices in a setting where (most) of the trades in the burst were not motivated by information revealed immediately prior to the commencement of the burst. Additionally, since there are no spikes in other trade sizes during a burst, this setting is particularly favorable for investigating fractional trading's price impact. The trades we identify are not a component of a mixed trade that contains a whole share and fractional leg or the whole share leg that was executed/reported at a different time than the fractional leg. Other studies which investigate fractional trading are unable to make the distinction of whether their results are caused by fractional trades or by related whole share trades. We find that over 93% of the OEOS trades which execute during a burst are above the midpoint of the NBBO at the time of execution (e.g., are buyer-initiated). Conversely, the non-OEOS trades which execute during bursts are evenly split between buyer- and seller-initiated trades, as expected. Across *all* trades which execute during bursts, over 68% are buyer-initiated while 31% are seller-initiated. Consistent with these statistics, we find that during bursts, the median OEOS net imbalance is 85% while the median non-OEOS net imbalance is 0.15%. Across all trades during bursts of inferred fractional trading, the median net imbalance is more than 36%. We find the 10th percentile burst has an OEOS net imbalance of over 65% and the net imbalance constructed using all trades during a burst is 10.35%. Together, this suggests that if fractional share trades have price impact, asset values should rise during even the least intense fractional share trading bursts. Despite the intense *buying* activity of inferred fractional share trades which execute during bursts, we find that the movement in the stock's fundamental value as proxied by the midpoint of the NBBO over the duration of the burst is muted. The median (mean) quote movement during a sample burst is zero (0.11) basis points. Of the 27,400 bursts which we calculate the price impact, 13,671 have a positive quote movement, 12,777 have a negative quote movement, and 952 have no quote movement during the burst.

While univariate statistics shed no evidence of intense, batched inferred fractional share trade reporting exerting any detectable price pressure, we conclude our analysis by examining the impact in a multivariate setting. Specifically, we examine how the midpoint of the underlying security moves during bursts conditional on the duration of the burst, the number of OEOS which execute during the burst, the net imbalance of both OEOS trades and non-OEOS trades during the burst, the SPY midpoint movement, and stock price indicator variables. If periods with intense inferred fractional share trading are informative as to the value of the underlying asset, or if market participants view bursts of OEOS trading activity as being informative, we expect bursts with higher OEOS trade counts, longer durations, and greater OEOS trade imbalances to be associated with positive price impact.

In contrast to the hypothesized positive relation between the imbalance in OEOS trading activity during bursts and price impact, we find that the relation between the movement of the underlying stock's price is insignificant when entered alone and is negatively correlated with the OEOS imbalance at the 1% level when entered jointly. We also present evidence that the duration and the number of OEOS trades are not related to the movement in the security's price while the intensity of the burst (OEOS count / duration) is negatively related to the movement in the security's price during bursts. We find that the price impact during a burst is primarily related to the non-OEOS order imbalance and the price impact of the SPY over the same time period of the burst. We find a near unit-elastic relation of the price impact of the underlying security and the price impact of the SPY as the coefficient is measured near one in all specifications. Interestingly, when we construct order imbalances within different on-exchange trade size bins, we find that almost all are positively related to the price impact, even the on-exchange-one-share imbalance. Therefore, it appears that OEOS imbalance's counterpart, the on-exchange-one-share imbalance coordinates with price impact, while the OEOS imbalance does not. The price impact within the burst remains negatively related to the OEOS-imbalance regardless of whether a stock is high-priced or low-priced.

To summarize, we identify periods of time during which elevated numbers of OEOS trades execute and provide evidence that many of these trades are the result of not held fractional share orders which are executed by DW in a batched manner. This batched execution of fractional share orders introduces a disconnect between the information prevailing when the investing decision was made and the information prevailing when the fractional share orders execute. This creates the ideal setting to investigate whether intense inferred fractional share trading devoid of extraneous information has price impact. Univariate and multivariate analyses present a clear and consistent message that even when inferred fractional share orders are batched and comprise over half of the trades during a burst, they have no price impact. Our results are not surprising given the conventional wisdom that a market participant can trade up to five percent of a stock's average daily volume without having price impact.[6] The cumulative volume of shares traded by OEOS trades in sample bursts is 3,432 shares at the 50th percentile, 9,434 shares at the 75th percentile, and 236,027 shares in the burst with the most OEOS trades.[7]

II. Data.

Our primary data source is the NYSE Trade and Quote (TAQ) database. We use nanosecond-resolution trade records and the NBBO for all stocks, from 2021 through 2024. Each trade record contains the symbol, SIP timestamp, participant timestamp, trade price, trade volume, and exchange code. The SIP timestamp records when the trade was disseminated to all market participants and the participant timestamp records when an exchange or trading venue executes a trade. Exchange code "D" is attached to trades that execute off-exchange and reported to a FINRA Trade Reporting Facility (TRF). Retail trades which execute off-exchange by brokers and wholesalers as well as institutional orders which execute in Alternative Trading Systems and Single Dealer Platforms are typically reported to a TRF.

We restrict all analyses to trades which execute during regular trading hours. To reduce issues associated with reporting latencies in the TAQ data, we use the prescription of Battalio et al. (2025). Specifically, we construct a latency-free (LF) NBBO by ordering all quotes across exchanges by their participant time and labeling the best bid as the highest bid and the best ask as the lowest ask. We sign on-exchange trades using the hybrid signing methodology proposed. Crucially for our paper, we sign off-exchange trades using the LF NBBO delayed by 1ms.[8] The focal test of our paper involves regressing intraday price changes of the NBBO on signed trade

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[6] See Battalio and Schultz (2006).
[7] Statistics pertain to the 'precise-burst' sample in Table 2.
[8] In an earlier draft of the paper, we use the SIP NBBO augmented with the LTA adjustment proposed by Holden et al (2023), our results are virtually identical. The one exception is that with the LF NBBO we sign more OEOS trades during bursts as buys.

imbalances, it is therefore imperative that we sign trades accurately and use an NBBO that is not plagued with latency errors.

We obtain weekly firm-level off-exchange volume data from FINRA's OTC Transparency portal to validate the method we use to identify fractional trades DW executes. FINRA requires broker-dealers to report their over the counter trading activity at the stock-week level. For each broker and stock, the data contain the total number of shares traded and the total number of transactions during the reporting week. We use the non-ATS (non-Alternative Trading System) reports, which capture principal and riskless-principal executions by individual broker-dealers rather than volume routed through dark pools.

III. Methodology and descriptive statistics.

We define a 'burst' as a period containing an abnormally large amount of OEOS trades. We begin by computing the percentage of OEOS trades in each stock *i* during minute *t* of trading day *d*:

$$\%\ OEOS_{i,d,t} = \frac{\#\ OEOS\ trades_{i,d,t}}{All\ trades_{i,d,t}}.$$

Next, we compute a robust z-score for each minute relative to the stock's own intraday distribution. For each stock-day, we take the median and the median absolute deviation (MAD) of $\%\ OEOS_{i,d}$ from 9:35 through 3:54. We exclude the first and the last five minutes of the trading day to avoid late openings and elevated trading prior to closing auctions. We compute the z-score as follows:

$$z_{i,d,t} = \frac{\%\ OEOS_{i,d,t} - Median(\%\ OEOS_{i,d})}{1.4826\ x\ MAD(\%\ OEOS_{i,d})}.$$

The scaling constant 1.4826 is the standard Gaussian consistency factor for the MAD, making the denominator comparable to a standard deviation under normality.[9] We use the MAD rather than the standard deviation because the distribution of OEOS trades within a trading day is highly skewed. A few burst minutes can consist almost entirely of OEOS trades while the $\% \, OEOS$ in the typical trading minute in the typical stock is around 10%.

A minute is identified as a *potential* burst minute if $z \geq 2$ and the number of OEOS trades during the minute exceeds 50. The count threshold ensures we do not identify minutes where $\% \, OEOS$ is high but the number of trades in the minute is small (e.g., 1 out of 2 trades being one-share). After identifying each of the potential burst minutes for a stock on a trading day, we next examine each of the 375 overlapping six-minute intervals (sliding one minute at a time) starting at 9:35am and ending at 3:54. If at least five of the six minutes in an interval are potential burst minutes, we identify each of the minutes in the six-minute interval as burst minutes. This procedure allows us to capture bursts of OEOS trading activity that begin within minute boundaries and accommodate occasional gaps within a burst episode.

[Insert Table 1 about here.]

We present summary statistics for the bursts during the four-year sample period beginning in January 2021 in Table 1. Overall, we identify 1,437 stocks as having at least one burst. As seen in Panel A, the average stock with at least one burst has 681 burst minutes and 35 bursts. The distribution is highly skewed, suggesting bursts are concentrated in a small subset of stocks. The median stock has 3 bursts, the 75th percentile stock has 8 bursts, and the maximum number of bursts in a stock is 912. As documented in Panel B, there are 49,700 bursts identified at the minute-

[9] See Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology*, *49*(4), 764-766.

level during our sample period. The average (median) burst lasts for 20 (13) minutes. The longest burst lasts for 159 minutes and is documented in the ETF IEMG on March 8th, 2022, running from 10:04 a.m. to 12:42 p.m., during which OEOS made up 26% of all trades.[10] The largest burst by OEOS count contains 235,548 OEOS, in Tesla on February 5th, 2024, from 10:12 a.m. to 11:06 a.m., of which OEOS trades comprised 38% of all trades.[11] Across the 1,005 trading days from 2021-2024 we identify bursts on 1,000 trading days. In our sample, an average of 37 stocks have a burst each day and the average day has 978 burst minutes. Twenty-five percent of the sample days have at least 66 stocks with a burst and contain more than 1,825 burst minutes. Finally, in Panel D we characterize the number of OEOS trades that occur inside and outside of sample bursts. There are 978,304 burst-minutes and 14,836,374 minutes outside of bursts.[12] The average minute inside (outside) of a burst has 365 (27) OEOS trades. For context, OEOS trades as a percentage of all trades during the average burst-minute is 45.6%, while the percentage of OEOS trades in the average minute outside of bursts is 11.4%. Finally, as our methodology considers six-minute intervals where one of the minutes is not identified as a ‘potential’ burst minute, there are minutes during our sample period where there are no OEOS trades in sample stocks inside or outside of bursts.[13]

[Insert Figure 2 about here.]

Panel A of Figure 2 plots the daily aggregate burst activity over the entire four-year sample period. The black line identifies the total number of burst minutes each day while the dashed line

[10] IEMG is the iShares Core MSCI Emerging Markets ETF.

[11] TSLA and AAPL compromise the 50 top bursts by OEOS trade counts.

[12] Minutes outside of a burst are totaled as stock-minutes not identified with a burst, on stock-days with an identified burst.

[13] For example, on 31 July 2024 the iShares MSCI Saudi Arabia ETF (KSA) records 181 OEOS executions in the 11:53 minute and 262 in the 11:55 minute, but zero in the intervening 11:54 minute, where total trading also collapses from roughly 260 trades per minute to just three (almost all activity can be attributed to the burst). A typical minute of trading in KSA on this same date had 0-3 OEOS trades per minute (outside of the burst).

denotes the number of stocks with a burst on each day. As evidenced in Panel A, burst activity significantly increases in March of 2023 and remains elevated through November 2024. An investigation of the data used to produce Panel A reveals that burst activity became elevated on March 15, 2023 and remained elevated through November 8, 2024. Panel B plots the average burst duration in minutes each day across all stocks. It also plots the number of burst-minutes for Tesla common stock (TSLA) over the sample period. As is the case in Panel A, Panel B illustrates that the duration of bursts increases in March 2023 and remains elevated through November 2024.

[Insert Figure 3 about here.]

To the extent that OEOS trades which execute during bursts represent the batched execution of fractional share not held orders, one might expect these trades to execute outside of normal trading hours depending upon when the orders are received by the corresponding broker. Figure 3 contains a plot of the daily number of OEOS trades which execute before 9:30am, execute during a burst within normal trading hours, or execute after equity markets close at 4pm.[14] The figure suggests that prior to March 2023, OEOS trades are more likely to execute outside of normal trading hours than during a burst in normal trading hours. However, consistent with the data presented in Panels A and B of Figure 2, between March 2023 and November of 2024, the number of OEOS trades which execute in bursts during the trading day dwarfs the number of OEOS trades which execute outside of trading hours.

The goal of this paper is to examine whether bursts of inferred fractional trades are associated with movements in the underlying stock's price, we impose two additional restrictions for a burst to be retained in the sample used to investigate price impact. First, we restrict the sample period to March 15, 2023 through November 8, 2024 as burst activity is highly concentrated within

[14] Pre-market and after-hours OEOS counts are only summed for stock-days which are identified with a burst.

this period as evidenced by Figure 3. Second, because our analysis measures the change in a stock's quoted midpoint from the start of a burst to its end, we require each burst's boundaries to be identified at the trade-level rather than the minute-level. We denote bursts which pass this second restriction as "precise-bursts."[15] Our procedure for classifying a burst as precise begins with identifying DW executed "burst-signature" trades (burst-signature trades are defined below) within each detected burst's window and anchoring the burst's start and end to the timestamps of the first and last such trades. Bursts for which we can locate these boundary trades are labeled precise-bursts and retained; those for which we cannot are discarded. This restriction simultaneously sharpens each burst's edges and concentrates the sample on trades attributable to DW.

The minute-level detection underlying Table 1 is permissive by design, the sliding five-of-six-minute window captures all anomalous OEOS activity. The minute-level detection procedure is appropriate for a first pass and unconditional descriptives but is too coarse for measuring price impact. The process for identifying a precise-burst is detailed fully in Appendix B with two examples from the data, but we discuss it briefly here. We first merge same-stock bursts separated by five minutes or fewer, so that a briefly interrupted episode enters as a single burst.[16] We then partition the minutes surrounding the starting minute boundary from the first pass into 15-second bins. We then partition the 15-second bins into 3-second bins. The "winning" 3-second bin is the highest OEOS activity bin relative to the stock's baseline before the burst. The burst begins at the

[15] Changes in the quoted midpoint from the start of a burst to the end of a burst are nearly identical when using the initially identified minute boundaries versus using bursts which survive this second restriction. While we concede that the precise-burst boundaries increase the technicality of the analysis we propose the precise burst boundaries as the most defensible method to estimate a start and stop time of a burst.

[16] It is common for longer bursts to have an intermission of one to three minutes where the OEOS count drops to its baseline levels before returning to an elevated rate. While splitting these into two bursts is useful for summary stats (a clean split between burst vs. non-burst minutes), we contend that for analyzing price impact it is appropriate to merge such splits into one burst to determine the price change from the start of the first burst to the end of the last. Price impact results are near identical without applying the merge. Bursts which are separated by more than five minutes are considered separate.

SIP-timestamp of the first burst-signature trade in the winning 3-second bin.[17] The end is located by the same procedure, except we identify the final trade in a burst by scanning from the final minute of the burst as opposed to the beginning minute of the burst.

Not every burst survives refinement. Some are too sparse in trading activity at the finer resolution or retain too few burst-signature trades to clear the thresholds. A precise-burst requires both a valid start and a valid end. We discard bursts that cannot be assigned both boundaries. Of the 49,700 bursts identified in Table 1, 41,847 occur between March 15, 2023 and November 8, 2024. Merging same-stock bursts separated by five minutes or fewer leaves 36,861 distinct episodes, of which we can assign precise start and end times to 27,400.

It is likely that not all OEOS trades within a burst interval are attributable to DW's fractional-share execution algorithm (and other participants may engage in fractional-share batch executions). To isolate the trades most likely generated by the algorithm, we identify OEOS trades during the burst episode that satisfy two additional criteria and label these trades as 'burst-signature' trades. The two criteria are that the participant timestamp is rounded to the nearest millisecond (e.g., the timestamp does not contain sub-millisecond precision) and the trade price falls on a whole-penny pricing-grid or on a x.xx88 sub-penny pricing-grid.[18] The timestamp rounding exploits FINRA Rule 6380A (effective November 2021), which permits participants to round timestamps to the millisecond. The executing broker rounds while most other market participants report with microsecond or full nanosecond precision, creating a separation. The pricing restriction comes from manually observing the trades in the largest bursts in high-interest

[17] We use the SIP timestamp as opposed to the participant timestamp as we wish to classify when the burst would have been observable to the market.

[18] Burst-signature OEOS trades consistently have 2-3% of trades executing with a trade price on the x.xx88 grid from March 15, 2023 to August 1, 2024. Starting August 2, 2024 the percentage of trades executing with this price pattern jumps to over 90%, which is why we allow OEOS trades with both price patterns to qualify as burst-signature trades.

stocks like TSLA and AAPL.[19] Together, these two criteria distinguish algorithmically generated burst OEOS trades from ordinary OEOS activity and allow us to more accurately assign a precise start and stop time to a burst.

[Insert Table 2 about here.]

Panel A describes the across stock number of bursts and burst-minutes for the 309 stocks with at least one burst during the truncated 418-day sample period. The average (median) number of burst minutes in a stock is 2,379 (35) minutes while the average (median) number of bursts for a sample stock is 89 (4) bursts. These statistics indicate that even in the revised sample, the distribution of bursts across stocks is highly skewed. Indeed, the top quartile of stocks have at least 137 bursts and 1,799 burst minutes over the 418-day sample period. The distribution of burst-activity becomes more skewed than what is presented in Table 1 as many bursts in illiquid stocks do not graduate to precise-bursts as we cannot identify an accurate start and stop time. In Panel B of Table 2 the average (median) burst has a duration of 1,558 (1,253) seconds and contains 11,678 (3,432) OEOS trades. Just over 6,800 bursts (25% of the sample) have a duration of at least 2,051 seconds and contain at least 9,434 OEOS trades. Panel C reveals that on the average day, there are 66 bursts and 59 stocks with at least one burst.

[Insert Table 3 about here.]

Table 3 displays 13 consecutive AAPL trades from the TAQ database on January 2, 2024, during a burst episode beginning around 10:48:27. Columns report the stock, exchange code, exchange timestamp (nanosecond precision), trade price, trade volume, participant timestamp, TRF timestamp, and TRF identifier. Rows 1-6 and 12 are burst-signature trades: each has volume of one share, exchange code "D" (off-exchange), a participant timestamp rounded to the

[19] We validate burst-signature trades being attributable to DriveWealth by matching to the FINRA OTC data, following Bartlett, McCrary, O'Hara (2024). Our quality of match is presented graphically in Figure 5.

millisecond, and a whole-penny price ($185.50 or $185.49). Rows 7 and 11 have a participant timestamp with sub-millisecond precision, illustrating a non-burst-signature one-share trade. Rows 8-9 are on-exchange trades (exchange Q, NASDAQ) with larger volumes (30 and 42 shares), showing ordinary market activity interleaved with burst trades. Row 10 is a two-share off-exchange trade. Row 13 is a one-share off-exchange trade whose participant timestamp is not rounded (.459681164), distinguishing it from burst-signature trades. The table is manually curated.

[Insert Figure 4 about here.]

Figure 4 contains DW's total weekly trade count across all stocks as reported to FINRA through OTC (non-ATS) transparency filings from 2021 through 2024. The FINRA OTC data allows us to observe the weekly trade counts and volume on a stock-by-stock basis each broker executes, we cannot observe a flag on the trade level that associates a trade with a broker. Consistent with the elevation in OEOS burst activity between March 2023 and November 2024 in Figures 1 and 2, the data presented in Figure 4 indicate that DW's weekly trade count is elevated over this same time frame. Indeed, DW's weekly trade count rises from around 2 million trades in January and February 2023 to more than 7 million trades during several weeks in the second half of 2024. The week which follows November 8, 2024 (the last day we observe synchronized bursts), DW's trade count decreases from 7 million trades to 2 million trades. While not tabulated, note that DW's share to trade ratio is near one throughout the entire sample, so presenting the executed volume or trade counts is equivalent.

[Insert Figure 5 about here.]

To investigate the effectiveness of the algorithm used to identify DW's fractional trades, we aggregate OEOS trades in TAQ which satisfy the requirements of a DW burst-signature trade and which *execute during bursts* by stock on a weekly basis and compare this to DW's weekly trade count as reported by FINRA. Using red dots to identify the weekly total of OEOS signature trades and grey bars to identify the number of trades that DW reports to FINRA, we present the weekly totals for fifteen stocks with different levels of trade reporting in Figure 5. The weekly number of DW signature trades is around 89% of the number of DW trades reported to FINRA for Tesla (TSLA), Apple (AAPL), and Microsoft (MSFT), three of the sample stocks with the highest volume of DW OEOS signature trades. There are limitations which may influence our match quality; there may be burst-signature trades within a burst not attributable to DW, this would inflate our counts relative to the OTC; DW may execute some of their volume outside of the burst, this would cause the OTC data to exceed our TAQ counts; or DW may be recorded in the De Minimis category for that stock-week in the OTC data.[20] The difference in trade counts for the fifteen stocks presented in Figure 5 range from 89% to 104%. Of the two limitations it appears that the first dominates for some stocks and the second for other stocks. Despite the limitations, the tracking across the stock-weeks is consistent. Overall, the data presented in Figure 5 suggest that the bursts of OEOS trades are primarily composed of inferred fractional share trades executed by DW.

[Insert Figure 6 about here.]

To confirm the bursts we identify predominantly arise from DW batched executions we compute the fraction of OEOS trades that are composed of burst-signature trades. We then plot the percentage of bursts which clear varying levels of burst-signature trades in Figure 6. As indicated by the first bar in Figure 6, DW burst-signature trades comprise at least half of all OEOS trades which execute during bursts for 94% of sample bursts. For just over half of the sample of bursts, DW signature trades account for at least 85% of OEOS trades which execute during bursts.

[20] Weekly trades will not be attributed to a specific FINRA member and will instead be aggregated and reported as exectuted by the De Minimis category if the firm did not complete 1,000 trades in that symbol-week or 1,000 trades in total across all symbols for the week.

Together with the data presented in Figure 5, the results in Figure 6 indicate that DW's inferred fractional trades are a large fraction of the OEOS trades which execute during bursts.

[Insert Figure 7 about here.]

Figure 7 Panel A plots the intraday distribution of burst activity, pooled across all trading days from March 15, 2023 to November 8, 2024 conditional on a stock's listing exchange. Data suggests that almost no burst activity occurs before 9:45 and the abrupt rise of activity at 9:45 is consistent with a fixed start-time. This concentration of bursts in the morning coupled with the anecdotal evidence presented in Figure 1, which shows the number of OEOS trades which execute for AAPL, AMZN, MSFT, NVDA, and TSLA are elevated at the same time, suggests that DW's fractional share trades occur in bursts that overlap in time. An exchange pattern also emerges. Bursts occurring in NYSE stocks begin at 9:45 and conclude by 10:30. NYSE Arca stocks (ETFs) also appear to burst starting at 9:45 but the density of OEOS trades are concentrated from 10:15 to 10:45. NASDAQ stocks which are associated with the highest count of OEOS, also are identified with a 9:45 am start but persist until 12:00. In Panel B we plot the intraday count of unique stocks we identify with a burst across days. We make three observations from Panel B: the fixed 9:45 start time is persistent across the sample, the beginning and conclusion of burst activity on the daily level is abrupt, and burst activity intraday appears to shift from being concentrated in one batch to two distinct batches towards the end of 2023 and beginning of 2024.

We provide a potential explanation for the abrupt start and stop of intense burst activity on March 15, 2023 and November 8, 2024, respectively. One of DW's introducing brokers is Revolut. Revolut is a Fin-Tech company based in the United Kingdom who provide a financial service where users can "round-up" transactions they make with their debit card and invest the difference. On November 8^{th} 2024, the last day we that detect the intense, synchronized burst activity, Revolut switched bank providers for their debit cards. Revolut required users to opt in, if they did not the accounts would be closed. We now present the following facts that led us to the conclusion that fractional share orders placed with Revolut make up the majority of the DW OEOS trades during this 20-month period. First, the OEOS volume from bursts we identify in the TAQ data tracks almost one to one to DW OTC data for a series of symbols, many of which coincide with the top symbols from Eaton, Shkilko, and Werner (2025, Table 1) who investigate overnight trading and attribute the activity to *global* investors (we also note many high activity burst symbols are emerging market ETFs). Second, DW is the stated broker of Revolut[21] and Revolut offers customers to round up transactions, automatically put them into savings accounts, and use these savings to purchase US equities in fractional amounts.[22] Third, over 90% of the OEOS trades within a burst are signed as buys. Finally, Revolut switches bank providers on November 8, 2024[23] and burst activity vanishes on November 8 2024. While we are unable to directly identify DW or Revolut fractional orders, we use these facts to conclude that the burst we identify in the TAQ data are likely Revolut fractional trades. Throughout the paper we refer to these trades as 'inferred' fractional trades.

[Insert Figure 8 about here.]

Figure 8 plots the daily number of burst signature trades from March 15, 2023, through November 8, 2024, along with a rolling 21-day average. In Figure 8 we use an x to indicate the number of OEOS trades which execute on Mondays and dots to specify the number of OEOS trades which execute on other weekdays. The data presented in Figure 8 indicate that bursts are more intense on Mondays, which is consistent with fact that Monday's not held fractional orders

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[21] See https://www.revolut.com/legal/RTL-best-execution-policy-disclosure/. Last accessed 08/17/2026.
[22] See https://help.revolut.com/en-US/help/app-features/vaults/how-do-spare-change-round-ups-work/ Last accessed 08/17/2026.
[23] See Changes for Revolut US: What you need to know | Revolut United States. Last accessed 08/17/2026.

could have been placed anytime between the close of trading on the prior Friday and the time that the orders execute on Monday.

[Insert Table 4 about here.]

While Figure 7 suggests that bursts primarily overlap in their occurrence, we further examine the extent to which bursts occur synchronously in Table 4. We break the sample period into two subsamples based on the observation that DW begins clustering fractional share trading activity by the stock's listing exchange on November 28, 2023.[24] We present statistics separately for bursts that occur between March 15, 2023, and November 27, 2023, and bursts that occur from November 28, 2023, through November 8, 2024. Panel A presents the number of concurrent bursts across stocks independent of listing exchange. The first row of Panel A reveals that less than 1% of sample bursts occur in isolation. In the earlier time period, 20.29% of the bursts occur concurrently with bursts in 20 to 24 other stocks and 69.22% of the bursts occur concurrently with bursts in 25 or more other stocks. The frequency of bursts that occur concurrently with bursts in 20 or more other stocks falls in the second subsample. Only 38.03% of bursts overlap with bursts in 25 or more other stocks, while 46% of the bursts occur concurrently with bursts in 10 to 19 other stocks.

Panels B and C of Table 4 respectively present the percentage of time that a burst in one stock overlaps with bursts in other stocks conditional on listing exchange for the earlier and the later subsample. The data presented in Panel B indicate that in the earlier subsample there is no relation between the exchange on which a bursting stock is listed and the exchange on which stocks

[24] This deduction is inspired by Figure 7 Panel B where we note that the count of unique stocks identified with a burst on the minute-level appears to change near the end of 2023. We manually observe that DriveWealth appears to batch all symbol regardless of their exchange from 9:45 to 10:45 from March 15, 2023 to November 27, 2023, following this, bursts are executed in the order of NYSE symbols first, NYSE Arca Symbols second and NASDAQ symbols third. This is why we split Table 4 on November 27, 2023.

with concurrent bursts are located. For example, independent of a bursting stock's listing exchange, 45% of the stocks with concurrent burst-time are listed on the NYSE, 38% are listed on Nasdaq, and 16% are listed on Arca. Conversely, the data presented in Panel C illustrates that in the second subsample there is a strong association between a stock's listing exchange and the listing exchange of other stocks with concurrent bursts. When a burst occurs in an NYSE-listed stock, 96.8% of the concurrent burst-time in other stocks is in NYSE-listed stocks, and the corresponding share is 93.3% when the burst occurs in a Nasdaq-listed stock. However, the clustering is weaker for Arca-listed stocks, where the share is 78.5%.

Overall, the data presented in Panel A of Table 4 suggest that inferred fractional trades are batch-executed in groups of stocks. The data presented in Panel B suggests the groups of stocks with synchronous bursts appear randomly selected in the first subsample.[25] Finally, the data presented in Panel C indicate that inferred fractional share trades are batch-executed in groups of stocks based on listing exchange. Together, these data support the hypothesis that DW likely executes not-held fractional share orders in groups of stocks in batches.

[Insert Figure 9 about here.]

In Figure 9 Panel A, we present additional evidence that suggests DW executes fractional share orders in batches. In Panel A, we present the time series of synchronous fractional share trades in five stocks, TSLA, NVDA, MSFT, AMZN, and AAPL, over 1,500 milliseconds starting at 10:31:46 on September 27, 2024. These stocks are a subset of the 37 stocks with concurrent bursts during this time interval and were chosen to illustrate how DW cycles through stocks when reporting inferred fractional shares to the tape. The legend on the right y-axis describes the number of burst-signature and non-signature OEOS trades during this short time interval, which range from

[25] We investigate stock listing exchange, and symbol ordering by alphabet in both the first and second subsample and find no relation.

45 burst-signature and 26 non-signature OEOS trades in AMZN to 219 burst-signature and 21 non-signature OEOS trades in AAPL. More interesting is the amount of time that elapses between each cluster of burst-signature OEOS trades. As illustrated with red horizontal lines in Panel A, the clusters of OEOS signature trades within each stock are separated by approximately 252 milliseconds between their *participant timestamps*. In Figure A2 in the appendix, we present a distribution in log scale of the time between participant time stamps of all burst-signature trades within a stock-burst. While there is considerable density near the origin (as many burst trades occur consecutively), peaks of near equal height can be clearly seen at ~250ms, ~500ms, ~750ms, ~1000ms, and 1,250ms. It is highly unlikely that these trades were executed when the inferred fractional share orders were placed by investors.

Figure 9 Panel A is a typical slice of burst activity. To demonstrate the intensity burst activity can reach we present a 25,000-millisecond time interval on March 7, 2024 in which 201,723 signature trades execute in the same five stocks in Panel B of Figure 9. These five stocks are a subset of the 21 stocks that have concurrent bursts during this time interval. Overall, there are 265,929 signature trades which execute in the 21 stocks identified with bursts during this time interval, which was chosen to highlight a period of intense inferred fractional share batch trade reporting. While this time interval is longer than the interval presented in Panel A, the number of signature trades ranges from 12,034 OEOS trades in AMZN to 68,313 OEOS trades in TSLA. During this period, 96.9% of all trades are a burst-signature OEOS trade. As is the case in Panel A, the signature trades illustrated in Panel B execute in waves across the stocks with concurrent bursts, suggesting that an algorithm is executing inferred fractional share orders in batches. It is implausible that the orders generating these trades were immediately executed when they were placed by investors.

[Insert Figure 10 about here.]

If fractional share orders execute as they are placed by investors, one would not expect there to be a relation between the duration of a burst and the number of OEOS trades within the burst. However, if not-held fractional share orders are batched and execute from an algorithm, one might expect there to be a positive relation between the duration of a burst and the number of OEOS trades within the burst. Figure 10 contains two log-log scatter plots of burst duration in seconds against the number of OEOS trades which execute within the burst for precise-bursts that occur from March 15, 2023 through November 8, 2024. Panel A plots the pooled relation with an OLS fitted line while Panel B plots the within-stock-date relation. As evidenced in both panels, there is a strong positive correlation between burst duration and the number of OEOS trades which execute during the burst. Leaning on the predictions of Jacklin et al. (1992), these results suggest that if market participants view fractional share trades to be informative, the price impact of a burst of fractional share trades should be greater for bursts of longer duration.

[Insert Table 5 about here.]

Panel A of Table 5 presents the distribution of OEOS and non-OEOS trades in sample bursts conditional on where their trade price is relative to the execution-time LF NBBO, along with the percentage of buys and sells, signed using the methodology outlined by Battalio et al. (2025).[26] The first column of data in Panel A reveal that just roughly 5% (4%) of the OEOS trades have execution prices that are below (equal to) the midpoint of the execution-time LF NBBO, which implies that over 91% of the OEOS trades have prices above the spread midpoint. When identifying the directions of trades, we find that 93% are signed as buys and about 7% are signed

[26] We note that in this table, the first seven rows of Panel A present the statistics of where a trade price lies relative to the LF NBBO and when the LF NBBO is temporarily locked or crossed we do not identify a location, therefore the percentages add up to just under 100%. In the last two rows of Panel A, we follow the full signing methodology of Battalio et al. and every trade is signed.

as sells. The distribution of non-OEOS trade prices is essentially symmetric around the midpoint of the execution-time NBBO, as approximately 49.5% of non-OEOS trades are classified as buyer-initiated and 50.5% are classified as seller initiated by the trade signing methodology recommended by Battalio et al.. Given there are similar amounts of OEOS and non-OEOS trades which occur during precise-bursts in our sample, the distribution of all trades which execute during bursts is approximately the average of the two distributions. Overall, there are more than ten times as many buyer-initiated OEOS trades than there are seller-initiated OEOS trades during sample bursts. Thus, if OEOS trades are informative as to the value of the underlying asset, one would expect asset prices to rise during a burst.

Panel B of Table 5 presents the distribution of buys, sells and imbalances on the burst-level across both OEOS and non-OEOS trades. Statistics are equal-weighted across all bursts. Consistent with the results presented in Panel A, the average percentage of OEOS trades that are buyer-initiated in the average burst is 90.91% and the net imbalance for OEOS trades is 81.83%. In contrast, the percentage of non-OEOS trades during the average burst is 50.68% and the net imbalance is 1.36%. The percentage of buys for all trades which execute during the average burst is 69.57% and the net imbalance is 39.14%. Clearly, the batched execution of fractional share trades influences the trade-weighted order imbalance. Panel B also presents the percentile points for the metrics across bursts. Interestingly, in the 10^{th} percentile, 82.88% of the OEOS trades are buyer-initiated and the 10^{th} percentile sorted by the net imbalance is 65.77%. Conversely, the net imbalance for non-OEOS trades (all trades) which execute during bursts is -13.75% (10.39%) in the 10^{th} percentile. Thus, even in the bursts with the lowest buy-weighted imbalances, market participants who view fractional share trades to be informative as to the underlying asset's value will believe the trading activity within the burst indicates prices will subsequently rise. A very least, while bursts may not be predictive of future price responses, if inferred fractional trades have any price impact or coordinate with other price pressure then they should be associated with contemporaneous price increases. Overall, the results presented in Table 5 suggest that if fractional share trades are informative, prices should rise during the typical burst. We investigate the association between bursts of fractional share trade reporting and underlying security prices in the next section.

IV. Does the batch execution of fractional share orders impact prices?

In this section, we examine how the midpoint of a security's NBBO, frequently used to approximate the market's assessment of the security's fundamental value, reacts during a burst of inferred fractional trade reporting. More specifically, for each burst we estimate the quoted midpoint impact per burst interval, or QMP, as follows:

$$\Delta QMP = \left(\frac{QMP_{End} - QMP_{Start}}{QMP_{Start}}\right) \times 10{,}000bps$$

[Insert Figure 11 about here.]

Figure 11 presents the distribution of QMP for bursts that occur between March 15, 2023, and November 8, 2024, split across varying sample periods.

Panel A of Figure 11 presents the distribution of quote movements for all sample bursts. During the mean (median) burst, the QMP is 0.11 bps (0bps). Just under 50% of the bursts have a positive QMP while nearly 47% have a negative QMP. This is in stark contrast to Dyhrberg et al. (2025), who find that the average price impact of a marketable retail order which executes by one of the eight wholesalers between January 2019 and December 2022 is 26.84 basis points for the full sample of stocks and is 3.13 for S&P 500 stocks.[27] Panel B censors the x-axis in Panel A to

[27] See Table 4.

only include bursts which are between -100 bps and 100 bps, here the symmetric distribution of the movement of the QMP during bursts is visible. Given the median (10^{th} percentile) burst has a net imbalance of ***all*** trades of 38.38% (10.29%), if market participants update their estimates of asset values based on trades in the manner outlined in Jacklin et al. (1992), we would expect the distribution of QMPs to be asymmetric with many more positive QMPs than there are negative QMPs. In Panel C, we focus on bursts occurring in the first portion of the sample that begins on March 15, 2023. Despite the fact that there is an abrupt and significant increase in OEOS trade reporting, the mean (median) QMP is -0.34 bps (0 bps) and 49% (47%) of the bursts have positive (negative) QMPs. These results suggest market participants did not update their estimates of fundamental value when abnormal amounts of OEOS trades report in batches to the market. Panels D, E, and F present the distribution of QMPs for other splits of the sample. Not surprisingly, there is little systematic movement in QMPs in any of these splits. Overall, the univariate results presented in Figure 11 suggest that the market does not view the intense reporting of mostly buyer-initiated OEOS trades during bursts as indicating assets are undervalued.

[Insert Figure 12 about here.]

Figure 12 presents a time-series of the equal-weighted QMP across all bursts each day from March 15, 2023 through September 14, 2023. We also present the equal-weighted all-trade imbalance in a smaller plot below. Based on the imbalance statistics presented in Table 5, if OEOS trades are informative or contain price impact, we expect the average QMP each day to be positive. In stark contrast to this expectation, the average QMP is positive (negative) for 65 (62) of the sample days and the equal-weighted average QMP is -0.42 bps. The OEOS imbalance is consistently 75% whereas there is no visible positive response of the QMP. Overall, the data presented in Figure 12 suggest there is no association between the batched execution of fractional share orders that are predominantly buyer-initiated and security prices.

[Insert Figure 13 about here.]

Figure 13 contains plots displaying the change in the QMP during bursts with whisker bands for naïve standard errors and date-clustered standard errors. Given the wide distribution of burst duration, we are unable to create the figure in a classic stacked event study manner with equal time interval bins. To navigate this, we take each burst and identify three regions, the pre-window, the active-window and the post-window. The pre- and post-windows are five-minute windows no matter the length of the burst, anchored to the start and stop time of each precise-burst, and are divided into 30 10-second bins. The active-windows are split into 20 equal bins, so a 5-minute burst would have 20 15-second bins and a 20-minute burst would have 20 one-minute bins. For each bin for each region of each burst we compute the change in the QMP, in basis points from the QMP at the start of the burst, to the close of that bin. We also compute the change in the QMP of the SPY ETF over the same timestamps. Each panel equal-weights the bins across all bursts. We partition the sample into varying windows: the full sample, the first day, the first week, the first month, the first 3 months and the first six months. We use a dark whisker for the 95% confidence interval assuming naïve standard errors and a lighter whisker for the 95% confidence interval assuming standard errors are correlated within a day. The red diamond represents the equal-weighted change in the QMP of the SPY, without any confidence interval. In a sub panel below the ΔQMP we plot the equal-weighted trade-imbalance using all trades for the pre- during- and post-bins.

Even though the trade imbalance is largely positive for the duration of the burst, the price impact of bursts is not statistically different from zero, nor from the price impact of the SPY over the same window. The data presented in Panel A also suggest that changes in the QMP of bursting stocks is positively correlated with changes in the midpoint of SPY as the two are coordinated in their movements. We test that relation subsequently. Panel B presents the average change in midpoints for the 41 bursts that occur on the first day of the synchronized sample (March 15, 2023). Even though the bursts have positive net trade imbalances, the price changes of the sample midpoints during bursts closely mirror the changes in the midpoint of the SPY. When the sample expands to the first week of bursts in Panel C, there appears to be positive quote changes during sample bursts. However, the midpoint of SPY also experiences positive price changes during the first week of bursts. Moreover, the bursts do not appear to impact the prices of bursting stocks as the post-burst midpoints return to pre-burst levels before the conclusion of the burst. When we focus on the first month of bursts in Panel D, the results suggest that bursts are associated with a positive change in the value of bursting stocks. However, the price path largely tracks the SPY price impact and at all bins the price impact confidence intervals include the SPY price impact in when utilizing date clustered standard errors. It is not surprising that the ΔQMP impact slightly exceeds that of the SPY in Panels C and D as the stocks in our sample have a mean Beta coefficient from the market risk premium of ~1.2.[28] While some subsamples appear to imply a positive price change at the 'peak' or 'middle' of the burst, when including date clustered standard errors there appears to be no significant price impact over that of the market. Overall, across all sample splits of bursts the quote midpoint following the end of a burst is not different than the midpoint that prevailed prior to the burst.[29]

[Insert Table 6 about here.]

[28] We collect beta coefficients from the Beta Suite provided by WRDS. Market Betas estimated using only market adjusted returns as well as Market Betas estimated using a Fama French 3-factor model are near identical.
[29] We present results for sample bursts in which at least 85% of the OEOS trades are 'burst-signature' trades in Figure A2 and find similar results.

As our hypothesis is that fractional trades do not exert price pressure, we would confirm our predictions with null results. We start by estimating price impacts in a simple setting with naïve inference and incrementally add control variables and more sophisticated standard errors. We begin by regressing the QMP impact on only a constant to estimate an unconditional price impact with OLS standard errors, presented in column (1). We find the unconditional price impact is 0.109bps, with a standard error of 0.350bps. Therefore, even in the simplest unconditional setting without any controls, we find that inferred fractional trades exert no price pressure and we do not document any economically or statistically significant price impact. In column (2) we include standard errors which are clustered by stock and by date (two-way), the standard errors inflate to 0.814bps.

While there is no significant unconditional price impact, we explore whether any characteristics of the burst display a significant relation to the price impact. In columns (3)-(8) we add one control variable at a time and include stock and date fixed effects which absorb the intercept and maintain the two-way standard errors. We add log(duration) where duration is the seconds from the beginning of the burst to the end, log(volume) where volume is the share volume, log(OEOS Count) where OEOS count is the number of OEOS trades in a burst, log(intensity) where $intensity = (OEOS\ Count)/Duration$ or otherwise written as $log(intensity) = log(OEOS\ Count) - log(duration)$, the OEOS imbalance which is the count of OEOS buys less OEOS sells divided by the sum and the Non-OEOS imbalance which is the count of Non-OEOS buys less Non-OEOS sells divided by the sum. We find that of the variables pertaining to the characteristics of a burst only the intensity (OEOS per second) of a burst is related to QMP price impact, yet it loads with a negative sign implying that higher intensity bursts are associated with a decrease in the QMP. We find that the OEOS imbalance when estimated on its own has no significant relation to the QMP price impact as it loads with an insignificant sign and the within R^2 is 0.0000, implying that none of the variance in the QMP is explained by the OEOS imbalance. The Non-OEOS imbalance on the other hand has a very high positive correlation with contemporaneous price movements and can explain about 11.58% of the variance in the QMP as signified by the within R^2.

In Panel B of Table 6 we estimate regressions using the QMP impact as the dependent variable again while including multiple controls simultaneously. In column (1) we regress the QMP impact on the OEOS imbalance, Non-OEOS imbalance, burst duration, burst volume and burst intensity.[30] We find that when entering all the variables, the OEOS imbalance is negatively associated with the price impact, whereas the Non-OEOS imbalance retains its sign and significance. In column (2) we add the SPY price impact over the bursts interval, we find that SPY price impact is a strong predictor and interpreting the coefficient it implies that a 1bps increase in the QMP of the SPY is associated with a 1.073bps increase in the QMP of the burst. This relation explains the seemingly amplified, positive impact of bursts of fractional share trade reporting on the movement of the prices of the underlying stocks relative to the SPY as documented in Figure 13. We also note that adding the SPY adds significant to the model's ability to the movement of stock prices during bursts, as the R^2 within rises from 0.121 to 0.196.

As our sample includes both common stocks and ETFs, it is possible that the deep liquidity of ETFs may be biasing our results and fractional trades can only exert price pressure in common stocks. We re-estimate the regression in column (3) using only common stocks. The OEOS imbalance coefficient falls from −16.485 to −5.961 and is no longer statistically significant, so the

[30] We cannot include intensity, duration and count all in one specification as it would be collinear. We elect to include the intensity and duration as the count and duration are highly correlated but intensity captures information orthogonal to duration and count.

absence of fractional-trade price impact is, if anything, clearer among common stocks. The coefficient on the Non-OEOS imbalance increases significantly, consistent with signed order flow moving with price changes at a higher rate in common stocks as opposed to ETFs. We are agnostic as to whether our design allows for causal inference on signed order flow inciting price changes. Establishing that fractional trades exert price pressure, as suggested in Da, Fang, and Lin (2025), requires two conditions. First, there must be a positive association between the order-flow imbalance computed using fractional share trades and returns. Second, on must identify the mechanism behind this association to rule out the hypothesis that the result is spurious. Our hypothesis requires neither. We ask only whether fractional-share trade imbalances comove with contemporaneous price changes and we find that they do not. Given that we find no relation between inferred fractional-trade imbalances and returns, there is no reason to investigate further.

It remains possible that all small-trade imbalances are not correlated with price impacts when compared to larger trades or perhaps our design does not have the power to test for a relation of small-trade imbalances. We investigate this in columns (4)-(6), by decomposing the Non-OEOS imbalance into imbalances of varying sizes, the 2-99 share imbalance, the 100-999 share imbalance and the 1,000+ share imbalance, and the On-Exchange One-Share Imbalance. We find that the 2-99 share imbalance carries the highest coefficient, which is consistent with O'Hara, Yao and Ye (2014) that odd-lots contribute to 35% of price discovery. In column (5) we include the On-Exchange One-Share imbalance, it is estimated with a coefficient of 41.421 (t-stat=6.377). The coefficient of the On-Exchange One-Share imbalance implies that while one-share trade order flow which executes on-exchange correlates with price changes, off-exchange one-share trades do not appear to possess any information, nor do they even comove with price changes within a burst. In column (6) we drop the OEOS imbalance variable and find all other coefficients are relatively unchanged.

Da, Fang and Lin (2025) claim that fractional trades in high-priced stocks can exert price pressure to the extent of creating a bubble in the underlying stock. We find that there is no price impact, unconditional of a stock's price in Table 6. We now test whether the relation is any different for high-priced stocks. In column (7) we estimate the regression without stock fixed effects and include indicator variables for the price of a stock at the timestamp the burst begins, we use price bins of \$25-100, \$100-250, and ≥ \$250 (<\$25 omitted bin). Two of the three indicators are positive but not at the 5% significance level. Furthermore, the indicator variable simply reflects a stock characteristic as opposed to a relation with the inferred fractional trades. To further test whether high price stocks react differently, we estimate the following regression,

$$\begin{aligned}\Delta QMP_k = {} & \lambda^O_{<25}\left(Imb^O_k \cdot D^{<25}_k\right) + \lambda^O_{25-100}\left(Imb^O_k \cdot D^{25-100}_k\right) + \lambda^O_{100-250}\left(Imb^O_k \cdot D^{100-250}_k\right) \\ & + \lambda^O_{\geq 250}\left(Imb^O_k \cdot D^{\geq 250}_k\right) + \lambda^N_{<25}\left(Imb^N_k \cdot D^{<25}_k\right) + \lambda^N_{25-100}\left(Imb^N_k \cdot D^{25-100}_k\right) \\ & + \lambda^N_{100-250}\left(Imb^N_k \cdot D^{100-250}_k\right) + \lambda^N_{\geq 250}\left(Imb^N_k \cdot D^{\geq 250}_k\right) + \beta_1 \log(duration)_k \\ & + \beta_2 log(volume)_k + \beta_3 log(intensity)_k + \beta_4 \Delta\mathrm{QMP}^{SPY}_k + \alpha_{i(k)} + \delta_{t(k)} + \varepsilon_k.\end{aligned}$$

We interact the OEOS Imbalance Imb^O_k with dummy variables which represent price bin membership, as well as interact the Non-OEOS imbalance Imb^N_k with the same dummy variables. We do not include an un-interacted imbalance variable, so each coefficient is that price bin's stand-alone price-impact coefficient. We also do not include un-interacted stock price bins as we retain stock fixed effects and stocks do not move across price bins frequently. We present the results in Table 7 with the coefficients side by side for interpretability. The interacted coefficients are all negative for the OEOS imbalances and all positive for the Non-OEOS imbalance. If inferred fractional trades did indeed exert a price pressure for high price stocks, we would expect a positive coefficient estimated for the high-price bins. We find that regardless of the price of a stock, bursts of inferred fractional trades do not exert any price pressure, nor carry information. The results imply that the OEOS imbalance is associated with opposite price movements.

Finally, we examine whether the price impact of the OEOS trades is recognized by the market with some delay. We test whether there is a delayed response by estimating a regression using the change in the QMP from the end of the burst to 60 seconds and 300 seconds post burst as the dependent variable as opposed to the within burst price impact. Specifically, $\Delta QMP = (QMP_t - QMP_{end})/QMP_{end} \times 10{,}000$ basis points, where $t = \{60, 300\}$. We present the results in Table 8. In column (1), we estimate the unconditional price change 60 seconds after the burst as an intercept with OLS standard errors and we find there is no delayed positive price impact, rather we find a negative price drift. In column (2) we cluster the standard errors two-way by stock and date, and the negative price drift post burst is no longer significant. In specification (3) we include control variables and find the OEOS imbalance within a burst does not appear to predict any future price changes. In column (4) we estimate the regression including only common stocks and we find no differing results. In columns (5)-(8) we use the 300 seconds post burst price impact and the results are unchanged. There is no significant positive price impact within or after a burst of inferred fractional trades.

Overall, the findings from Tables 6, 7 and 8 along with Figures 10, 11 and 12 demonstrate that bursts are not associated with a price impact in a univariate or multivariate setting. Perhaps these results are not surprising given the volume of inferred fractional share trades which execute during the median burst is less than 3,500 shares. While appearing small in count, we note that the mean number of OEOS trades on the stock-day level in Da, Fang and Lin (2025) is 153.[31]

V. Conclusions.

[31] See Table 1.

We identify time intervals that contain intense, coordinated OEOS trades and provide evidence these 'bursts' predominately contain trades resulting from the batched execution of not-held, inferred fractional share orders by the broker DW. Given the fact that DW does not execute the not-held fractional orders immediately after they are placed by investors with the originating broker, the bursts of fractional share trades, most of which are buyer-initiated, provides an ideal setting for examining whether concentrated fractional share trading activity in the absence of information events have price impact. We find that while the trade-weighted order imbalance for non-OEOS trades is close to zero during bursts, the trade-weighted OEOS order imbalance during bursts is large enough to significantly influence the overall trade-weighted imbalance. Despite this finding, the evidence generated by our univariate and multivariate analyses consistently demonstrates that intense fractional share trading does not impact the price path of the underlying asset.

As noted in our introduction, Da et al. (2025) conclude that when coordinated by attention generating events, fractional share trades "can cause significant price fluctuations in high-priced stocks." Our results suggest that fractional share trades may not be a necessary ingredient for attention grabbing events to have price impact.

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Table 1. Descriptive statistics for bursts: 2021 through 2024.

This table reports distributional summary statistics for the full 2021‑2024 sample of bursts. A burst minute is any minute flagged by the 5-of-6 sliding window methodology: within a sliding six-minute window, a stock-minute is classified as bursting if at least five of the six minutes have an off-exchange one-share trade percentage exceeding a MAD-based threshold for that stock-day. OEOS (off-exchange one-share) trades are defined as one-share trades which execute off-exchange. All statistics use core trading minutes (9:35‑15:54).

Panel A. Distribution of bursts across stocks. There are 1,437 stocks that have at least one burst during the sample period.

		Percentile				
	Mean	Min	25th	50th	75th	Max
# Burst Minutes	681	5	13	39	125	27,105
# Bursts	35	1	1	3	8	912

Panel B. Distribution of bursts across sample period. There are 49,700 bursts in 1,437 stocks.

		Percentile				
	Mean	Min	25th	50th	75th	Max
Burst Duration (minutes)	20	5	7	13	26	159
# OEOS Trades in Burst	7,175	256	723	1,685	4,790	235,548

Panel C. Distribution of bursts across days. There are 1,000 days we identify a burst.

		Percentile				
	Mean	Min	25th	50th	75th	Max
# Stocks per Day	37	1	7	17	66	270
# Burst Minutes per Day	978	5	96	334	1,825	6,819
# Bursts per Day	50	1	9	21	95	310

Panel D. Distribution of OEOS trades within and outside of burst minutes. There are 14,836,374 non-burst minutes and 978,304 burst minutes.

		Percentile				
	Mean	Min	25th	50th	75th	Max
# OEOS Trades: Bursts	365	0	88	158	365	72,113
# OEOS Trades: Non-Burst	27	0	3	11	26	20,313
%OEOS Trades: Bursts	45.6%	0.0%	27.9%	43.1%	61.9%	100.0%
%OEOS Trades: Non-Burst	11.4%	0.0%	3.8%	8.3%	14.9%	100.0%

Table 2. Descriptive statistics for precise-bursts: March 15, 2023 through November 8, 2024.

To identify a precise-burst we first merge same-stock bursts separated by five minutes or fewer. We then locate the start (and end) in two stages. In the first, we partition a four-minute window centered on the burst's starting minute into fifteen-second bins, count the DW burst-signature trades in each, and select the first pair of adjacent bins whose counts both exceed a threshold set by the local baseline arrival rate. In the second, we partition the half minute spanned by that pair into three-second bins and select the first bin with elevated activity. The burst begins at the timestamp of the first burst-signature trade in the selected bin. The end is located by the mirror-image procedure. Of the 49,700 bursts identified in Table 1, 41,847 occur between March 15, 2023 and November 8, 2024. Merging same stock bursts separated by five minutes or fewer leaves 36,861 distinct episodes, of which we can assign precise start and end times to 27,400.

Panel A. Distribution of bursts across stocks. There are 309 stocks that have at least one precise burst during the sample period.

		Percentile				
	Mean	Min	25th	50th	75th	Max
# Burst Minutes	2,387	2	7	35	1,799	26,123
# Bursts	89	1	1	4	137	536

Panel B. Distribution of precise-bursts. There are 27,400 precise-bursts in 308 symbols.

		Percentile				
	Mean	Min	25th	50th	75th	Max
Burst Duration (seconds)	1,558	30	612	1,253	2,051	10,031
# OEOS Trades in Burst	11,678	72	1,211	3,432	9,434	236,027
# All Trades in Burst	26,592	93	3,203	8,805	21,895	723,089

Panel C. Distribution of bursts across days. There are 418 days.

		Percentile				
	Mean	Min	25th	50th	75th	Max
# Stocks per Day	59	6	37	70	78	110
# Burst Minutes per Day	1,759	87	1,377	1,676	2,143	3,035
# Bursts per Day	66	8	39	80	88	158

Table 3. Rounded participant timestamps for OEOS trades in Apple on January 2, 2024.

Row #	Symbol	Exchange	Time	Price	Volume	Participant Timestamp	TRF Timestamp	TRF
1	AAPL	D	10:48:27.054132913	185.50	1	10:48:27.015000000	10:48:27.054109145	Q
2	AAPL	D	10:48:27.054256876	185.50	1	10:48:27.026000000	10:48:27.054232005	Q
3	AAPL	D	10:48:27.055482403	185.50	1	10:48:27.012000000	10:48:27.055458797	Q
4	AAPL	D	10:48:27.072245471	185.50	1	10:48:27.029000000	10:48:27.072223351	Q
5	AAPL	D	10:48:27.089983145	185.50	1	10:48:27.022000000	10:48:27.089961346	Q
6	AAPL	D	10:48:27.091831626	185.50	1	10:48:27.019000000	10:48:27.091807645	Q
7	AAPL	D	10:48:27.112001451	185.49	1	10:48:27.039132000	10:48:27.111979093	Q
8	AAPL	Q	10:48:27.126564319	185.495	30	10:48:27.126548258	-	-
9	AAPL	Q	10:48:27.126567654	185.495	42	10:48:27.126548258	-	-
10	AAPL	D	10:48:27.203903439	185.495	2	10:48:27.202000000	10:48:27.203881320	Q
11	AAPL	D	10:48:27.209887442	185.49	1	10:48:26.897193000	10:48:27.209862768	Q
12	AAPL	D	10:48:27.456610101	185.49	1	10:48:27.432000000	10:48:27.456585487	Q
13	AAPL	D	10:48:27.459960633	185.495	1	10:48:27.459681164	10:48:27.459934054	Q

Table 4. Distribution of synchronous precise-bursts across stocks, before and after the batching of stocks by listing exchange.

Panel A. Reports the distribution of burst time across concurrency levels. The concurrency level is the number of stocks identified with a burst at the same time. Values are the share of burst-seconds occurring at each concurrency level. Columns sum to 100%. There are 6,776 bursts in 160 stocks between March 15, 2023 and November 27, 2023 and there are 20,624 bursts in 250 stocks between November 28, 2023 and November 8, 2024.

	% of Bursts	
# Overlapping Bursts	20230315 – 20231127	20231128 – 20241108
1	0.94%	0.39%
2-3	1.11%	0.65%
4-5	0.53%	0.33%
6-8	1.2%	1.94%
9-10	1.3%	4.92%
11-15	2.67%	23.89%
16-20	2.75%	23.74%
21-25	20.29%	6.1%
26 and more	69.22%	38.03%

Panel B. Listing exchange of stocks with overlapping bursts. Percentages are computed by taking the seconds in each burst and computing how much they overlap with bursts in other stocks conditional on the stock listing exchange. Rows sum to 100%. The sample is from March 15, 2023 - November 27, 2023.

	Exchange-Listing of Stocks with Overlapping Burst		
Burst Stock's Listing Exchange	NYSE	Nasdaq	Arca
NYSE	44.3%	39.0%	16.7%
Nasdaq	47.2%	36.0%	16.8%
Arca	45.8%	37.9%	16.3%

Panel C. Listing exchange of stocks with overlapping bursts. Percentages are computed by taking the seconds in each burst and computing how much they overlap with bursts in other stocks conditional on the stock listing exchange. Rows sum to 100%. The sample is from November 28, 2023 - November 8, 2024.

	Exchange-Listing of Stocks with Overlapping Burst		
Burst Stock's Listing Exchange	NYSE	Nasdaq	Arca
NYSE	96.8%	0.5%	2.7%
Nasdaq	1.0%	93.3%	5.6%
Arca	10.5%	11.0%	78.5%

Table 5. Distribution of OEOS and Non-OEOS trade prices relative to the prevailing National Best Bid and Offer: March 15, 2023 through November 8, 2024.

This table describes the distribution of trades within the start and stop of precise-burst intervals by their price location relative to the prevailing LF NBBO, for the key sample (March 15, 2023 through November 8, 2024). OEOS is an off-exchange ("D") trade whose volume is one-share. In Panel A, we first report the trades location relative to the LF NBBO. Note that these columns will sum to just under 100%, the LF NBBO may have states where the market is momentarily locked or crossed and these trades which occur in these periods is uninformative. In the final two rows of panel A we present the % of buys and % of sells which use the full signing methodology outlined by Battalio et al. (2025). The final two rows sum to 100% as all trades are signable following Battalio et al. (2025). Panel B reports per-burst summary statistics (mean, percentiles) of OEOS trade percentages in each NBBO location category, where each burst contributes one observation.

Panel A. Pooled trade counts and percentages across all bursts, separately for OEOS trades, non-OEOS trades, and all trades.

	Trade Type		
	OEOS	Non-OEOS	All Trades
Below Bid	0.32%	1.29%	0.86%
At Bid	2.10%	26.39%	15.72%
Above Bid, Below Midpoint	2.48%	12.55%	8.13%
At Midpoint	4.05%	17.67%	11.69%
Above Midpoint, Below Ask	26.40%	13.57%	19.20%
At Ask	62.72%	24.93%	41.53%
Above Ask	1.85%	1.18%	1.47%
% Buys	93.08%	49.46%	68.62%
% Sells	6.92%	50.54%	31.38%
Number of Trades	319,997,134	408,767,711	728,764,845

Table 5 (Continued).

Panel B. Across-burst summary statistics of buyer-initiated, seller-initiated, and net trade-weighted order imbalances. The first column reports the mean and the other five columns present the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile columns. There are 27,400 precise-bursts identified from March 15, 2023 to November 8 2024.

	Average	10^{th} Percentile	25^{th} Percentile	Median	75^{th} Percentile	90^{th} Percentile
OEOS Trades						
% Buys	90.91%	82.88%	88.04%	92.78%	95.89%	97.82%
% Sells	9.09%	2.18%	4.11%	7.22%	11.96%	17.12%
Net Imbalance	81.83%	65.77%	76.09%	85.57%	91.78%	95.64%
Non-OES Trades						
% Buys	50.68%	43.31%	46.75%	50.08%	53.76%	58.53%
% Sells	49.32%	41.47%	46.24%	49.92%	53.25%	56.69%
Net Imbalance	1.36%	-13.37%	-6.51%	0.15%	7.52%	17.07%
All Trades						
% Buys	69.57%	55.20%	60.41%	68.22%	78.61%	86.45%
% Sells	30.43%	13.55%	21.39%	31.78%	39.59%	44.80%
Net Imbalance	39.14%	10.39%	20.82%	36.43%	57.22%	72.90%

Table 6. Multivariate analysis of the price impact of fractional share trading bursts.

This table reports OLS regressions at the burst-interval level, where the dependent variable is the quoted midpoint impact in basis points:

$$\Delta QMP = \frac{QMP_{End} - QMP_{start}}{QMP_{start}} \times 10{,}000bps\ .$$

OEOS trades are all off-exchange one share trades regardless of trade price or participant timestamp. The sample consists of all precise-burst intervals during March 15, 2023 through November 8, 2024.

Panel A. Specification (1) includes no fixed effects and no controls; the intercept is the unconditional average burst-level price impact, with ordinary standard errors. Specification (2) adds standard errors clustered by stock and date. Specifications (3-8) add stock and date fixed effects and introduce one variable at a time. In (3) we add log(duration) where duration is the length of the burst in seconds; in (4) we add log(volume); in (5) we add log(intensity); in (6) we add log(#OEOS trades); in (7) we add the OEOS imbalance; in (8) we add the Non-OEOS imbalance. The OEOS imbalance is the count of (buys − sells)/(buys + sells) for OEOS trades; non-OEOS imbalance is defined analogously for non-OEOS trades. Log(intensity) is computed as log(OEOS)-log(duration) and is analogously written as log(OEOS/duration). We report the R^2 within, and the total R^2. Standard errors are presented in parentheses. The sample used is the 27,400 precise-bursts which span 309 stocks, and 418 days from March 15, 2023 to November 8, 2024. Significance is denoted as * < 0.10, ** < 0.05, *** <0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.109 (0.350)	0.109 (0.814)						
Log(Duration)			0.918 (0.695)					
Log(Volume)				0.285 (0.597)				
Log(Intensity)					-3.781*** (1.159)			
Log(#OEOS Trades)						-0.374 (0.537)		
OEOS Imbalance							2.620 (3.549)	
Non-OEOS Imbalance								149.958*** (22.672)
Stock FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
SE	OLS	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way
R^2 (within)	—	—	0.0001	0.0000	0.0006	0.0000	0.0000	0.1184
R^2 (total)	0.0000	0.0000	0.1221	0.1220	0.1225	0.1220	0.1220	0.2259

Table 6 (continued).

Panel B. The dependent variable is the change in quoted midpoint impact over the burst, in basis points. Every specification includes the controls: log(duration), log(volume), and log(intensity). In Specifications (1)-(3) our variables of interest are the OEOS imbalance and the Non-OEOS imbalance, in specification (2) we include the SPY quoted midpoint impact over the burst. In specification (3) we restrict the sample to only common stocks (TAQ security type A). In Specifications (4)-(6) we decompose the Non-OEOS order imbalance into three categories; the 2-99 Share Imbalance, the 100-999 Share Imbalance, and the 1000+ Share Imbalance, and the On-Exchange One-Share Imbalance. In Specification (7) we add price-bin indicators for the price of a stock. The price bins are \$25-100, \$100-250 and \$250+ (price below \$25 omitted). We assign the price bins using the first trade of the precise bursts trade price. In (7) we also omit stock fixed effects and include date fixed effects only. We report the R^2 within, and the total R^2. Standard errors are presented in parentheses and are clustered two-way by stock and date. The sample used is the 27,400 precise-bursts which span 309 stocks, and 418 days from March 15, 2023 to November 8, 2024. Significance is denoted as * < 0.10, ** < 0.05, *** <0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OEOS Imbalance	-19.648***	-16.485**	-5.961	-22.228***	-13.551**		-2.296
	(7.597)	(6.656)	(5.374)	(8.051)	(6.193)		(3.427)
Non-OEOS Imbalance	152.515***	138.929***	243.974***				111.015***
	(22.792)	(21.664)	(38.411)				(18.619)
On-Exchange One-Share Imbalance					41.421***	41.834***	
					(6.377)	(6.414)	
2-99 Share Imbalance				128.462***	85.010***	83.044***	
				(20.976)	(14.758)	(14.608)	
100-999 Share Imbalance				16.959**	9.919	10.124	
				(6.683)	(6.308)	(6.314)	
1,000+ Share Imbalance				7.797***	7.352***	7.323***	
				(1.310)	(1.186)	(1.179)	
SPY Impact		1.073***	0.893***	1.068***	1.038***	1.039***	1.107***
		(0.121)	(0.095)	(0.120)	(0.117)	(0.117)	(0.125)
Price \$25–100							2.022
							(2.369)
Price \$100–250							4.242*
							(2.387)
Price ≥ \$250							4.681*
							(2.539)
Log (Burst Duration)	0.202	-0.087	-0.495	0.553	0.240	-0.634	0.568
	(1.106)	(1.003)	(1.303)	(1.139)	(1.056)	(1.014)	(0.783)
Log (Volume)	1.952**	2.262**	2.021	2.049*	2.224**	2.698***	2.549***
	(0.994)	(0.915)	(1.310)	(1.053)	(0.916)	(0.952)	(0.659)
Log (Intensity)	-4.056**	-3.960**	-0.931	-3.590**	-3.034**	-3.891**	-3.232***
	(1.742)	(1.569)	(1.542)	(1.650)	(1.531)	(1.539)	(0.802)
Sample	All	All	Common	All	All	All	All
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.1210	0.1956	0.2133	0.2030	0.2332	0.2327	0.1712
R^2 (total)	0.2282	0.2937	0.3294	0.3017	0.3282	0.3278	0.2394
N	27,400	27,400	16,587	26,484	26,436	26,436	27,400

Table 7. Multivariate analysis of the price impact of fractional share trading bursts conditional on stock price.

All cells come from a single regression of the quote-midpoint change over the burst (basis points) on OEOS and non-OEOS imbalance, each interacted with four price-bin indicators assigned on the burst's starting price, plus log burst duration, log share volume, log intensity, and the change in the SPY midpoint, with stock and date fixed effects. We present the coefficients in a side-by-side manner for readability.

$$\begin{aligned}\Delta QMP_k = {} & \lambda^{O}_{<25}\left(Imb^{O}_k \cdot D^{<25}_k\right) + \lambda^{O}_{25-100}\left(Imb^{O}_k \cdot D^{25-100}_k\right) + \lambda^{O}_{100-250}\left(Imb^{O}_k \cdot D^{100-250}_k\right) \\ & + \lambda^{O}_{\geq 250}\left(Imb^{O}_k \cdot D^{\geq 250}_k\right) + \lambda^{N}_{<25}\left(Imb^{N}_k \cdot D^{<25}_k\right) + \lambda^{N}_{25-100}\left(Imb^{N}_k \cdot D^{25-100}_k\right) \\ & + \lambda^{N}_{100-250}\left(Imb^{N}_k \cdot D^{100-250}_k\right) + \lambda^{N}_{\geq 250}\left(Imb^{N}_k \cdot D^{\geq 250}_k\right) + \beta_1 \log(duration)_k \\ & + \beta_2 log(volume)_k + \beta_3 log(intensity)_k + \beta_4 \Delta \mathrm{QMP}^{SPY}_k + \alpha_{i(k)} + \delta_{t(k)} + \varepsilon_k\end{aligned}$$

There is no un-interacted imbalance term, so each coefficient is that bin's stand-alone price-impact coefficient. We report the R^2 within, and the total R^2. Standard errors are presented in parentheses. The sample used is the 27,400 precise-bursts which span 309 stocks, and 418 days from March 15, 2023 to November 8, 2024. Significance is denoted as * < 0.10, ** < 0.05, *** <0.01.

	OEOS λ	Non-OEOS λ	N
Price <$25	-16.678** (7.491)	229.034*** (62.749)	4,266
Price $25–100	-16.143** (6.400)	97.813*** (24.875)	8,939
Price $100–250	-8.529* (4.791)	116.783*** (23.188)	8,611
Price ≥ $250	-7.141 (5.011)	91.501*** (21.976)	5,584
Fixed effects	Stock + Date		
R^2 (within)	0.2143		
R^2 (total)	0.3101		
N	27,400		

Table 8. Multivariate analysis of the price impact of fractional share trading bursts on subsequent prices.

The dependent variable is the change in the symbol's quote midpoint from the burst's end to 60 seconds (columns 1–4) and 300 seconds (columns 5–8) after the end, in basis points. Within each horizon, specifications (1) and (2) contain only an intercept, with conventional OLS standard errors in (1) and standard errors clustered two-way by stock and date in (2). Specification (3) adds log burst duration, log share volume, log intensity, the change in the SPY midpoint over the same post-burst window, and the OEOS and non-OEOS imbalances measured within the burst, with stock and date fixed effects and two-way clustered standard errors. Specification (4) estimates (3) on common stock (TAQ security type A). Each specification retains every burst complete on its own variables. We report the R^2 within, and the total R^2. Standard errors are presented in parentheses. The sample used is the 27,400 precise-bursts which span 309 stocks, and 418 days from March 15, 2023 to November 8, 2024. Significance is denoted as * < 0.10, ** < 0.05, *** <0.01.

	+ 60 s				+ 300 s			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	-0.212***	-0.212			-0.041	-0.041		
	(0.072)	(0.130)			(0.171)	(0.333)		
OEOS Imbalance			-0.035	-0.493			-3.409	-3.604
			(0.604)	(1.007)			(2.099)	(3.172)
Non-OEOS Imbalance			0.116	-0.297			3.303**	2.590
			(0.688)	(1.004)			(1.434)	(2.508)
SPY Impact (window)			1.227***	1.160***			1.299***	1.223***
			(0.159)	(0.129)			(0.134)	(0.124)
Log (Burst Duration)			0.370	0.284			0.274	0.014
			(0.277)	(0.459)			(0.648)	(0.994)
Log (Volume)			-0.288	-0.227			0.046	0.230
			(0.209)	(0.344)			(0.546)	(0.877)
Log (Intensity)			-0.061	-0.197			0.023	-0.122
			(0.171)	(0.304)			(0.442)	(0.794)
Sample	All	All	All	Common	All	All	All	Common
Symbol FE	No	No	Yes	Yes	No	No	Yes	Yes
Date FE	No	No	Yes	Yes	No	No	Yes	Yes
SE	OLS	Two-way	Two-way	Two-way	OLS	Two-way	Two-way	Two-way
R^2 (within)	—	—	0.1129	0.0853	—	—	0.1141	0.0841
R^2 (total)	0.0000	0.0000	0.1952	0.2068	0.0000	0.0000	0.2275	0.2384
N	27,400	27,400	27,400	16,587	27,400	27,400	27,400	16,587

Figure 1. A period of intense off-exchange one-share trades for five stocks on January 2, 2024.

This figure plots the percentage of trades in a given minute that are one-share trades, for AAPL, AMZN, MSFT, NVDA, and TSLA on January 2, 2024. Panel A includes one-share trades on all exchanges. Panel B restricts to one-share trades which execute off-exchange (exchange code "D" indicating execution reported through a FINRA Trade Reporting Facility). Panel C further restricts to off-exchange one-share trades whose participant timestamp is rounded to the millisecond, in other words the timestamp has no sub-millisecond precision. The denominator in all three panels is total trades (all sizes, all exchanges) in that stock-minute. The data covers regular trading hours (9:30‑16:00 ET).

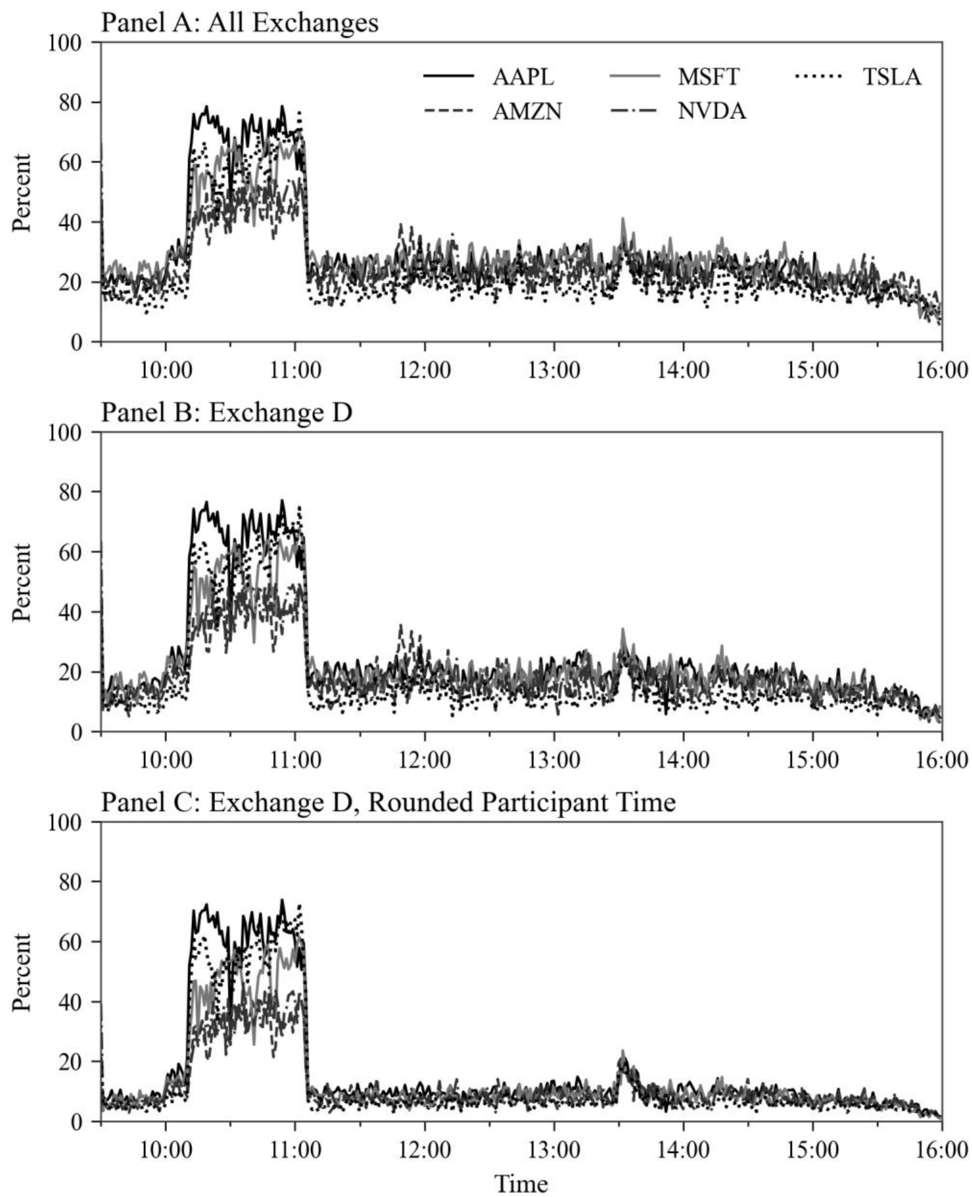


Figure 2. Aggregate daily burst activity.

This figure plots daily aggregate burst activity over the full 2021-2024 sample. Panel A shows two series on a dual axis: the total number of burst minutes per day (left axis) and the number of unique stocks identified with at least one burst on that day (right axis). Panel B shows the average burst duration in minutes per day, plotted separately for all stocks and for TSLA alone. TSLA is chosen as it is one of the higher burst activity stocks. A burst minute is any minute flagged by the 5-of-6 sliding window methodology described in the sample construction. Burst duration is computed as the number of contiguous minutes in each burst interval (end minute minus start minute plus one); the daily average is taken across all burst intervals on that date. Both panels use the full unconditional sample.

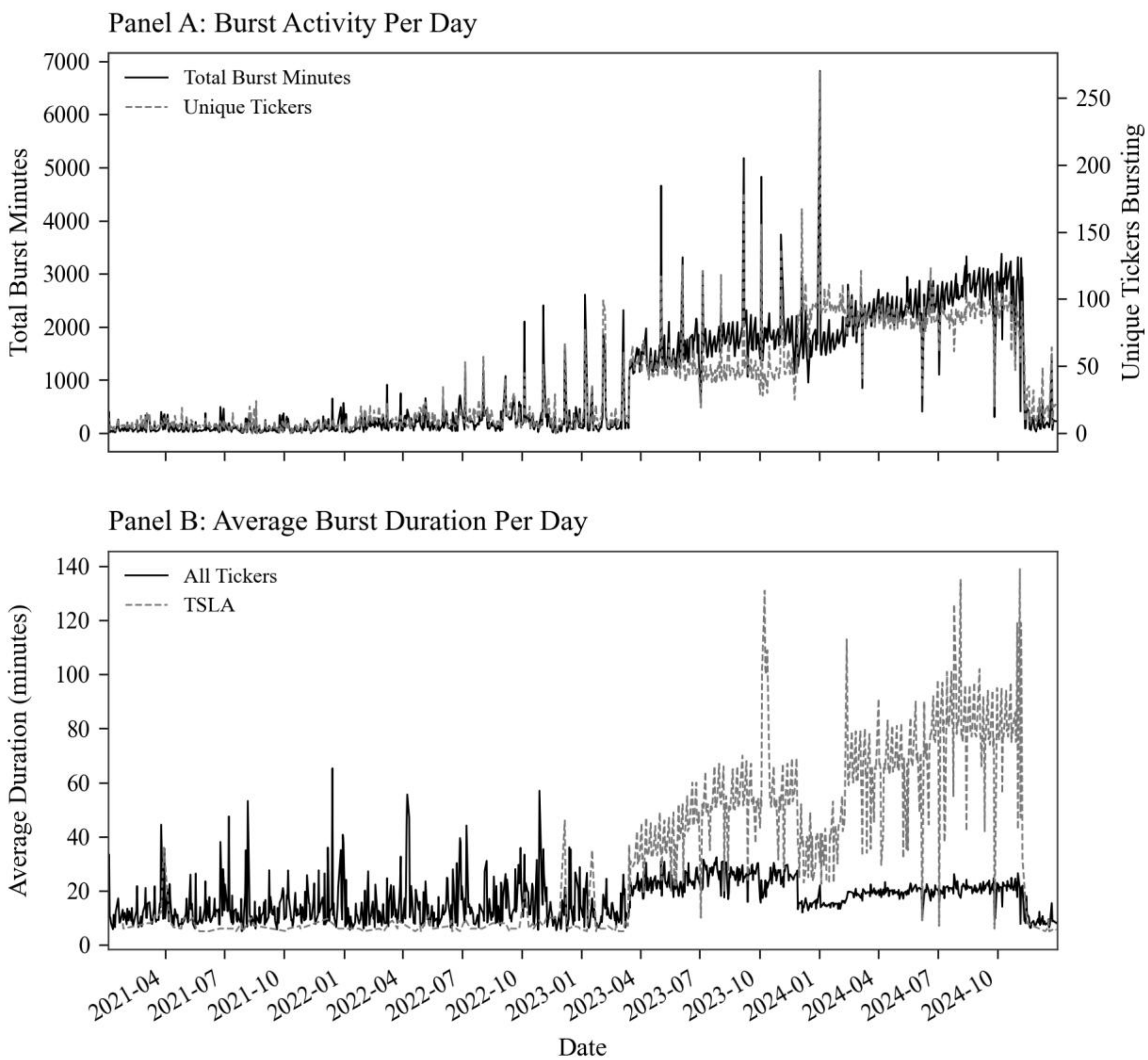


Figure 3. OEOS trading activity during different trading sessions.

The figure plots OEOS counts for the three various trading sessions. The gray hatched bars represent the count of all OEOS shares which report before the official market open in the TAQ data, 4:00am - 9:30am. The dark bars plot the count of OEOS which execute within a burst during regular trading hours 9:30am - 4:00pm. The light gray dotted bars represent the total count of OEOS trades which execute after-hours 4:00pm - 8:00pm. The sample used is the unconditional full sample from January 1, 2021 to December 31, 2024.

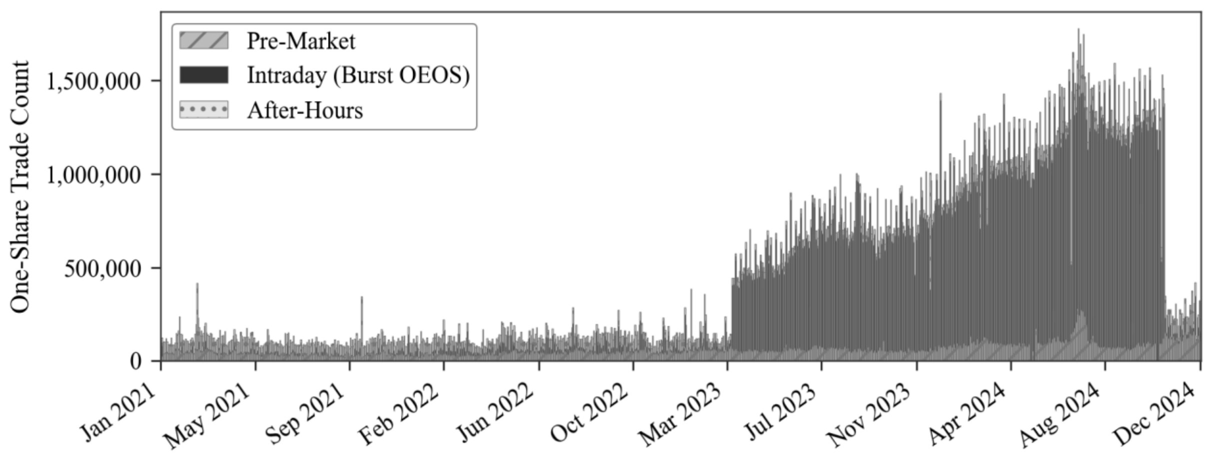


Figure 4. DriveWealth weekly trade counts.

This figure plots DriveWealth's total weekly trade count across all stocks as reported to FINRA through the OTC (non-ATS) transparency filings, from 2023 through 2024. Each bar represents one reporting week. As DriveWealth executes only fractional trades the count of trades is equal to the volume reported. The red vertical dashed lines mark the start (March 15, 2023) and end (November 8, 2024) of the revised sample period which we investigate precise-bursts.

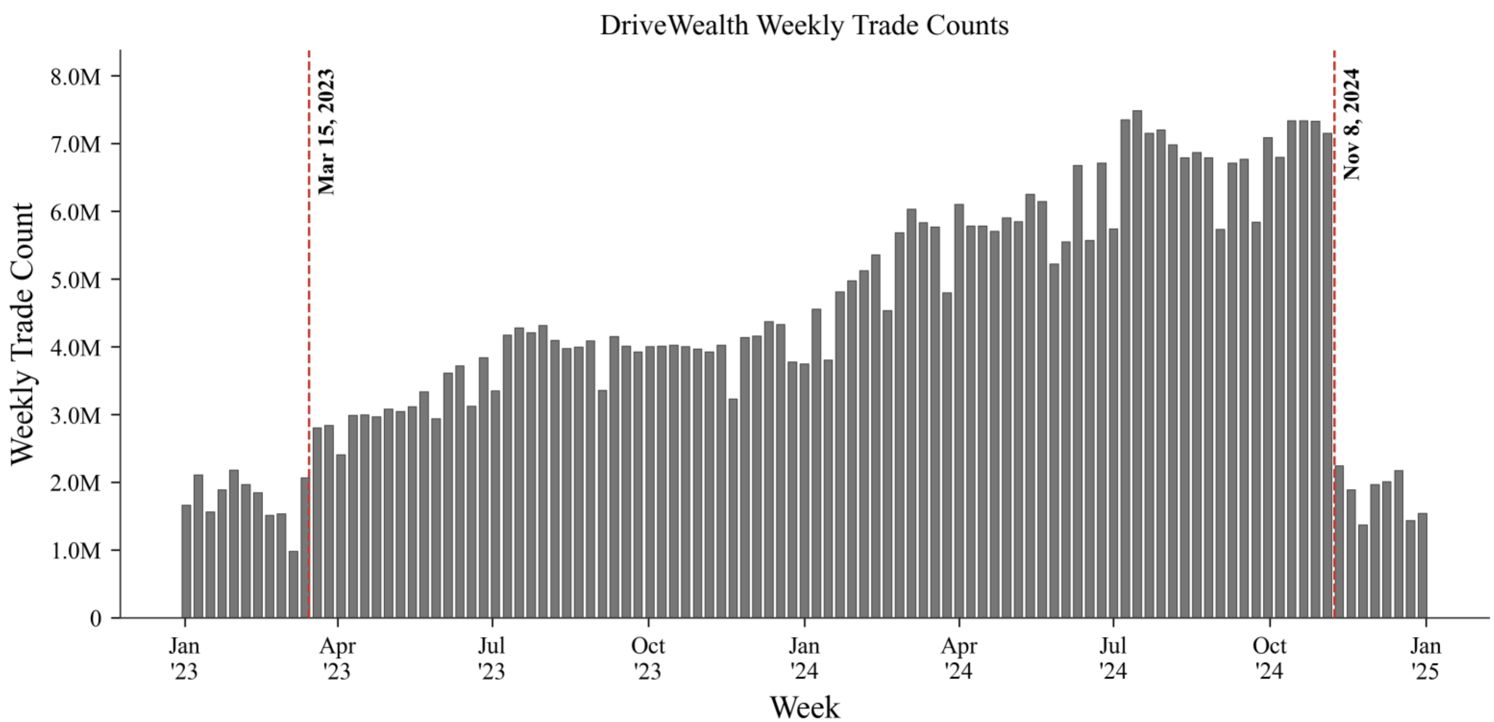


Figure 5. Burst-signature trade volume versus DriveWealth FINRA-reported volume, by stock.

The figures below plot the DriveWealth weekly trade counts during the revised sample of March 15, 2023 to November 8, 2024. Some of the panels have a different x-axis as we suppress weeks where the DriveWealth trade count is zero. Along with the bars which represent the DriveWealth OTC trade counts, we plot a red dot for the count of OEOS burst-signature trades which we identify within a burst. A burst signature trade is an OEOS trade with a rounded participant timestamp to the millisecond as well as a trade price which is on a whole penny or x.xx88 pricing grid. Each panel is indicated by the stock's ticker and the percentage in parentheses displays the ratio of burst signature trades-to-OTC reported trades by DriveWealth. A ratio above 100% indicates that there is a higher count of OEOS trades within bursts and a ratio below 100% indicates that the count of OTC reported trades exceeds the count of burst-signature OEOS trades we identify within bursts.

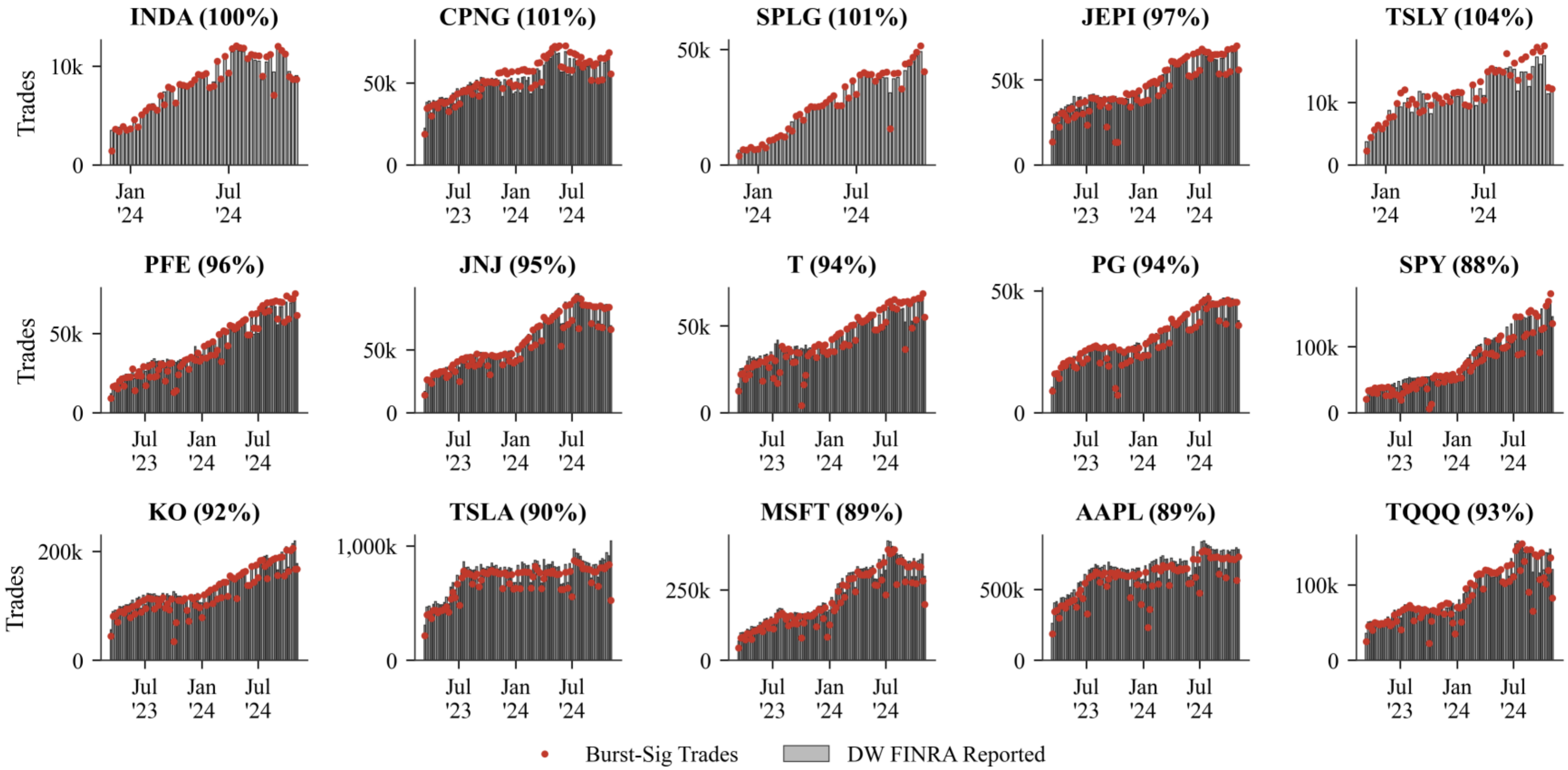


Figure 6. Burst signature trades composition of bursts

The figure displays bars for the proportion of bursts which are constituted of varying thresholds of burst-signature trades. A burst-signature trade is an OEOS trade which has a rounded participant timestamp and the pricing is a whole penny or on a x.xx88 pricing grid. The burst-signature fraction is computed by taking all burst-signature OEOS trades and dividing by all OEOS trades unconditional of possessing the burst-signature traits.

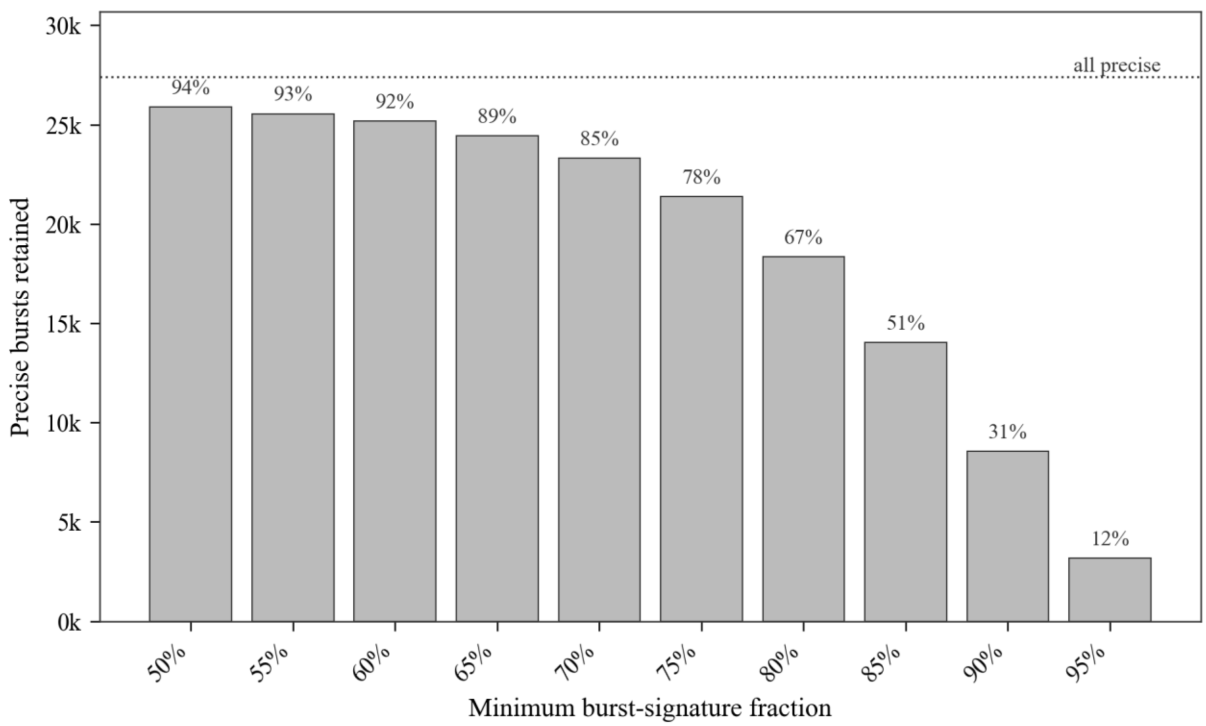


Figure 7. Distribution of burst minutes during the trading day conditional on the stock's listing exchange.

Panel A of the figure plots the intraday distribution of burst activity, pooled across all trading days during the revised sample of March 15, 2023, through November 8, 2024. For each minute of the trading day (9:35–15:54), we sum the count of OEOS trades which report during an identified burst. We present the counts partitioned by a stock's primary listing exchange: NASDAQ (Q), NYSE (N), and NYSE Arca (P). Panel B displays a heatmap which uses a sample of January 1, 2023 to December 31, 2024 to signify the abrupt start and stop of burst activity. The heatmap has dates on the x-axis with the time of day on the y-axis, each point on the plane is colored based on the number of unique stocks which are identified with a burst simultaneously.

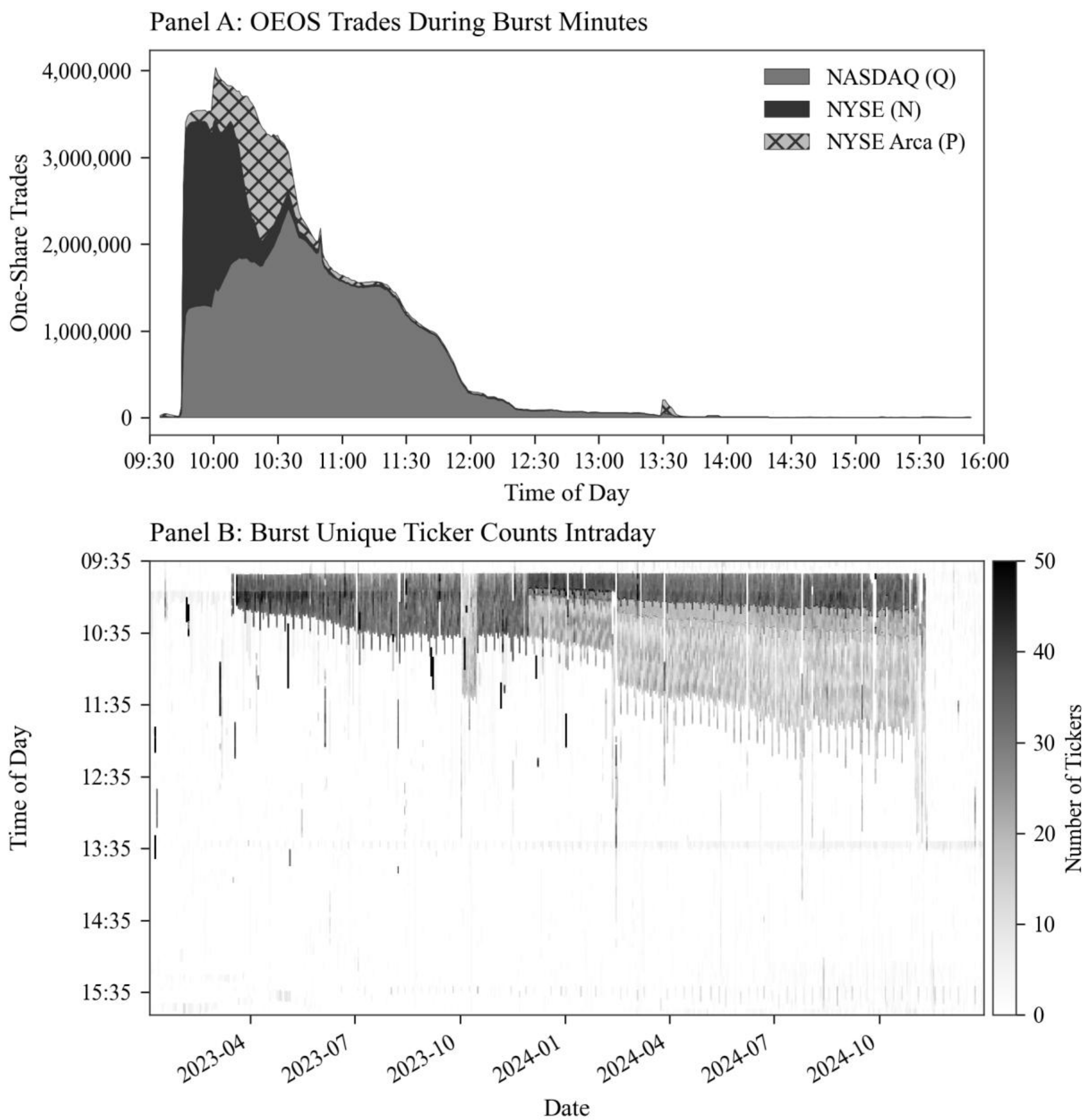


Figure 8. Burst signature trading volume through time.

The daily number of burst-signature trades as dots with Monday observations as an x are plotted for the truncated sample March 15th, 2023 - November 8th, 2024, with a rolling 21-day average. Burst-signature trades are classified as a trade which is one-share, off-exchange ("D"), has a rounded participant timestamp to the millisecond and a price ending in a round penny increment or x.xx88.

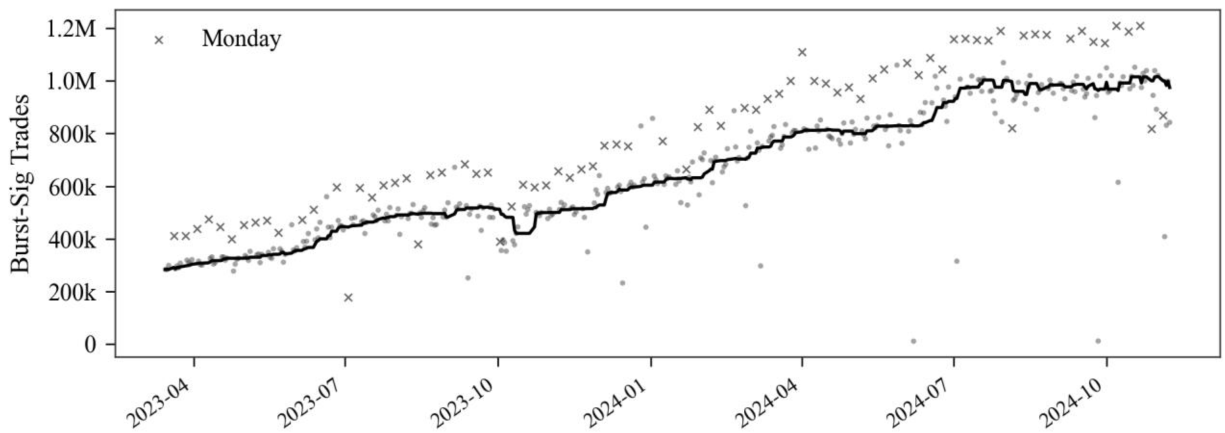


Figure 9. Evidence consistent with the use of an algorithm to execute fractional shares.

Panel A. The figure illustrates how fractional trades in TSLA, NVDA, MSFT, AMZN and AAPL were reported over the 1,500-millisecond interval beginning on 10:31:46 on September 27, 2024. Trades are arranged by *participant timestamp*. The black numbers identify the number of inferred DriveWealth fractional trades denoted as 'sig' which execute during the burst as well as the number of non-burst-signature trades denoted as 'non-sig'. The black lines (grey dots) identify DriveWealth fractional trades (other OEOS trades). The red lines illustrate the amount of time elapsing between clusters of OEOS trades in a stock, where the annotation is the number of milliseconds (ms) between the last trade of a cluster and first trade of the next cluster within stock.

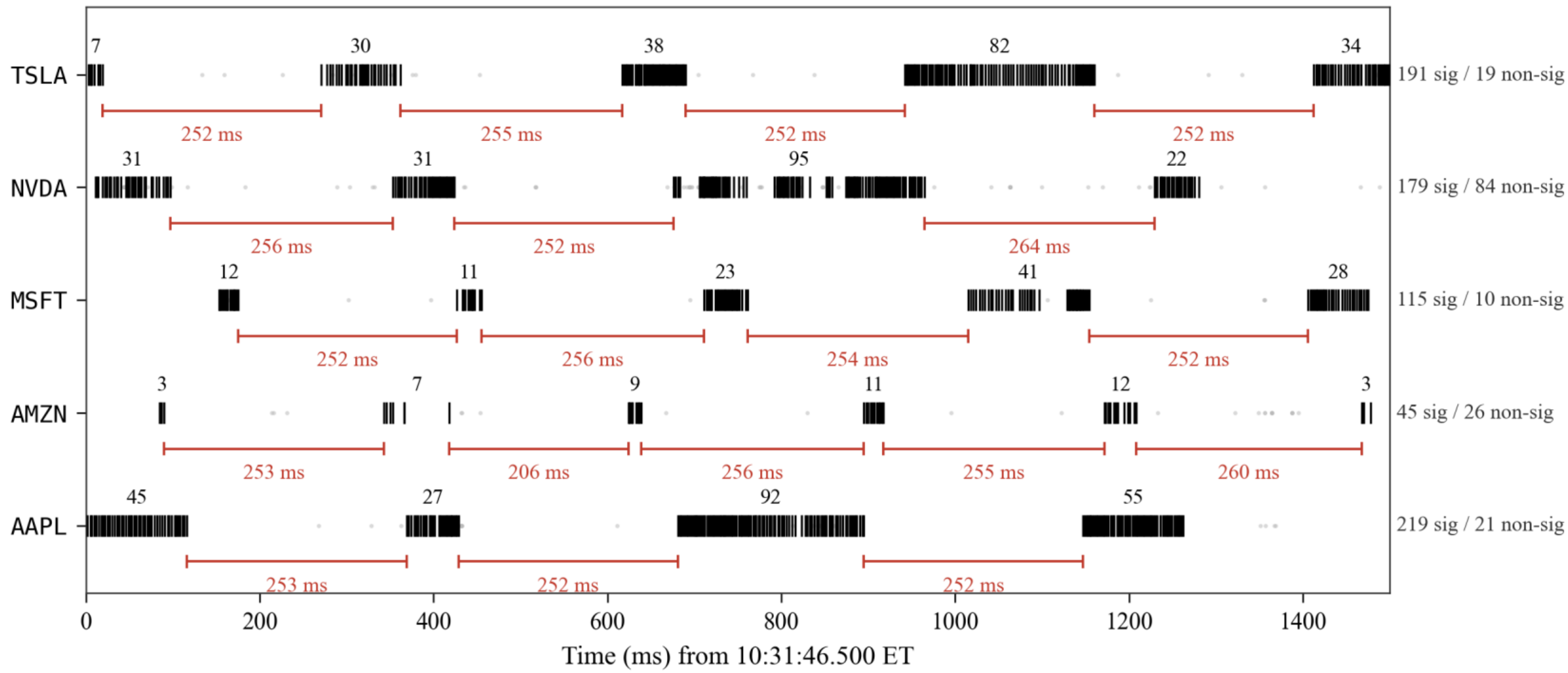


Figure 9 (continued).

Panel B: The figure illustrates a 25,000-millisecond interval beginning at 10:49:55.000 during which 201,723 DriveWealth-inferred fractional trades ("signature" trades) execute in TSLA, NVDA, MSFT, AMZN and AAPL on March 7, 2024. During this time interval, a total of 6,501 non-signature trades (trades not inferred to be DriveWealth fractional trades) execute in these five symbols. Black lines (grey dots) identify inferred DriveWealth fractional trades (all other trades). Trades in this figure are arranged by their SIP timestamps. Clusters of inferred DriveWealth fractional trades are annotated with the count of trades. We use a k to denote thousands.

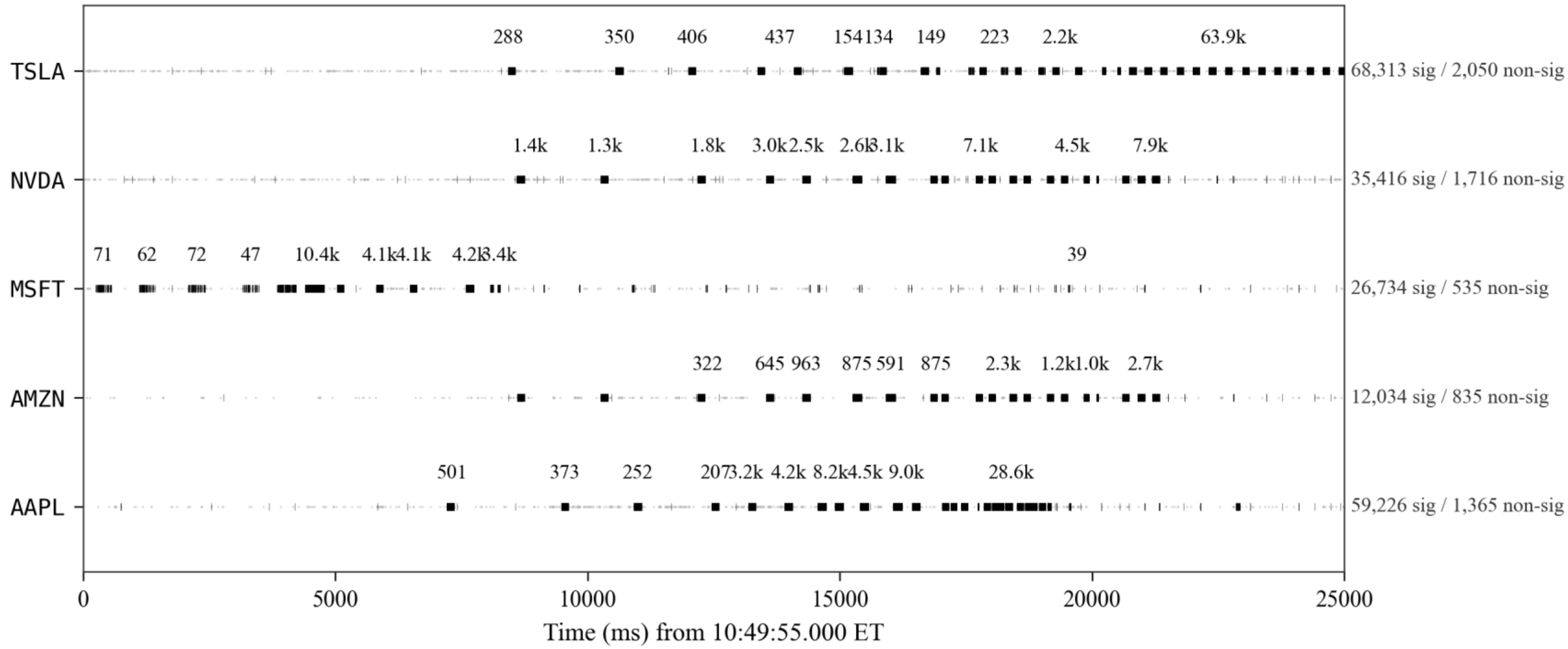


Figure 10. Burst duration versus OEOS trade count (log–log).

This figure shows two log-log scatter plots of burst duration (seconds) against the number of OEOS trades within a precise-burst, restricted to the sample March 15, 2023 - November 8, 2024. Panel A plots the pooled relation with an OLS fit (no fixed effects); Panel B plots the within-stock-date relation after including stock and date fixed effects by demeaning. Each panel reports the estimated slope coefficient and R^2.

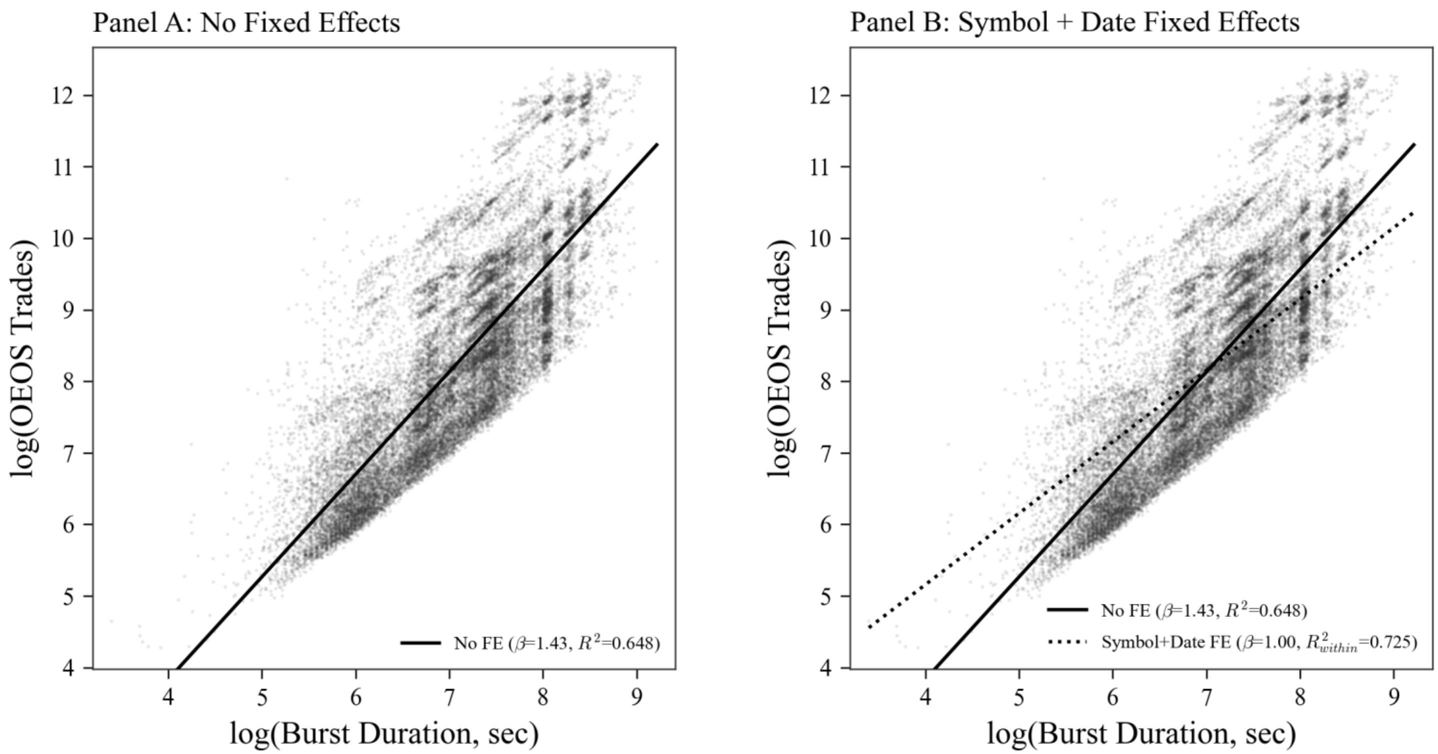


Figure 11. Distribution of Burst-level ΔQMP

This figure displays six panels of histograms showing the quoted midpoint (QMP) impact per burst interval, measured as $(QMP_{end} - QMP_{start})/QMP_{start}$ ×10,000 basis points, where start and end refer to the precise burst boundaries. Burst-signature trades are those of one share, executed off-exchange ("D"), with a rounded participant timestamp to the millisecond, and priced at round penny increments or x.xx88. The sample consists of all precise-edge burst intervals during March 15, 2023 through November 8, 2024. Panel A shows the full-sample distribution; Panel B censors to bursts which have a ΔQMP between {-100bps,+100bps}. Panels C through F show the distribution for four sub-periods: March 15 through September 30, 2023 (Panel C); October 3 through November 27, 2023 (Panel D); November 28, 2023 through February 13, 2024 (Panel E); and February 14 through November 8, 2024 (Panel F). Each panel reports the mean, median, standard deviation, sample size, and the counts of positive, negative, and zero-impact bursts.

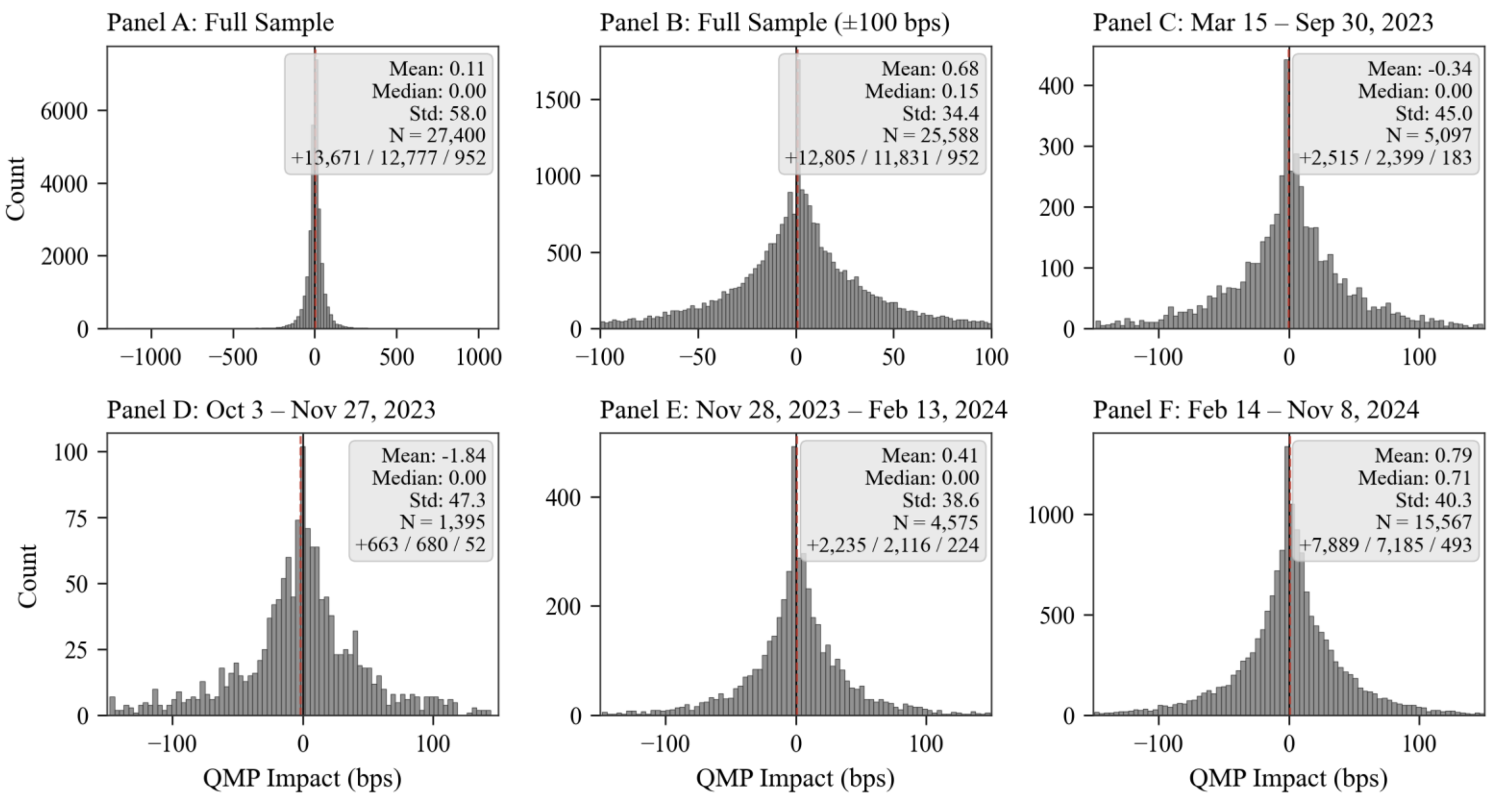


Figure 12. Time-series of the changes in the prices of stocks during bursts of fractional share trade reporting.

This figure plots one bar per trading day which presents the unconditional mean quoted midpoint (QMP) impact in basis points across all precise-burst intervals on that day. We only plot the first six months of synchronized bursting which is March 15, 2023 to September 14, 2023. QMP impact is defined as (QMPend − QMPstart)/QMPstart × 10,000 bps. Bars are shaded darker for positive-impact days and lighter for negative-impact days. An annotation reports the equal weighted mean impact across days and the number of positive versus negative days. The second panel below plots the OEOS imbalance equal-weighted across precise bursts per day with trades signed using the BHPSW methodology.

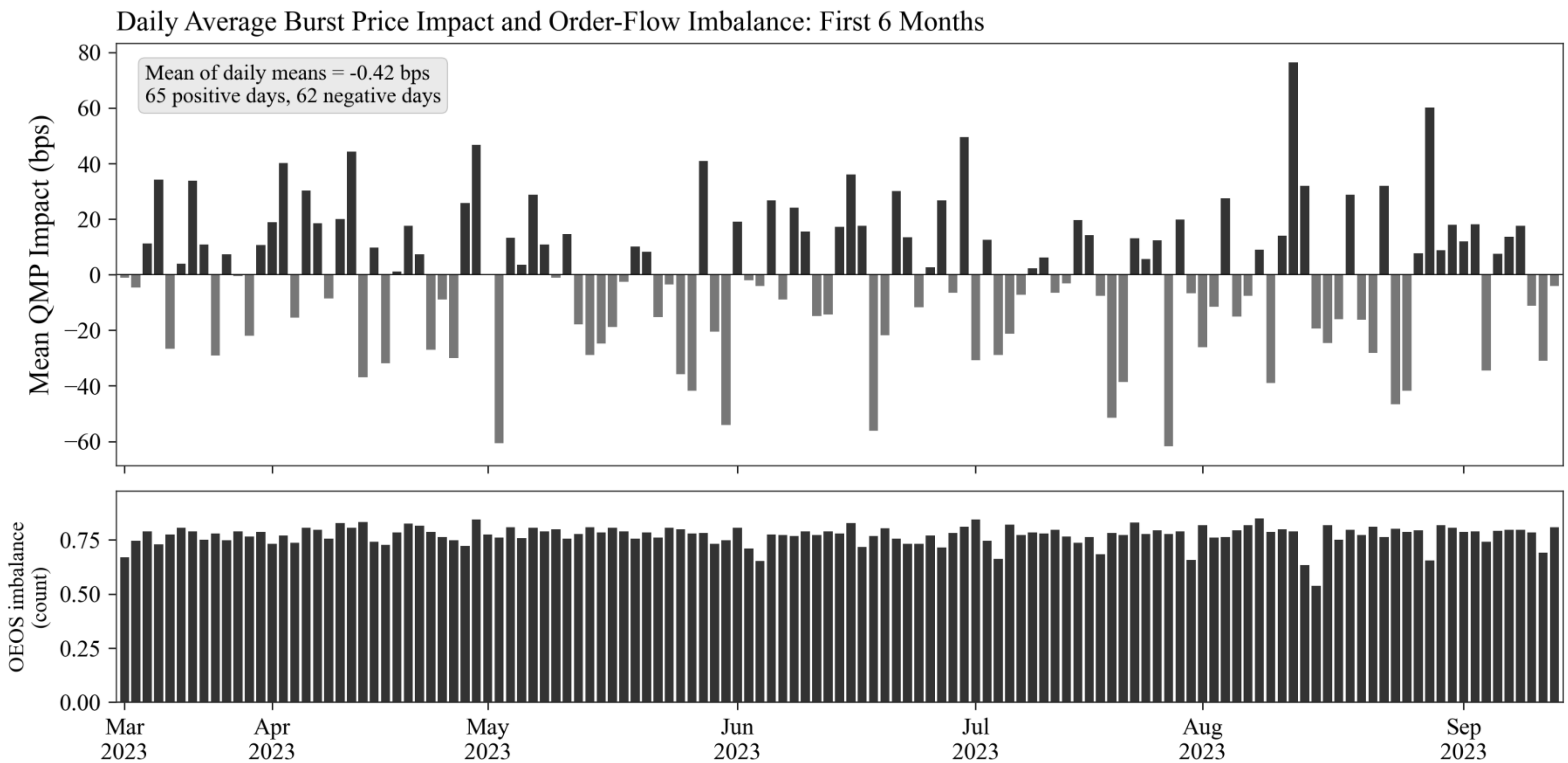
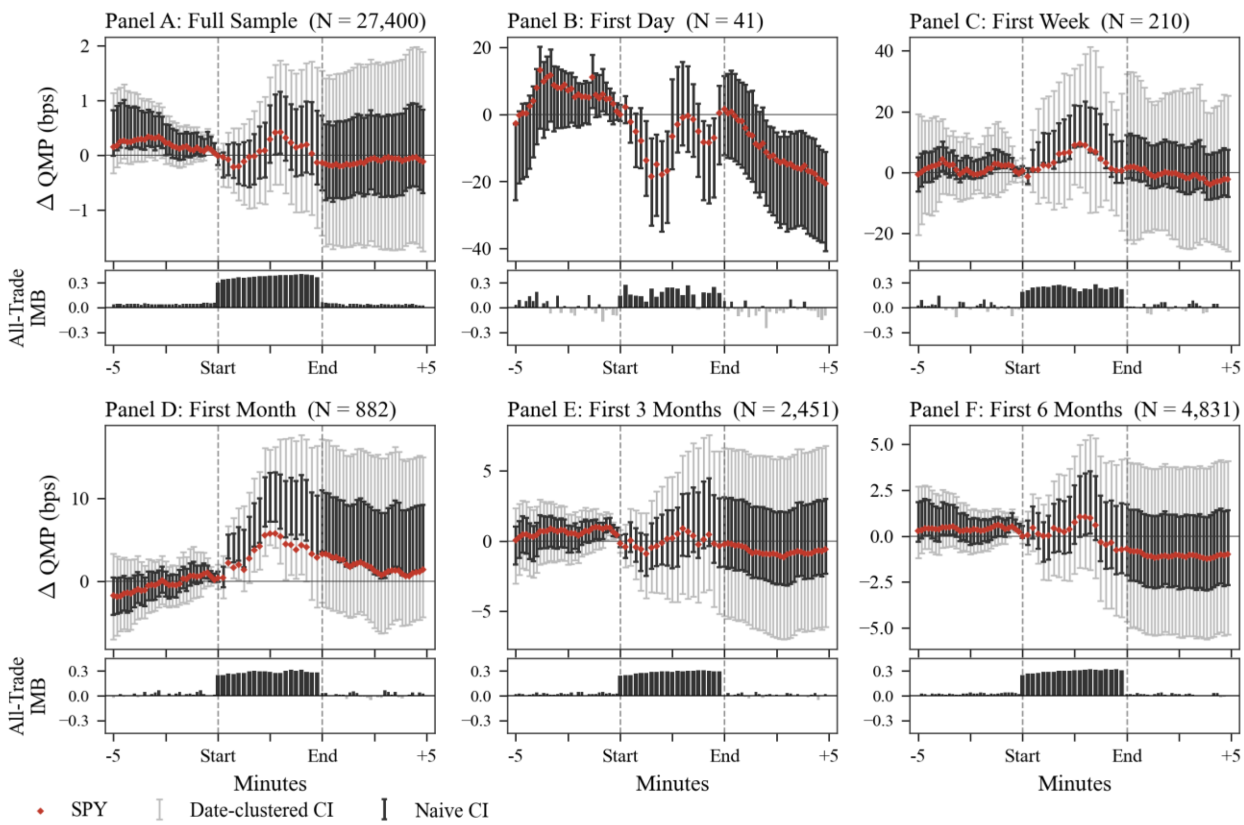


Figure 13. Event-time univariate analysis of changes in stock prices during bursts.

This figure displays six panels plotting the average change in the quoted midpoint (in basis points) around precise-bursts. The x-axis is divided into three regions: 5 minutes before the burst start (sampled at 10-second intervals, 30 bins), the burst itself (divided into 20 equal-duration bins regardless of absolute burst length), and 5 minutes after the burst end (sampled at 10-second intervals, 30 bins). Each bin is equal weighted across all bursts and then plotted with a 95% confidence interval using naïve standard errors as the darker whiskers and date clustered standard errors as the lighter colored whiskers. Each panel has two plots, in the first plot the vertical axis measures $(QMP_t - QMP_{start})/QMP_{start} \times 10{,}000$ bps, anchored to the quoted midpoint at the precise burst start. In the second plot the vertical axis displays all trade imbalance with trades signed using the methodology proposed by BHPSW. The Panels display the statistics across varying sample windows: all precise-edge bursts from March 15, 2023, through November 8, 2024 (Panel A), the first day only (Panel B), the first week (Panel C), the first month (Panel D), the first three months (Panel E), and the first six months (Panel F).



APPENDIX

Appendix Table 1.

This table uses the precise-burst sample, but all variables including the quoted midpoint change are computed using the coarse minute boundaries as opposed to the precise boundaries. The dependent variable is the change in quoted midpoint impact over the burst, in basis points. Every specification includes the controls: log(duration), log(volume), and log(intensity). In Specifications (1)-(3) our variables of interest are the OEOS imbalance and the Non-OEOS imbalance, in specification (2) we include the SPY quoted midpoint impact over the burst. In specification (3) we restrict the sample to only common stocks (TAQ security type A). In Specifications (4)-(6) we decompose the Non-OEOS order imbalance into three categories; the 2-99 Share Imbalance, the 100-999 Share Imbalance, and the 1000+ Share Imbalance, and the On-Exchange One-Share Imbalance. In Specification (7) we add price-bin indicators for the price of a stock. The price bins are \$25-100, \$100-250 and \$250+ (price below \$25 omitted). We assign the price bins using the trade price of the first burst-signature trade in the starting minute of the burst. In (7) we omit stock fixed effects and include date fixed effects only. We report the R^2 within, and the total R^2. Standard errors are clustered on stock and date, presented in parentheses. The sample used is the 27,400 bursts which are identified as precise-bursts which span 309 stocks, and 418 days from March 15, 2023 to November 8, 2024. Significance is denoted as * < 0.10, ** < 0.05, *** <0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OEOS Imbalance	-18.432**	-15.176**	-5.902	-21.086***	-12.018*		-1.416
	(7.907)	(6.902)	(5.683)	(8.136)	(6.308)		(3.861)
Non-OEOS Imbalance	156.231***	142.248***	252.947***				112.853***
	(23.668)	(22.429)	(40.560)				(19.173)
On-Exchange One-Share Imbalance					42.737***	43.114***	
					(6.539)	(6.578)	
2-99 Share Imbalance				128.439***	84.848***	83.111***	
				(21.407)	(15.069)	(14.927)	
100-999 Share Imbalance				18.938***	12.138*	12.306*	
				(6.777)	(6.710)	(6.712)	
1,000+ Share Imbalance				7.620***	7.065***	7.053***	
				(1.374)	(1.248)	(1.244)	
SPY Impact		1.056***	0.860***	1.050***	1.019***	1.021***	1.084***
		(0.122)	(0.094)	(0.121)	(0.118)	(0.118)	(0.126)
Price \$25–100							1.844
							(2.435)
Price \$100–250							4.248*
							(2.540)
Price ≥ \$250							4.532*
							(2.726)
Log (Duration)	0.201	0.140	0.523	0.988	0.632	-0.188	0.274
	(1.165)	(1.044)	(1.299)	(1.162)	(1.140)	(1.040)	(0.835)
Log (Volume)	2.009**	2.183**	1.331	1.818*	2.005**	2.423***	2.901***
	(0.923)	(0.853)	(1.143)	(0.961)	(0.879)	(0.884)	(0.681)
Log (Intensity)	-3.791**	-3.725**	-0.755	-3.296**	-2.744*	-3.549**	-3.355***
	(1.665)	(1.517)	(1.628)	(1.603)	(1.510)	(1.475)	(0.846)
Sample	All	All	Common	All	All	All	All
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.1194	0.1926	0.2107	0.1981	0.2295	0.2292	0.1653
R^2 (total)	0.2363	0.2998	0.3384	0.3058	0.3331	0.3328	0.2313
N	27,400	27,400	16,587	26,563	26,518	26,518	27,400

Appendix Table 2.

This table uses all bursts detected between March 15, 2023, and November 8, 2024, regardless of whether a burst graduates to a precise-burst. All variables including the quoted midpoint change are computed using the coarse minute boundaries as opposed to the precise boundaries. The dependent variable is the change in quoted midpoint impact over the burst, in basis points. Every specification includes the controls: log(duration), log(volume), and log(intensity). In Specifications (1)-(3) our variables of interest are the OEOS imbalance and the Non-OEOS imbalance, in specification (2) we include the SPY quoted midpoint impact over the burst. In specification (3) we restrict the sample to only common stocks (TAQ security type A). In Specifications (4)-(6) we decompose the Non-OEOS order imbalance into three categories; the 2-99 Share Imbalance, the 100-999 Share Imbalance, and the 1000+ Share Imbalance, and the On-Exchange One-Share Imbalance. In Specification (7) we add price-bin indicators for the price of a stock. The price bins are $25-100, $100-250 and $250+ (price below $25 omitted). We assign the price bins using the trade price of the first burst-signature trade in the starting minute of the burst. In (7) we omit stock fixed effects and include date fixed effects only. We report the R^2 within, and the total R^2. Standard errors are clustered on stock and date, presented in parentheses. The sample used is the 36,861 burst intervals, which include those for which precise edges could not be assigned, spanning 1,039 stocks, and 418 days from March 15, 2023 to November 8, 2024. Significance is denoted as * < 0.10, ** < 0.05, *** <0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OEOS Imbalance	-12.380***	-10.285***	-7.041**	-13.820***	-10.713***		-1.977
	(3.087)	(2.756)	(3.140)	(3.718)	(3.015)		(3.405)
Non-OEOS Imbalance	126.287***	114.490***	218.772***				109.431***
	(16.839)	(15.641)	(32.327)				(18.425)
1-Share Imb. (On-Exchange)					38.655***	39.219***	
					(5.584)	(5.669)	
2–99 Share Imb.				91.866***	59.611***	55.270***	
				(15.344)	(10.862)	(10.368)	
100–999 Share Imb.				30.063***	22.035***	23.130***	
				(6.728)	(6.225)	(6.262)	
1,000+ Share Imb.				7.598***	7.004***	6.984***	
				(1.231)	(1.129)	(1.126)	
SPY Impact		1.078***	0.888***	1.074***	1.039***	1.042***	1.075***
		(0.122)	(0.097)	(0.121)	(0.117)	(0.118)	(0.124)
Price $25–100							2.390
							(2.311)
Price $100–250							4.910**
							(2.384)
Price ≥ $250							4.984*
							(2.544)
Log (Duration)	0.366	0.570	0.357	1.072	0.826	0.145	-0.008
	(1.370)	(1.286)	(1.325)	(1.370)	(1.379)	(1.375)	(0.851)
Log (Volume)	0.772	0.740	1.046	0.447	0.727	0.992	2.671***
	(1.129)	(1.076)	(1.140)	(1.214)	(1.191)	(1.202)	(0.641)
Log (Intensity)	-3.947**	-3.739**	-3.313	-3.540**	-2.888*	-3.695**	-3.046***
	(1.641)	(1.490)	(2.273)	(1.560)	(1.496)	(1.522)	(0.805)
Sample	All	All	Common	All	All	All	All
Symbol FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.0953	0.1679	0.1948	0.1694	0.1988	0.1975	0.1567
R^2 (total)	0.3013	0.3574	0.2857	0.3620	0.3870	0.3861	0.2187
N	36,861	36,861	20,906	34,734	34,637	34,637	29,277

Appendix Table 3.

All cells come from a single regression of the quote-midpoint change over the burst (basis points) on OEOS and non-OEOS imbalance, each interacted with four price-bin indicators assigned on the burst's starting price, plus log burst duration, log share volume, log intensity, and the change in the SPY midpoint, with stock and date fixed effects. We present the coefficients in a side-by-side manner for readability.

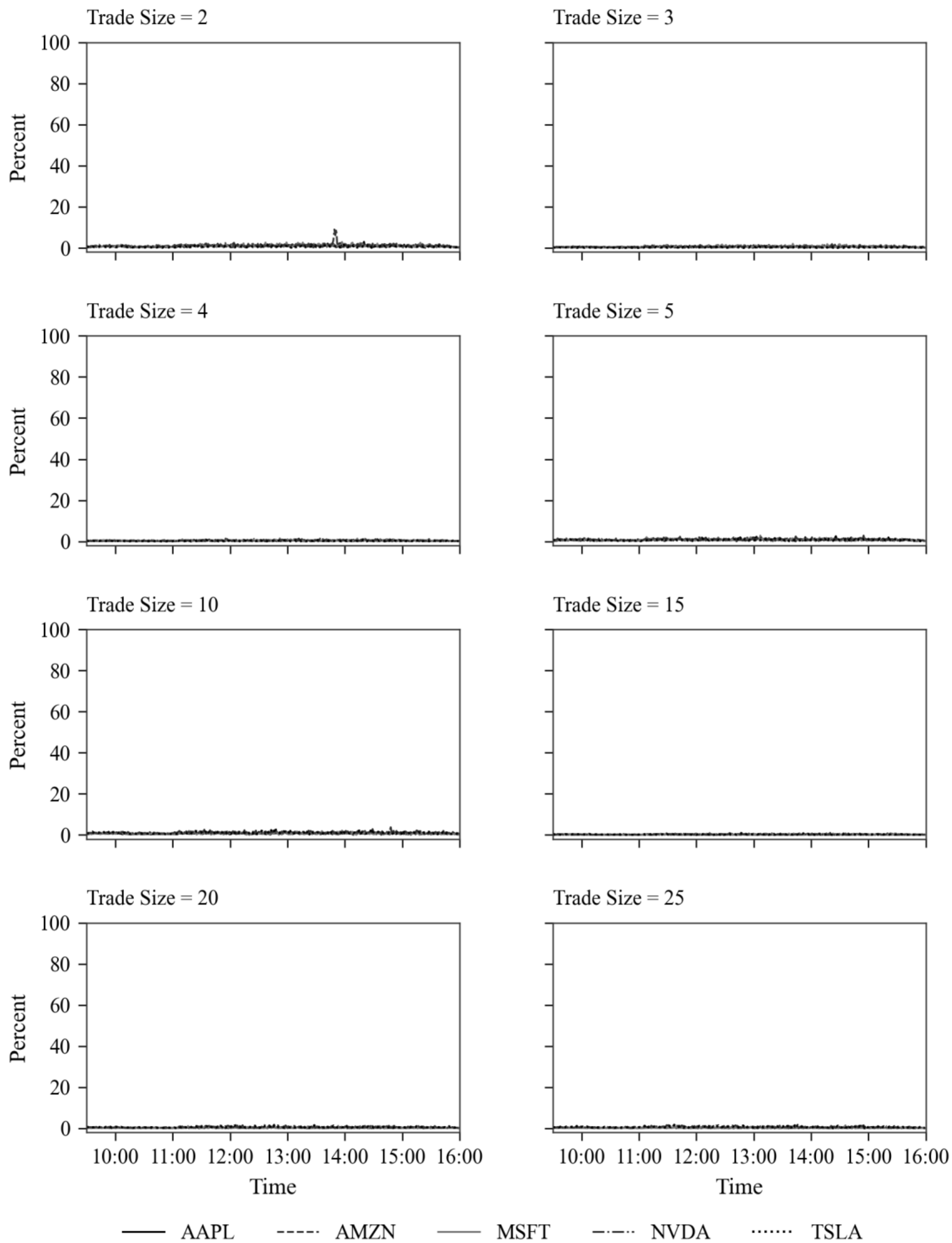
$$\begin{aligned}\Delta QMP_k = {} & \lambda^{O}_{<25}\left(Imb^{O}_k \cdot D^{<25}_k\right) + \lambda^{O}_{25-100}\left(Imb^{O}_k \cdot D^{25-100}_k\right) + \lambda^{O}_{100-250}\left(Imb^{O}_k \cdot D^{100-250}_k\right) \\ & + \lambda^{O}_{\geq 250}\left(Imb^{O}_k \cdot D^{\geq 250}_k\right) + \lambda^{N}_{<25}\left(Imb^{N}_k \cdot D^{<25}_k\right) + \lambda^{N}_{25-100}\left(Imb^{N}_k \cdot D^{25-100}_k\right) \\ & + \lambda^{N}_{100-250}\left(Imb^{N}_k \cdot D^{100-250}_k\right) + \lambda^{N}_{\geq 250}\left(Imb^{N}_k \cdot D^{\geq 250}_k\right) + \beta_1 \log(duration)_k \\ & + \beta_2 log(volume)_k + \beta_3 log(intensity)_k + \beta_4 \Delta \text{QMP}^{SPY}_k + \alpha_{i(k)} + \delta_{t(k)} + \varepsilon_k\end{aligned}$$

There is no un-interacted imbalance term, so each coefficient is that bin's stand-alone price-impact coefficient. We report the R^2 within, and the total R^2. Standard errors are clustered two-way on stock and date, presented in parentheses. The sample used is the 16,587 precise-bursts in common stocks from March 15, 2023 to November 8, 2024. Significance is denoted as * < 0.10, ** < 0.05, *** <0.01.

	OEOS λ	Non-OEOS λ	N
Price <$25	-8.479 (9.192)	412.567*** (82.666)	2,551
Price $25–100	-3.896 (6.024)	195.728*** (21.438)	4,127
Price $100–250	1.283 (4.768)	175.602*** (29.285)	6,856
Price ≥ $250	-1.630 (6.565)	136.787*** (24.622)	3,053
Fixed effects	Symbol + Date		
R^2 (within)	0.2501		
R^2 (total)	0.3608		
N	16,587		

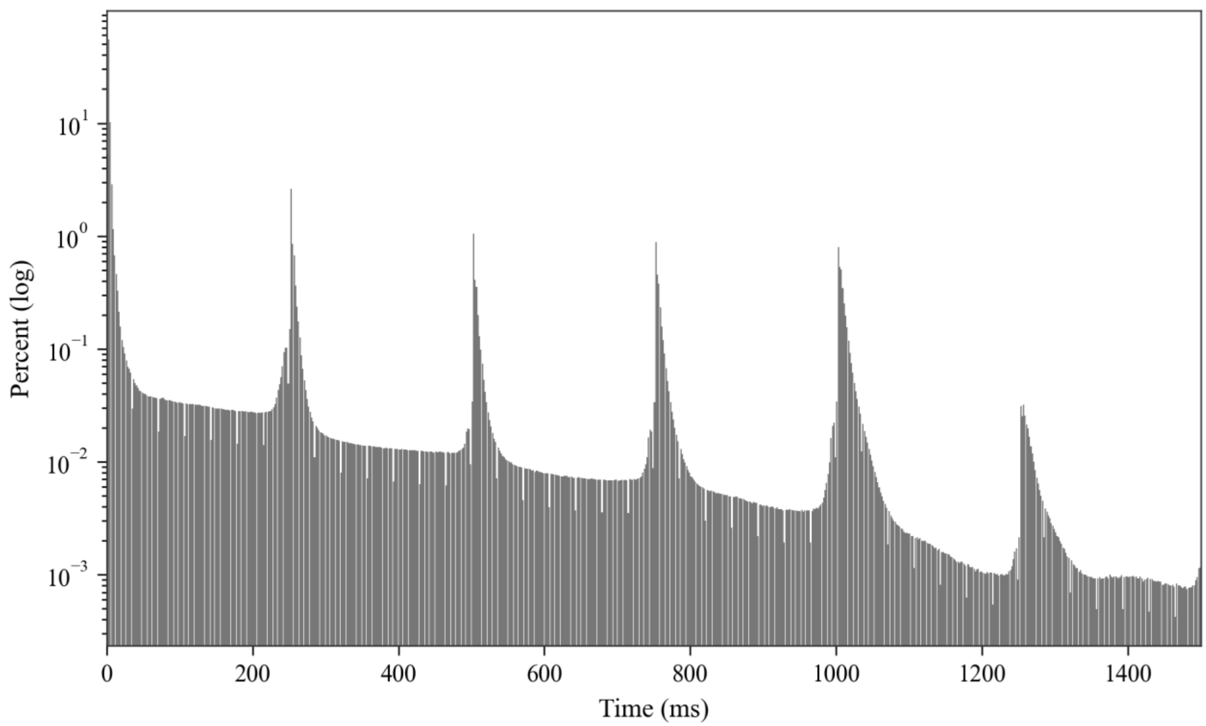
Appendix Figure 1.

This figure plots the percentage of trades in each minute recorded in varying trade sizes, for AAPL, AMZN, MSFT, NVDA, and TSLA on January 2, 2024. The numerator is the count of trades in that size during the stock-minute and the denominator is total trades (all sizes, all exchanges) in that stock-minute. Each panel title displays the trade size in the numerator of the fraction. The trade sizes in the numerators of the panels are: 2, 3, 4, 5, 10, 15, 20, and 25. The data covers regular trading hours (9:30‑16:00 ET).



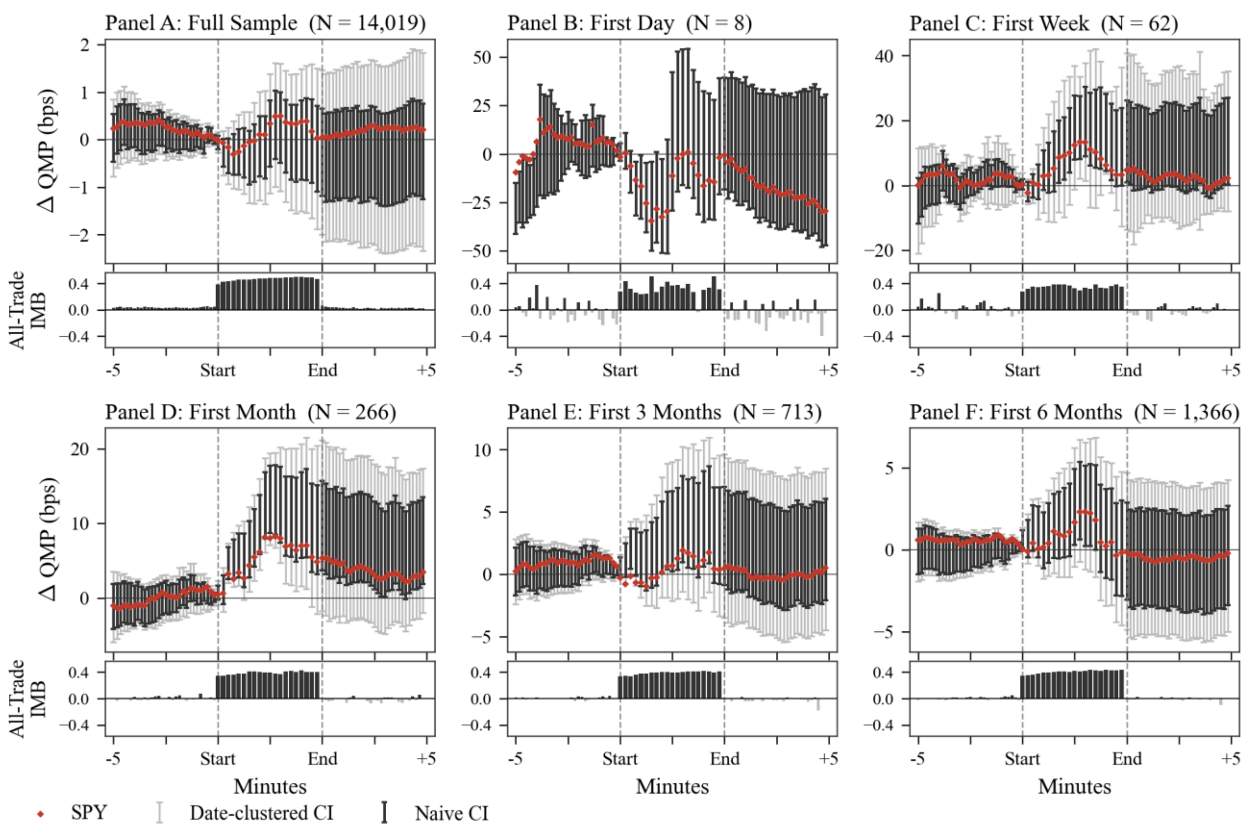
Appendix Figure 2.

The figure below presents the difference in participant timestamps between consecutive burst-signature trades within a stock during a precise burst. The y-scale is the log percentage of all trades, and the x-scale is the lag in milliseconds.



Appendix Figure 3.

This figure displays six panels plotting the average change in the quoted midpoint (in basis points) around precise-bursts. The x-axis is divided into three regions: 5 minutes before the burst start (sampled at 10-second intervals, 30 bins), the burst itself (divided into 20 equal-duration bins regardless of absolute burst length), and 5 minutes after the burst end (sampled at 10-second intervals, 30 bins). Each bin is equal weighted across all bursts and then plotted with a 95% confidence interval using naïve standard errors as the darker whiskers and date clustered standard errors as the lighter colored whiskers. Each panel has two plots, in the first plot the vertical axis measures $(QMP_t - QMP_{start})/QMP_{start} \times 10{,}000$ bps, anchored to the quoted midpoint at the precise burst start. In the second plot the vertical axis displays all trade imbalance with trades signed using the methodology proposed by BHPSW. This figure only retains precise bursts which have 85% of their OEOS trades identified as burst signature trades. Burst signature trades are OEOS trades with a rounded participant timestamp, and round penny pricing or pricing on a x.xx88 grid. The panels display the statistics across varying sample windows: all precise-edge bursts from March 15, 2023 through November 8, 2024 (Panel A), the first day only (Panel B), the first week (Panel C), the first month (Panel D), the first three months (Panel E), and the first six months (Panel F).



Appendix B. Precise Burst Identification

Below we outline the precise-burst detection which 'graduates' a burst from containing minute-level boundaries to precise timestamp boundaries. While some of the methodology is rooted in statistics such as varying thresholds being set two times the Poisson distribution standard deviation, much of the methodology is tuned. The full process for identifying a precise burst was created through manual inspection and iteration over varying methodologies. The goal in mind was to retain the largest amount of bursts in the sample, whilst still assigning a 'reasonable' start and stop time. When viewing the raw data manually, it is generally quite easy to determine when a burst starts and stops, as is evidenced by the figure at the conclusion of this appendix. However, it is unrealistic and unreproducible to manually assign burst start and stop times for over 30,000 bursts. Therefore, we develop the outlined methodology. While the first pass minute-detection flags using OEOS counts, all counts in this methodology use burst-signature trades exclusively. The main results of the paper pertaining to price impact are insensitive to whether precise-bursts or minute-level boundary bursts are used.

We identify DriveWealth (DW) executed burst-signature trades within each detected window and anchor the burst's beginning and end to the timestamps of the first and last of such trades. Bursts for which we can locate these boundary trades are labeled precise-bursts and retained, those for which we cannot are discarded. This restriction simultaneously sharpens each burst's edges and concentrates the sample on trades attributable to DW. We classify a burst-signature trade as a trade for one share, reported off exchange, carries a participant timestamp rounded to a whole millisecond, and prints either at a whole penny or at the .XX88 sub-penny increment. The pricing pattern changes within our sample, penny pricing runs through 1 August 2024 and .XX88 pricing follows it, so our filter accepts both throughout. We use SIP timestamps as opposed to participant timestamps to mark the beginning and end of precise-bursts as that is what participants consuming the tape would view.

We first merge same-stock bursts separated by five minutes or fewer, so that a briefly interrupted episode enters as a single burst. The boundary estimation is carried out on the merged intervals. We then partition a four-minute window from two minutes before to two minutes after the initial minute-level start boundary into 16 fifteen-second bins. The fifteen-second bins are denoted as layer 1 (L1). We count the burst-signature trades in each bin. The baseline rate $\hat{\mu}$ is the mean count over the window's first minute (four fifteen-second bins), and we flag the first two adjacent bins whose counts both exceed $\max(\hat{\mu} + 2\sqrt{\hat{\mu}}, 8)$. As $\sqrt{\hat{\mu}}$ is the standard deviation of a Poisson count, our test requires a two-standard-deviation excess over the baseline rate. The second argument within the function is a fixed constant. The floor of eight trades prevents triggering on a near-empty baseline. This parameter is tuned from manual inspection of the data. Some bursts occur in illiquid ETFs where the baseline rate is often zero burst-signature trades. If no adjacent pair qualifies, we take the first single qualifying bin. If no bin qualifies at all, the start is not identified and the burst is discarded.

We then partition the flagged thirty-second span (or fifteen-second span if only one bin qualified), padded by three seconds on each side, into three-second bins. The three-second bins are denoted as layer 2 (L2) and select the first bin whose count reaches $\max(2, d + 2\sqrt{d}, 0.05D)$ where d is the count in the first padding bin and D is the count in the first flagged fifteen-second bin. The first argument is a constant which serves the same purpose as the L1 floor and is meant to provide a hurdle for relatively low activity burst-signature stocks. The second argument is once again two times the Poisson standard deviation. The third argument requires the selected bin to carry a nontrivial share of the flagged fifteen-second bin's activity, so that a faint leading stream of trades cannot anchor the boundary of an intense burst. If no three-second L2 bin qualifies, the flagged fifteen-second L1 bin itself serves as the selected bin. The burst begins at the timestamp of the first burst-signature trade in the selected bin (either L1, or L2), and the QMP of that trade is used as the starting price of the burst.

The end is located by the mirror-image procedure with one asymmetry in the search window. The search window runs from two minutes before the burst's final flagged minute to three minutes after it. The reason for the difference is so that the search window at the beginning and the conclusion are both of equal length. The baseline is the mean count over the window's last minute, and we scan backward, selecting the last qualifying adjacent pair of fifteen-second bins, then the last qualifying three-second bin, with the trailing padding bin supplying *d*. The end of the burst is therefore the timestamp of the last burst-signature trade within the selected bin. The identified trade's QMP at the time of execution provides the end price of the burst.

Only L1 can reject a burst, but it can be rejected at either the start or the end of the burst. A burst does not graduate to a precise-burst if no fifteen-second bin in the search window clears the threshold. This can happen for two reasons in practice. The window holds too few burst-signature trades, which is the case when minute-level detection has flagged one-share activity that does not carry the DW signature. Or the window holds many burst-signature trades arriving at a steady rate. A heavy baseline rate can occur when a minute which appears to be a component of the burst coincides with elevated trade activity. This can cause minute intervals to not be flagged from the first minute-level pass but contain high arrival rates of burst-signature trades. This therefore increases the baseline count and can make it difficult for a bin to clear the thresholds. While we likely sacrifice many 'valid' bursts due to this issue, a precise start and stop midpoint is pivotal for our analysis. Of the 36,861 merged bursts detected over the 418 trading days from 15 March 2023 through 8 November 2024, 27,400 are retained, roughly 74 percent.

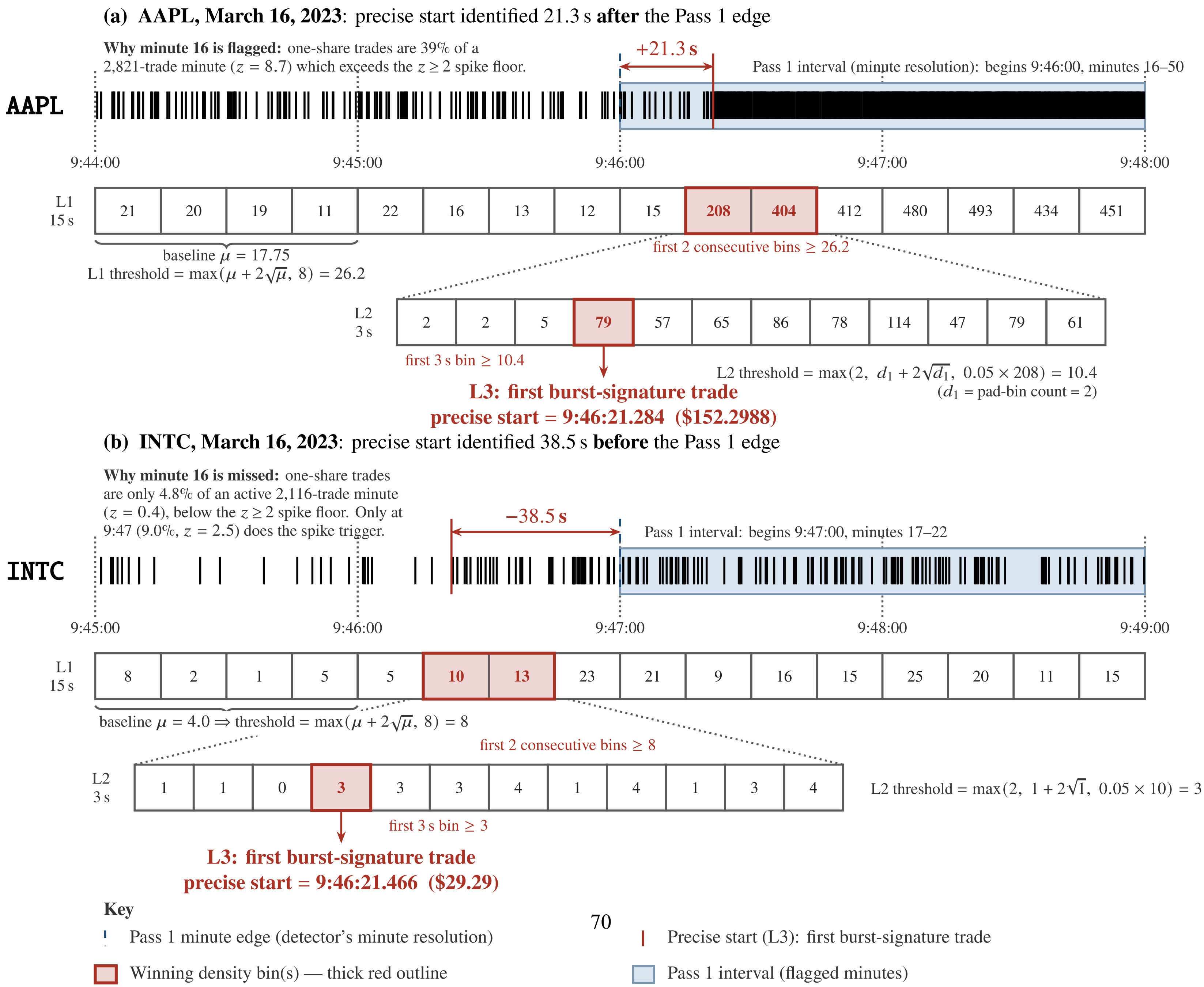
Below we provide two example of bursts which graduate to precise bursts and occur on the same date. We walk through the identification of the start time. Note that in the first example the detection window is after the first-pass minute boundary and in the second example the detection window is before the first-pass minute boundary. Remarkably, the start of the bursts when identified at the minute level are one minute apart (60,000 milliseconds). Once the precise detection is passed on the tape of each stock, the detection is under 200ms apart between the start of the two bursts. This highlights the degree of synchronization across stocks, further evidence of the batching of trades.

Example a. AAPL March 16, 2023.

The first example provides the case where the burst begins after the initial detection. Consider first a burst which occurs in AAPL on March 16, 2023. The minute-level detector which flags persistent spikes as the percentage of OEOS trades relative to all trades detects a burst which begins at 9:46:00am (minute 16) where OEOS trades compose 39% of AAPLs trades. We present the tape for AAPL's burst-signature trades in the figure below. Black lines denote a burst-signature trade and the initial burst window is outlined in blue. It is immediately clear that the intense burst activity does not begin until mid-way through minute 16. To detect the exact moment that burst-signature activity is elevated we partition the two minutes before the minute-level start boundary and the two minutes after into 15 second bins, denoted as level 1 (L1). The mean of the first four bins denoted μ is 17.75 and is considered the baseline rate. We then search forward after the baseline bins, to find the first two neighboring bins which both exceed the threshold defined by $\max(17.75 + 2\sqrt{17.75}, 8) = 26.2$. The two bins which exceed the threshold are highlighted in red. We then partition these two 15-second bins into 10 3-second bins with a padding bin on either side of 3-seconds. The 3-second bins are denoted as level 2 (L2). We then select the first 3-second bin which exceeds the threshold defined by $\max(2, 2+2\sqrt{2}, 0.05 \times 208) = 10.4$, where the first argument 2 is the count of burst-signature trades in the 3-second padding at the beginning of L2 and the 208 is the count of burst-signature trades within the 15-second bin which the selected 3-second bin is located in. The selected bin is in red and contains 79 burst-signature trades. To move to level 3 (L3) we select the first burst-signature trade within the selected L2 bin and assign the burst start to its SIP timestamp. In this example, the time of the precise burst is 9:46:21.284 and the trade price associated with the trade is \$152.2988. The precise-burst detection assigned the start 21.3 seconds after the minute boundaries, which reflects when the elevated activity occurs.

Example b. INTC March 16, 2023.

The second example provides the case where the burst begins before the initial detection. In this example we are brief in our description. For a more complete explanation refer to Example a above. Consider a burst which occurs in INTC on March 16, 2023. The minute level detection begins at 9:47:00am (minute 17). On the L1, we find that the baseline rate is 4 burst-signature trades per 15-second bin, and the two neighboring bins which clear the threshold precede the minute-level start boundary. The fourth 3-second bin at L2 clears the L2 threshold and the first burst-signature trade within that window has a SIP timestamp of 9:46:21.466 and a trade price of $29.29.



(a) AAPL, March 16, 2023: precise start identified 21.3 s after the Pass 1 edge
Why minute 16 is flagged: one-share trades are 39% of a 2,821-trade minute (z = 8.7) which exceeds the z ≥ 2 spike floor.
+21.3 s
Pass 1 interval (minute resolution): begins 9:46:00, minutes 16–50
AAPL
9:44:00
9:45:00
9:46:00
9:47:00
9:48:00
L1 15 s
21 20 19 11 22 16 13 12 15 208 404 412 480 493 434 451
baseline μ = 17.75
L1 threshold = max(μ + 2√μ, 8) = 26.2
first 2 consecutive bins ≥ 26.2
L2 3 s
2 2 5 79 57 65 86 78 114 47 79 61
first 3 s bin ≥ 10.4
L2 threshold = max(2, d1 + 2√d1, 0.05 × 208) = 10.4
(d1 = pad-bin count = 2)
L3: first burst-signature trade
precise start = 9:46:21.284 ($152.2988)
(b) INTC, March 16, 2023: precise start identified 38.5 s before the Pass 1 edge
Why minute 16 is missed: one-share trades are only 4.8% of an active 2,116-trade minute (z = 0.4), below the z ≥ 2 spike floor. Only at 9:47 (9.0%, z = 2.5) does the spike trigger.
−38.5 s
Pass 1 interval: begins 9:47:00, minutes 17–22
INTC
9:45:00
9:46:00
9:47:00
9:48:00
9:49:00
L1 15 s
8 2 1 5 5 10 13 23 21 9 16 15 25 20 11 15
baseline μ = 4.0 ⇒ threshold = max(μ + 2√μ, 8) = 8
first 2 consecutive bins ≥ 8
L2 3 s
1 1 0 3 3 3 4 1 4 1 3 4
L2 threshold = max(2, 1 + 2√1, 0.05 × 10) = 3
first 3 s bin ≥ 3
L3: first burst-signature trade
precise start = 9:46:21.466 ($29.29)
Key
Pass 1 minute edge (detector's minute resolution)
Precise start (L3): first burst-signature trade
Winning density bin(s) — thick red outline
Pass 1 interval (flagged minutes)