Unpacking Retail Trading Costs: the Role of Options Trading and Limit Order Usage

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Abstract

Prior studies of retail trading costs focus on stock market orders, largely overlooking the role of limit orders and the boom in retail options trading. We show that these underexplored factors are critical for assessing overall retail trading costs. First, non-marketable limit orders account for 17% of stock volume but 41% of option volume in Form 606 reports by retail brokers. Second, using trader-level data on 451,299 option and 607,922 stock retail trades from 2020 to 2022, we estimate effective spreads using actual trade direction to average 1.07% for options, much higher than 0.16% for stock trades. But these realized option costs are 60% lower than the 2.59% conventional effective spreads because retail investors commonly use limit orders to minimize trading costs. We observe similar patterns across trader styles. Finally, execution performance persists within traders.

JEL Classification Codes: G13, G14

Keywords: trading costs, retail trading, options, bid-ask spread

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1 Introduction

The recent surge in retail trading has been particularly pronounced in options. Individual investors are estimated to account for nearly half of all option trades (Bryzgalova, Pavlova, and Sikorskaya, 2022), and options represent about a third of total retail trading volume in a dataset of retail investor trades (Bogousslavsky and Muravyev, 2024). Although commission-free trading has slashed explicit costs, retail investors still pay implicit costs through bid-ask spreads. Option spreads often exceed several percent even for most active contracts (Muravyev and Pearson, 2020). Thus, active investors who routinely cross these wide spreads can suffer large losses. Retail investors face the greatest risk because they often demand immediate execution and may lack full understanding of trading costs.

Despite the practical importance of trading costs, particularly in options markets, little is known about retail investors' actual costs or execution strategies. Investors can choose between market and non-marketable limit order types.[1] A market order executes immediately at the best available price, whereas a limit order specifies a target price but risks non-execution. The literature has focused on retail investors' marketable orders but largely ignored limit orders, which can earn the spread instead of paying it. Bryzgalova et al. (2022) identify option market orders that receive price improvement via option auctions (SLAN) but exclude other orders. Huang, Jorion, and Schwarz (2024) study execution costs across brokers by placing market orders and acknowledge that "other orders such as marketable and non-marketable limit orders may be treated differently."[2] We provide estimates of retail trading costs that reflect all order types and explore how they vary across traders.

Although limit orders typically incur lower costs than market orders (e.g., Harris and Hasbrouck (1996)), prior research assumed that retail investors rarely employ limit orders due to execution uncertainty, increased complexity, and monitoring costs. Our analysis of

[1] For brevity, we use "market orders" to refer to market orders and marketable limit orders, and "limit orders" to refer to nonmarketable limit orders.

[2] Similarly, proxies for retail stock trading in TAQ capture a subset of marketable retail trades (Boehmer, Jones, Zhang, and Zhang (2021) and Barber, Huang, Jorion, Odean, and Schwarz (2023)).

Form 606 reports challenges this assumption by showing that modern retail investors often rely on non-marketable limit orders, especially in options. Form 606 reports require retail brokers to disclose all trading in exchange-traded equity securities and listed options at the asset class level. Using payment for order flow (PFOF) reported in Forms 606, we estimate that non-marketable limit orders constitute 17% of stock trades and 41% of option trades over 2020-2022. The limit order share for options varies from 24.3% to 52.5% across brokers, but remains remarkably stable over time. Furthermore, this limit share excludes complex (multi-leg) option trades that account for 18% of option volume across brokers.

We next study how the widespread use of limit orders, missing in prior studies, affects trading costs. A trader-level dataset from Bogousslavsky and Muravyev (2024) provides detailed records of verified retail trades across multiple brokers in both options and underlying stocks from 2020 to 2022. The dataset includes trader IDs, tickers, option parameters, timestamps, trade prices, sizes, and direction. We merge these retail trades with public market data (OPRA for options and TAQ for stocks). This merge yields 451,299 uniquely matched option trades worth $477 million in premiums, and 607,922 stock trades worth about $4 billion, paired with their pre-trade National Best Bid and Offer (NBBO). We extensively validate this merged dataset; for instance, the fraction of limit order volume for options matches that implied from the Form 606 analysis.

Our main measure of retail trading costs builds on the familiar concept of effective bid-ask spread but makes two key adjustments. First, we benefit from verified rather than inferred trade direction. For option purchases, we define the "true" effective spread as twice the percentage difference between the retail execution price and the pre-trade midquote. Thus, the spread estimates round-trip costs and is usually positive but can be negative when retail investors supply liquidity. Second, retail trades resulting from aggressive limit orders set the NBBO and thus the reference midquote, making it appear that they earn rather than pay the spread. To avoid understating costs, we undo this mechanical effect by adjusting the pre-trade midquote to exclude the trader's own quote and instead use the next best available

quote on that side of the market.[3] Prior literature overlooks this adjustment because it only considers market orders, which do not affect pre-trade NBBO. Our measure improves upon the conventional effective spread, which is computed for the inferred liquidity-taking side and is always non-negative.

While we focus on options, stock trades provide an important benchmark. The median quoted spread for stock trades is 0.16% in our sample. However, actual round-trip trading costs, measured by true effective spreads, are much lower at 0.05%. These estimates align with the 0.06% effective spreads that Dyhrberg, Shkilko, and Werner (2022) infer from Form 605 broker reports. The realized costs can be lower than quoted spreads due to retail price improvement and hidden liquidity for market orders, or due to the use of limit orders, an underexplored channel that we focus on.

Retail trading costs in options dwarf stock costs, which highlights their crucial role in understanding total retail costs. Options quoted spreads average 3.62% for our trade sample. Although regular effective spreads are lower with a 2.59% average and 1.38% median, they still vastly exceed stock trading costs.[4] Regularly paying such large spreads can lead to large losses. Strikingly, true effective spreads for retail option trades are on average 1.07% (0.66% median), about 60% lower than the conventional effective spreads. Thus, while options trading costs remain sizable, conventional spreads greatly overstate the actual retail costs.[5]

The gap between true and conventional effective spreads persists across trader types and styles. We categorize traders based on holding period, trade size, and number of trades per

[3]E.g., a limit buy at \$1.00 sets the NBBO together with \$1.05 best ask. We replace the \$1.00 bid with the next best quote (e.g., \$0.90) to compute the midquote (\$0.975 after the adjustment). Specifically, we adjust the midquote if the trade executes at NBBO (or worse) and the trade exchange is the only one quoting the relevant NBBO price, which affects 22.2% of option trades in our sample. The \$1.00 limit order can become aggressive either upon arrival or when market prices drift against it. We term this "mechanical" because the midquote would naturally revert to our adjusted value immediately after the trade.

[4]Our estimates of conventional effective spread are lower than in prior studies (e.g., Muravyev and Pearson (2020); Christoffersen, Goyenko, Jacobs, and Karoui (2018); Goyenko, Ornthanalai, and Tang (2015)) for two reasons. First, these studies use older data (2004-2015) when spreads were wider. Second, retail option trading concentrates in liquid underlying (Bogousslavsky and Muravyev (2024)). For example, Christoffersen et al. (2018) find effective spreads of 6.41% and 5.25% for calls and puts on S&P 500 stocks during 2004-2012.

[5]Based on Form 606 data, we can calculate an upper bound for retail option costs. By assuming the 41% of trades executed as limit orders incur zero cost and the remaining market orders pay the full 2.59% conventional effective spread, the resulting upper-bound for the true spread is 1.56%.

month. Notably, costs are lower for more sophisticated traders, proxied by larger average trade size. Furthermore, execution skill is highly persistent. Investors who minimize costs early in their tenure, as measured by the effective-to-quoted (E/Q) ratio, tend to maintain this advantage, while investors who incur high costs early tend to keep incurring high costs.[6] Among traders in the bottom quintile of execution costs in the first half of their tenure, 52% remain in this quintile in the second half, far above the 20% random baseline. This pattern holds across brokers, indicating that it is driven by investor behavior, rather than broker-specific practices.

The gap between conventional and true effective spreads arises from our ability to observe true trade direction. Conventional spread measures assume retail investors always take liquidity, but retail often supply it through limit orders.[7] We identify 41.5% of options trades in our sample as limit orders, which aligns perfectly with the 41.2% estimate from Form 606 analysis above. While our data do not report order type, we infer it by comparing trade prices to the pre-trade quote midpoints after adjusting for observed trade direction; e.g., buys below mid-quote indicate limit orders. Most option trades execute at the NBBO, facilitating this classification.Importantly, true effective spreads depend only on trade direction and price relative to the mid-quote, and thus the trading cost findings hold regardless of this limit-vs-market classification.

Consistent with prior research on equities, market orders incur higher costs than limit orders. Market orders pay a 2.44% average spread (1.33% median), only slightly lower than a 2.61% conventional effective spread. While some retail market orders receive price improvement, 67.6% of market orders in our retail sample execute at the NBBO. In contrast, limit orders earn part of the spread, with a true average spread of -1.01% (-0.68% median). They do not earn the whole effective spread because 22% of options trades are aggressive limit orders that execute near the true midquote. While these estimates highlight the cost

[6]The E/Q ratio to measure execution quality by comparing actual trading costs (effective spread) to available market prices (quoted spread).

[7]E.g., Grauer, Schuster, and Uhrig-Homburg (2024) show that signing customer trades in public option data is problematic; thus, knowing true trade direction is key.

advantages of limit orders, they do not account for the opportunity costs from limit order cancellations, as we only observe executed trades. However, these opportunity costs may be limited as about four out of five retail option limit orders are executed, or only one in five is canceled or revised. This high fill rate is derived from Form 606 reports, which show that option limit orders account for 52% of all submitted orders and 41% of all executed volume.

We examine what drives retail investors' choice between market and limit orders. In theory, investors strategically choose between them to balance the cost savings of limit orders against the execution risk. Retail investors in our sample behave consistent with this trade-off. For instance, they rely more on market orders when market depth is high, which aligns with theoretical models of optimal order choice (e.g., Parlour (1998)).

To compare retail and non-retail trades, we match each retail trade with five OPRA option trades immediately before and after in the same stock (though not necessarily the same option contract). These control trades, while not exclusively non-retail, provide a benchmark less influenced by retail activity. Systematic differences between the matched samples can help identify retail option trades in public OPRA data. These differences also help us estimate retail share for individual trade attributes like SLAN used by Bryzgalova et al. (2022), assuming a baseline retail share in the control sample.

We quantify retail-control differences by regressing a retail indicator on trade attributes in the pooled retail-control trade sample. Retail trades are 12% more likely to be single-contract, validating this simple retail measure. Retail investors are more likely to trade zero-days-to-expiration (0DTE) options, which may contribute to their overall popularity. While SLAN trades are also more likely to be retail, this relationship varies by exchange. SLAN retail activity concentrates at PHLX, consistent with its favorable treatment of retail orders (Battalio, Griffith, and Van Ness, 2021). Separating limit and market orders, retail market orders concentrate in PFOF exchanges, consistent with brokers maximizing PFOF (Battalio, Corwin, and Jennings, 2016). Retail limit orders often execute when a single exchange quotes NBBO, consistent with those orders being picked off by market makers.

We contribute to several strands of literature. A growing literature examines routing and price improvement for retail orders, with most studies focusing on stocks rather than options and market orders rather than limit orders.[8] The existing options literature focuses on market orders and finds that SLAN trades (a subset of retail market orders) pay an effective spread of 6.7% (Bryzgalova et al., 2022). While these orders receive substantial price improvement (Hendershott, Khan, and Riordan, 2022), orders routed to exchanges instead of SLAN are rarely price improved and thus pay the full spread (Ernst and Spatt, 2022; Huang et al., 2024). Anand and Muravyev (2024) further argue that internalization makes quotes less competitive. We expand this literature by showing that retail trading costs are much smaller than previously thought, as retail investors often use limit orders to reduce costs. While our cost estimates are precise, they represent a small segment of the retail population. We leverage trader-level nature of our data to show strong execution persistence and confirm our results across retail trading styles. Our Form 606 analysis, which represents the entire retail universe, nicely complements our account-level analysis.

To our knowledge, only two papers explicitly study retail limit orders. Anand, Samadi, Sokobin, and Venkataraman (2024) examine stock trading, finding that limit orders comprise 18% of executed shares and have lower trading costs than market orders in their sample of 300 stocks from May 2020. Our analysis of Form 606 reports, which covers all stocks from 2020 to 2022, matches almost exactly their estimate. Moreover, we extend their work by focusing on options, where retail trading costs are much larger. Battalio et al. (2021) examine option limit orders, but focus on how retail brokers route these orders to exchanges offering large liquidity rebates, comparing fees between maker-taker and PFOF exchanges. In contrast, we focus on estimating retail trading costs.

Bogousslavsky and Muravyev (2024) use the parent trade version of the same retail dataset, while this paper focuses on the underlying child trades that can be merged with OPRA data to estimate trading costs. They examine why retail investors trade options and

[8] E.g., Anand, Samadi, Sokobin, and Venkataraman (2021); Battalio and Jennings (2023); Ernst, Malenko, Spatt, and Sun (2023); Huang, Jorion, Lee, Schwarz, et al. (2024) study stock trades.

their resulting losses, finding that investors lose 0.97% per trade on average. When compared with our finding of 1.07% true effective spreads, this suggests that realized transaction costs can potentially explain nearly all of the average realized losses retail investors experience.

We also contribute to the options literature by estimating trading costs for an important class of investors. This estimate can help assess the net performance of options trading strategies. While prior work establishes that option trading costs are substantial (Goyenko et al., 2015; Christoffersen et al., 2018; Muravyev and Pearson, 2020), quantifying these costs for specific investor groups has been challenging due to limited trader-level data and trade direction information. We estimate that retail investors pay only 40% of conventional effective spreads, which provides an upper bound relative to institutional algorithmic trading costs. We further argue that trading costs should be adjusted for the mechanical effect of aggressive limit orders on the reference midquote.

The paper is organized as follows. Section 2 presents evidence on the use of non-marketable limits order from Forms 606 reports. Section 3 describes the retail trade data, how it is merged with public data, and how we measure trading costs. Section 4 contains our empirical results on retail option and stock trading costs. Section 5 describes differences between retail and control trades. Section 6 concludes.

2 Limit Orders: Forms 606 Evidence

To motivate our main analysis, we first show that (non-marketable) limit orders represent a substantial fraction of stock and options orders submitted by retail investors.

Retail brokers in the U.S. must submit Form 606 reports to comply with SEC Rule 606 under the Security Exchange Act. Among other information, these reports provide monthly information on market orders, marketable limit orders, non-marketable limit orders, and other orders for S&P 500 stocks, other stocks, and options. Form 606 reports the fraction of each order type received by the broker. However, limit orders may be canceled. To back

out *executed* volume for each order type, we divide the total net payment received by the average net payment received per share (Dyhrberg et al., 2022). Specifically, for each broker and asset class, we calculate each month the share of trading volume receiving payment associated with different order type as well as the broker's market share in the overall PFOF receiving volume.

Table 1 reports the average distribution of executed volume by order type across retail brokers from 2020 to 2022. Non-marketable limit volume represent a substantial fraction of *option* volume across all brokers. The lowest fraction of limit volume across all brokers is 24.8% reported by Apex. The highest fraction of limit volume across all brokers is 55.0% reported by Interactive Brokers. We calculate the average percentage for each order type, asset class, and broker across months. The row "Total" reports the weighted averages calculated across all brokers and months in each asset class. The total average fraction of non-marketable limit order volume is 41.2%. In contrast, market and marketable limit volume account for 12.7% and 33.7% on average across brokers, respectively. The "Other" category includes order types such as immediate-or-cancel orders, stop orders, etc. that are not liquidity-providing.[9] The importance of other orders volume varies widely across brokers: 46.2% for Interactive Brokers versus 3.2% for Robinhood.

For S&P stocks and other stocks, the fraction of non-marketable limit volume tends to be lower but remains substantial.[10] On average across brokers, the fraction of such volume is 31.8%. Market and marketable limit orders account for 56.5% of volume, with the remaining 11.7% accounted for by other orders.

Thus, comprehensive public data shows that non-marketable limit orders are important, especially so for options. Prior literature focuses on retail market orders in options (Bryzgalova et al., 2022; Huang et al., 2024) and only recently examines retail limit orders in stocks (Anand et al., 2024). Our main contribution is to use a dataset of retail stock and

[9]See SEC Rule 11Ac1-5 for details:
`https://www.sec.gov/rules-regulations/2001/03/disclosure-order-execution-routing-practices`

[10]For stocks, we must exclude Fidelity and Vanguard since they do not accept PFOF. We also exclude Interactive Brokers because of differences between their Lite and Pro platforms.

option trades that includes *both* market and limit orders to study retail execution costs.

3 Data and Methodology

This section describes our data as well as our approach to measure retail trading costs in stocks and options.

3.1 Retail Sample

We construct a sample of retail trade execution costs using the retail stock and option trade data of Bogousslavsky and Muravyev (2024), which we refer at as "journal" data. Retail investors who wish to use advanced analytics can use a trading journal, which will automatically import and verify trades from their brokerage account. Bogousslavsky and Muravyev (2024) gather stock and option trading data from a specific trading journal for which trading information was publicly available by default. A typical option trade in this dataset is the purchase of an option on the S&P index or a high-price technology stock held for a few hours. We refer to Bogousslavsky and Muravyev (2024) for detailed information about the dataset.

For a subset of the original dataset, complete price, size, trade direction, and time information is available. We use this information to match journal trades to option trade records in OPRA and stock trade records in TAQ. We next describe our matching procedure.

For option trades, we match journal trades data with OPRA trade and quote data provided by SpiderRock.[11] Because the timestamps of retail trade data do not feature sub-second increments, we match option contract trades between the two databases using the following algorithm. We first match trades by underlying symbol; date; time (hour, minute, second);

[11] Speicifically, we use their Options Print Set dataset, "created on every option print along with the quote, surface, size, and trade volume at the print time plus all relevant options analytics. The print set also contains exchange published print types (single, complex, auction, block, sweep, etc.) and SpiderRock estimates of the trade side (buy, sell). Records also contain T+1M and T+10M forward mark details to support trade cost analysis (TCA)."

option parameters (call/put; strike price; expiration date); and transaction price. We remove a matched trade if its non-missing trade size in journal data differs from the OPRA trade size to which it is matched. This step results in matching of 746,661 option trades out of all the 795,899 journal option trades for which we have timestamps.

Among these matched retail trades, 485,417 are one-to-one matches; i.e., cases where an individual journal trade matches an individual OPRA trade. For matched trades of this type with missing trade size in retail data, we use OPRA trade size and keep them in the sample. All such cases enter our final sample. In contrast, 198,717 journal trades represent one-to-many matches, where one journal trade is matched with multiple OPRA trades; 22,610 trades represent many-to-one matches, where multiple journal trades match a single OPRA trade; and lastly, 39,917 journal trades represent many-to-many matches, where multiple journal trades match multiple OPRA trades. In each case among these no one-to-one matches we first remove rows with missing trade size in retail data or those where trades sizes reported by retail data and OPRA data are unequal. From the remaining matches, we randomly draw a single row of data and discard the remaining rows associated with that particular case. Table A.1 in the Appendix summarizes these steps. Our algorithm leads us to obtain a total of 614,980 singular journal-OPRA matched trades. Last, we exclude option trades for which the second-best bid price is less than 10¢ since a low price complicates relative cost measurement. We also exclude SPX index option trades from our main sample since these options are only traded on CBOE, but we consider these trades separately later. This leaves us with a final sample 451,299 retail option trades.

For stock trades, we follow a slightly different approach because a given stock tends to can trade many times within one second. First, out of the 2,275,555 journal trades, we focus on the 1,085,000 trades occurring in the 100 most frequently traded stocks in the retail trade data. We then use tickers, dates, and timestamps to match each journal trade to the prevailing national best bid and ask price (NBBO) at the end of the previous second in TAQ data, with NBBOs constructed following Holden and Jacobsen (2014). Our final sample

contains 607,922 retail stock trades that occur within regular trading hours.

While the journal dataset reports order direction, we do not observe order type. We classify buy (sell) orders executed below (above) the prevailing quote midpoint as limit. Panel A of Figure 1 shows that the estimated fraction of option limit order volume in our dataset is in the same range as the average fraction of such volume inferred from Forms 606 (Section 2). In addition, both our data series and the Form 606 series exhibit a slight downward trend over the sample period. Thus, estimated limit order volume in our data matches the representative number obtained from public reports. Importantly, this figure suggests that about 40% of executed option orders in our dataset are limit orders, which have been ignored by prior literature on retail trading costs.

3.2 Control Sample

We match each of the 451,299 retail option trades to "control" trades in OPRA data to compare known retail trades with similar trades that may or may not involve retail investors. From OPRA, we first exclude the two trades in the same underlying symbol that occur immediately before and the two trades that occur immediately after each retail trade. We then flag the five trades that occurred just before and the five trades that occurred just after each retail trade, with all the ten trades associated with the same underlying symbol and occurred on the same day as the retail trade. Like our main sample of retail option trades, we exclude any control trades associated with a second best bid price below 10¢. Our final sample contains 4,178,910 control trades.

3.3 Descriptive Statistics

Table 2 reports descriptive statistics for option retail trades, option control trades, and stock retail trades.

The average option trade value is $1,056 and the median value is $265. The average number of days to expiration is 10.7, but the median value is only 2, with 21.8% of trades

being 0DTE trades. Bryzgalova et al. (2022) focus on orders executed in single-leg price improvement auctions (SLAN flag in OPRA). These represent 27% of trades in our sample.

3.4 Trading Cost Measurement

We measure retail trading costs using several measures. Two of these measures are commonly used in the literature, when the true trade direction, i.e., buy versus sell, is unknown (Bryzgalova, Pavlova, and Sikorskaya, 2023; Dyhrberg et al., 2022). Relative quoted spread is the bid-ask spread divided by the respective NBBO midpoint, scaled by 100, measured for options and stocks, respectively, at the time of transaction and at end of the second prior to the transaction. Similarly, relative effective spread is 2 times estimated trade direction, $+1$ for by trades and -1 for sell trades (constructed using Lee and Ready (1991)'s algorithm), times the difference between transaction price, divided by the respective NBBO midpoint. The other trading-cost measures exploit the availability of trade directions in our data. Signed *unadjusted* relative effective spread is identical to relative effective spread except that it uses the true trade direction, i.e., $+1$ for buy and -1 for sell trades, instead of the Lee-Ready inferred trade directions.

For option trades we also construct signed relative effective spreads, after adjusting for the mechanical effects that arise due to a use of aggressive limit orders. Retail investors may opt to post a limit order inside the prevailing NBBO, in which case their limit order will receive price priority and is likely to trade against an incoming marketable order from the opposite side of the market. In this case, the signed unadjusted effective spread understates true trading costs. To see this, suppose that the prevailing bid and ask prices are \$2.40 and \$2.60, respectively, and hence the midpoint is \$2.50. An investor posts a limit buy order at \$2.45, which will shift the prevailing bid to \$2.45 and the midpoint to \$2.525. The signed unadjusted relative effective spread will equal $+1 \times (2.45 - 2.525)/2.525 \times 100 \approx -2.97\%$ if this limit order is filled at \$2.45. However, the prevailing midpoint that shaped the investor's decision is \$2.50, on which basis the trading costs will be $+1 \times (2.45 - 2.50)/2.50 \times 100 = -2\%$,

about 1 percentage point greater than the estimate that does not account for this mechanical effect.

SpiderRock compiles information on both the first best and the second best prevailing bid and ask prices at the time of each transaction, the number of exchanges at the top of the order book, as well as the identity of the exchange at which each transaction occurs. This allows us to introduce the signed (adjusted) relative effective spread that accounts for to the downward bias described above. We first identify trades that (1) occur either at the best bid or the best ask price; (2) occur when a single exchange prevails the bid (ask) side of order book with the trade price being below (above) the corresponding midpoint; (3) occur in the same single exchange as that prevailing the bid (ask) side of order book. For these trades, we use the second best bid (ask) price, when the trade price is below (above) the corresponding midpoint, to calculate the second best quote midpoint. By using this second best midpoint, instead of the traditional first best midpoint, in the calculation of signed effective spread we adjust for the mechanical effects driven by the use of aggressive limit orders. The key assumption here is that the second best (adjusted) quotes are those prevailing when an aggressive limit orders are placed.[12]

4 Retail Trading Costs

This section reports our main empirical results on retail option and stock trading costs. All outcome variables are winsorized at 0.1% and 99.9% each day.

4.1 Signed Spread vs Conventional Spread

Figure 2 presents our main result. In this figure, we plot the effective spreads of option trades for the signed retail trades in our dataset, unsigned retail trades, and unsigned control trades.

[12]This assumption is too strong for our retail stock trades since we rely on timestamps without sub-second increments and the order book can see significant changes within one second. Thus, our adjustment is not feasible for our equity retail trades.

Unsigned retail effective spreads are large on average, 2.59%, and about the same magnitude as the average control effective spreads of 2.68%. Strikingly, however, *signed* retail effective spreads are on average much lower at 1.07%. Thus, taking into account the trade direction is crucial as it reduces effective spreads by about 60%. This result suggests that conventional spreads substantially overstate the actual trading costs of retail investors in the options markets.

Table 3 reports estimated option quoted spreads and effective spreads for retail and control trades. Quoted spreads associated with our retail trades are on average 3.62%. However, conventional effective spreads are on average 2.59%. After accounting for trade direction, average effective spread drops to 0.60%. This number, however, ignores a potential mechanical effect if the retail order itself sets the NBBO. Once we compute effective spreads relative to the second-best NBBO, as explained in Section 3.4, we get to an average effective spread of 1.07%.

If instead we consider median trading costs, we get a similar picture. The median quoted spread is 1.91%. The median effective spread is 1.38%. The median signed effective spread—adjusted for mechanical effects—is 0.66%, which is 52% smaller than the unsigned effective spread.

By construction, conventional effective spreads cannot be negative as they always take the point of view of a liquidity consumer. For a liquidity supplier, the effective spread is negative. Table 3 shows that 30.25% of retail option effective spreads are negative in our data.

In the Internet Appendix, we report results for the top-10 most actively traded tickers. As expected, spreads are smaller, but the patterns remain the same. Since these options tend to be much more liquid, the second-best NBBO adjustment has a much smaller effect.

Finally, the bottom two rows of Table 3 report effective spreads and quoted spreads for control trades, constructed as described in Section 3.2. Our *unsigned* retail trades appear similar to control trades.

How do retail trading costs in options compare to stocks? Figure 3 plots (signed) effective and quoted spreads for option and stock trades. Unsurprisingly, stock trading costs are much lower than option trading costs. Stock quoted spreads are on average 0.3% and effective spreads are on average 0.17%. Table 4 reports the distribution of estimated retail trading costs in stocks. For equity trades in top-10 option tickers, the average effective spread is about 0. The difference between quoted spread and signed effective spread reflects the use of limit orders, retail price improvement, and hidden liquidity.Using an expanded version of the dataset under consideration, Bogousslavsky and Muravyev (2024) find that investors are close to breaking even on their stock trades. They conjecture that minimal transaction costs for small retail trades in modern U.S. equity markets can explain this result. The results in Table 4 lend support to this conjecture. The large difference between retail option trading costs and stock trading costs is worth emphasizing given the substantial increase in retail option trading in recent years.

We next discuss our interpretation of the main results so far. As shown by the analysis Form 606 data in Section 2, limit orders are widely used by retail investors. We confirm in our data that true effective spreads are much lower than conventional effective spreads, consistent with the use of limit orders. Thus, analyses of retail trading costs based on market orders only are incomplete.

The use of limit orders has implications for aggregate trading costs paid by retail investors to the market making sector. Since option market makers are on the other side of most option trades, any reduction in trading costs is not a zero-sum game from the point of view the retail sector. Thus, our headline 1.07% number provides an estimate of the cost of option trading for retail investors. While the precise number may be subject to selection issues in our specific sample, the fraction of limit volume estimated in our dataset is remarkably consistent with the fraction of limit obtained from 606 data.

Though we can estimate the total monetary cost of trading paid by retail investors from effective bid-ask spread paid, we cannot estimate the cost of a limit order vs a market order

from the point of view of a retail investor since we do not observe opportunity costs. For example, assuming a standard binomial model of stock prices, a risk-neutral investor is indifferent between using a market order and a limit order once we account for the opportunity cost of buying at a higher price when the order is not executed (e.g., Hasbrouck (2021)). Anand et al. (2024) find that retail stock limit orders do better than retail market orders even accounting for opportunity costs.[13]

4.2 Variation in Trading Costs

Next, we regress two measures of trading costs on indicator variables to examine what drives variation in trading costs. Our first measure is the effective spread. Our second measure is the effective-to-quoted spread (EQ) ratio. The EQ ratio measures a trader's ability to time trades and minimize costs relative to prevailing market prices. A low EQ ratio indicates low execution costs. In some specifications, we add underlying fixed effects, date fixed effects, and trader fixed effects.

Table 5 reports the results for effective spread in Panel A and EQ ratio in Panel B. First, we consider at-the-money and out-of-the-money indicator variables. At-the-money (out-of-the-money) options have higher (lower) prices and therefore are likely to have lower (higher) relative effective spreads. This is confirmed in Panel A. There is no clear pattern, however, for the EQ ratio.

Second, we add an indicator for 0DTE trades. Panel A shows that effective spreads are higher for these options. Absent fixed effect, a 0DTE option is associated with a 0.67% higher effective spread, all else equal, with a t-statistic of 6.54. The coefficient estimate remains about the same—0.61%—-with the inclusion of underlying, date, and trader fixed effects. Again, we do not observe a consistent pattern in the EQ ratio.

Third, buy trades are associated with lower effective spread and EQ ratio than sell trades. The effect is economically large and robust across specifications. In the baseline specification

[13]The importance of opportunity costs depends on whether traders are pre-committed to trading or not (Harris and Hasbrouck, 1996).

without fixed effects, a buy trade is associated with a 0.37% decrease in effective spread, with a t-statistic of 4.32.

Fourth, effective spread and EQ ratio are higher for trades executed on payment for order flow (PFOF) exchanges, as opposed to make-take (MT) exchanges. This result is consistent with Battalio et al. (2016).

Fifth, SLAN trades are associated with lower EQ ratio.

Finally, we also find that trading costs tend to be lower in the first half of the sample (January 2020 to June 2021). EQ ratio tends to be lower for call options, while no strong pattern emerges for effective spread. For trades in top-10 tickers, while the point estimates are consistently negative, they tend to be statistically insignificant across specifications.

4.3 Trader Types and Persistence in Trading Costs

How does the gap between true and conventional effective spread vary across trader types? We consider the following groups: traders with a median trade duration lower than one day ("Fast trader"); traders with a median trade size less than $200 ("Low stakes"); traders with a median trade size greater than $5,000 ("High stakes"); traders with a median number of trades per month lower than 10 ("Few trades"); and traders with a median number of trades per month greater than 30 ("Many trades").

Table 6 reports differences between relative effective spreads of signed and unsigned retail trades across trader groups. As shown in the table, the difference between signed and unsigned spreads is large across all trader groups. The unsigned to signed spread ratio is never lower than 2.3. One may argue that the results in Table 3 are exclusively driven by sophisticated traders who employ limit orders. If this is the case, then we should observe much smaller differences between signed and unsigned effective spreads for less sophisticated traders. However, even among low-stakes traders, which are presumably less sophisticated, this ratio is 2.32.

Table 6 suggests that investor skill matters for trading costs. High-stakes traders have

much lower signed effective spread than all other trader groups; i.e., 0.58 whereas none of the other groups has signed spread that is statistically lower than one.

To provide further evidence on the role of investor skill, we examine persistence in trading costs. We split each trader's history into two halves and compute EQ ratio for both periods. In Table 7, we sort traders into groups based on EQ ratio during the first half of their tenure and report their second-half EQ ratio and the probability of staying in the same group. The results show clear persistence in EQ ratio across traders. Average EQ ratio in the second half increases monotonically across quintiles sorted on first-half EQ ratio.

If EQ ratio is random across traders, then the probability of staying in the same EQ ratio quintile should be 20%. Instead, this probability follows a U-shape across quintiles. Low EQ traders have a 52% probability of staying in bottom EQ ratio quintile, whereas high EQ ratio traders have a 51% probability of staying in the top EQ ratio quintile. Panels B and C show that the results are robust to looking at TD trades and non-TD trades. Thus, persistence in execution skill, as proxied by EQ ratio, is driven by investor behavior, rather than broker-specific practices.

4.4 Market vs Limit Orders

In this section, we shed more light on market vs limit orders. Unfortunately, we do not directly observe order types in the dataset. To infer order type, we compare trade prices to the corresponding quote midpoints after adjusting for observed trade direction. A buy (sell) order executed below (above) the quote midpoint is classified as a limit order. We again take into account the adjustment for the use of aggressive limit orders detailed in Section 3.

Table 8 examines retail option trading costs by order type. Panel A restates our main estimate of 1.07% effective spread across all trades while breaking down orders between those that need an adjustment and those that don't. Panel B shows that market orders in our sample pay a 2.53% average spread and a 1.38% median spread. Panel C shows that limit orders earn part of the spread, with a -1.00% average spread and a -0.68% median spread.

They do not earn the entire spread because some limit orders are aggressive and execute near the true midquote.

We examine the determinants of order choice in our dataset. We emphasize that this analysis should be taken with caution. First, our limit orders are by definition conditional on execution, which affects the interpretation of the results. Second, causality can often run both ways. For example, higher volatility could predict higher limit order submission (Foucault 1999) or volatility could be higher simply because the market is less active, with fewer market orders. Our aim is simply to assess whether limit order choice is associated with market conditions in a way consistent with the theoretical literature on order choice.

In Table 9, we regress a limit-order indicator on variables motivated by the theoretical literature on optimal order choice. Absent asymmetric information, the choice between market order and limit order reflects a trade-off between sure execution at a worse price and uncertain execution at a better price (e.g., Rosu, 2009). As predicted by Parlour (1998), higher depth predicts increased order aggressiveness. Intuitively, higher depth lowers limit order execution probability.

Buy trades are associated with greater limit order usage. One explanation is that traders are more patient when entering a position than when exiting a position. This could explain why buy trades have lower execution costs than sell trades in Table 5.

The evidence also suggests that limit orders are less likely to be routed to PFOF exchanges. Put differently, market orders are more likely to be routed to PFOF exchanges, which could be consistent with avoiding make fees.

5 Identifying Retail Trades in OPRA

To compare retail and non-retail trades, we match each retail trade with five OPRA option trades immediately before and after in the same stock (though not necessarily the same option contract) as further explained in Section 3.2. These control trades, while not exclusively non-

retail, provide a benchmark less influenced by retail activity. Systematic differences between the matched samples can help identify retail option trades in public OPRA data. These differences also help us estimate retail share for individual trade attributes like SLAN used by Bryzgalova et al. (2022), assuming the baseline retail share, as we explain further using examples below.

We quantify retail-control differences by regressing a retail indicator on trade attributes in the pooled retail-control trade sample. A higher regression coefficient indicates that trades with a given attribute are more likely to be retail. Our independent variables include indicators for auction trades (SLAN), trades executed on PHLX, and their interaction, single-lot, and round-lot trade sizes, instances where only one exchange quotes at NBBO, zero days to expiration options, and trades on payment for order flow exchanges. In our sample, these indicators are turned on for 12% (SLAN), 15% (PHLX), 3% (SLAN$\times$PHLX interaction), 25% (single-lot), 42% (round-lot), 18% (one exchange at NBBO), 8% (zero days to expiration), and 35% (payment for order flow exchanges) of all trades. We include effective spreads as a continuous control and add fixed effects for the underlying stock, trading date, and individual traders. We estimate these models separately for the full sample, market orders only, and limit orders only, with standard errors clustered by stock and date.

Our regression analysis in Table 10 reveals several distinctive characteristics between trades in our retail and matched control samples. Single-lot trades show the strongest relationship with our retail sample, being 6 percentage points more likely to appear in the retail versus control sample (t-stat = 19.59), representing a 60% increase relative to the baseline (trades from our identified retail sample comprise about 10% of our pooled sample). The interaction between SLAN and PHLX trading emerges as another strong predictor, with these trades being 8 percentage points more likely to appear in the retail versus control sample (t-stat = 7.67), an 80% increase over the baseline. Notably, while PHLX trades alone are slightly more common in the retail sample (0.93 percentage point increase, t-stat = 2.02), SLAN trades in isolation show no significant difference between samples. Round-lot trades

also exhibit a significant positive association with our retail sample, being 3.6 percentage points more likely (t-stat = 14.56). Zero-day-to-expiration options demonstrate a strong retail pattern, being 3.7 percentage points more likely in the retail sample (t-stat = 8.54). Examining limit orders specifically, we find they are 3.3 percentage points more likely to execute when a single exchange quotes the NBBO in the retail versus control sample (t-stat = 7.95), consistent with these orders being susceptible to adverse selection. Importantly, these results remain robust across specifications controlling for underlying stock fixed effects, date fixed effects, and trader fixed effects, with coefficient magnitudes and statistical significance largely unchanged.

The regression coefficient provides a direct measure of how the probability of a trade being retail changes with a trade attribute such as single-lot status, given the baseline retail fraction in the control sample. We provide an example of the back-of-the-envelope calculation. Let us assume that the control sample contains 50% retail trades. We define a binary variable *Retail* that equals 1 for retail trades and 0 otherwise. Regressing *Retail* on an indicator for single-lot trades (*Size*), we obtain a coefficient of 0.06. This coefficient represents the difference in the probability of a trade being retail when it is a single-lot trade versus when it is not. Mathematically, this corresponds to $E[Retail|Size = 1] - E[Retail|Size = 0] = 0.06$. Given that $E[Retail|Size = 0]$ corresponds to the overall retail fraction in the control sample of 0.5, we solve for $E[Retail|Size = 1]$ as $0.5 + 0.06 = 0.56$. This implies that 56% of single-lot trades in the control sample are retail trades. This calculation assumes that all other indicator variables are zero in the regression. We supplement the multivariate indicator regressions with univariate regressions in Table A.6 in the Appendix.

6 Conclusion

This paper provides new insights into retail trading costs in options markets by leveraging comprehensive data on all order types and precise trade direction information. Our analysis

yields several important findings that challenge conventional wisdom about retail trading behavior and costs. First, we document that retail investors make extensive use of limit orders in both stock and options markets, with non-marketable limit orders accounting for approximately 17% of stock retail volume and 41% of option volume. This finding stands in stark contrast to the traditional view that retail investors predominantly use market orders. The widespread use of limit orders appears driven by the substantially wider spreads in options markets, which create stronger incentives for retail traders to provide rather than take liquidity.

Second, we show that conventional spread measures substantially overstate actual retail trading costs in options markets. While quoted spreads average 3.67% and conventional effective spreads average 2.67% in our sample, true effective spreads—which account for verified trade direction and adjust for the mechanical effect of aggressive limit orders on reference prices—are only 1.07% on average. This 60% reduction in estimated trading costs has important implications for understanding retail trading performance and market quality.

Third, we find significant heterogeneity in execution costs across trader types and persistence in execution skill. More sophisticated traders, as measured by larger average trade sizes, achieve lower trading costs. Furthermore, traders who demonstrate superior execution ability early in the sample tend to maintain this advantage, with 49% of top-quintile performers remaining in the top quintile in the subsequent period. This persistence holds across different brokers, suggesting it reflects investor skill rather than broker-specific practices.

Fourth, our analysis of order choice reveals that retail investors strategically adapt their trading strategies to market conditions. They are more likely to use limit orders when quoted spreads are wide, indicating sensitivity to trading costs. However, during periods of high volatility, they shift toward market orders, suggesting they appropriately balance cost savings against execution certainty.

These findings have important implications for our understanding of retail market participation and market structure. The substantial use of limit orders by retail traders suggests

they contribute more to market liquidity than previously thought. Moreover, the lower true trading costs we document indicate that options markets may be more accessible to retail traders than conventional spread measures suggest, though costs remain substantially higher than in equity markets.

Several promising directions for future research emerge from our analysis. Researchers could examine how the introduction of zero-commission trading has affected retail order placement strategies and execution quality, informing ongoing policy debates about payment for order flow and retail market structure. Additionally, investigating whether the execution skill persistence we document stems from better timing, more sophisticated order placement strategies, or other factors could yield valuable insights for retail trader education and market design, particularly in complex financial instruments where trading costs are substantial.

Our findings highlight the importance of comprehensive data and precise measurement in understanding retail trading behavior and costs. As retail participation in options markets continues to grow, these insights can help inform market structure decisions and improve our understanding of retail trader performance.

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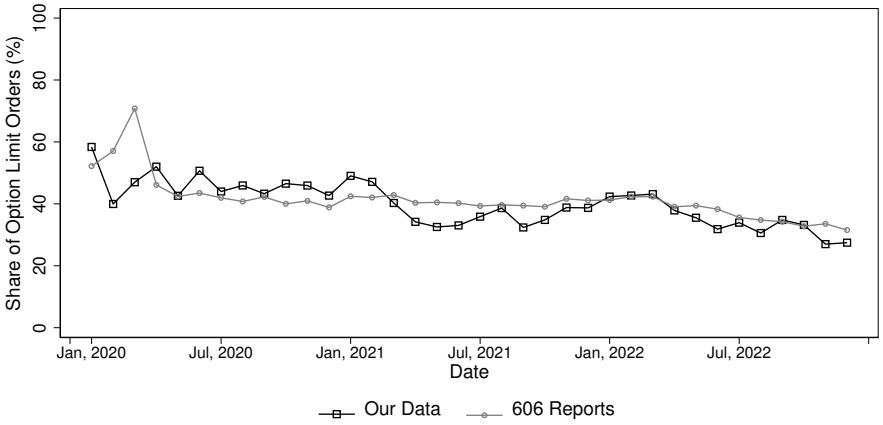
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Figures and Tables

Figure 1. Share of Limit Order Volume Underlying Option and Stock Retail Trades.
This figure compares the estimated fraction of limit-order volume in our dataset to the fraction of limit order volume receiving PFOF as reported in 606 reports. Monthly shares of limit order volume handled in stocks and options are extracted from 606 reports of the following retail brokers from the first quarter of 2020 through the last quarter of 2022: Apex, Charles Schwab, E*TRADE, Fidelity, Interactive Brokers, Robinhood, TD Ameritrade, Vanguard, Webull. These brokers account for 88.4% and 92.3% of executed retial volume, respectively, in options and stocks. The monthly share of limit-order volume executed by these brokers are reported over time.

Panel A: Options



Panel B: Stocks

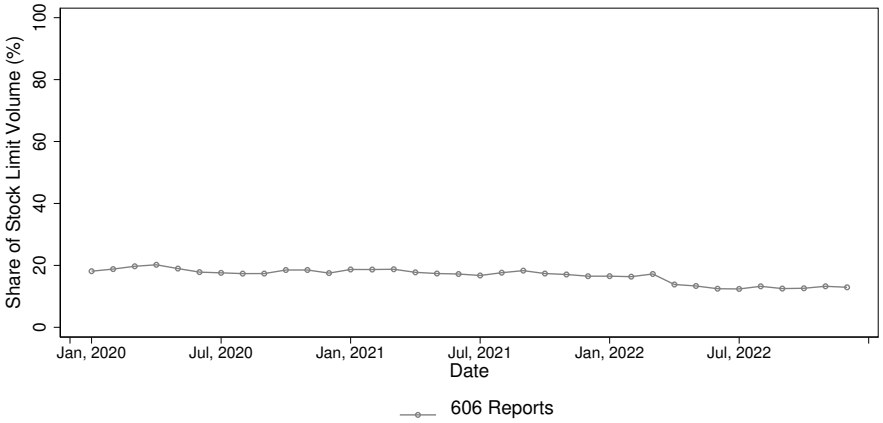


Figure 2. Effective Spreads of Option Trades

"Signed Retail" denotes true effective spreads, which is our main measure, "Unsigned Retail" and "Unsigned Control" denote conventional effective spreads for the retail trade sample and control samples.

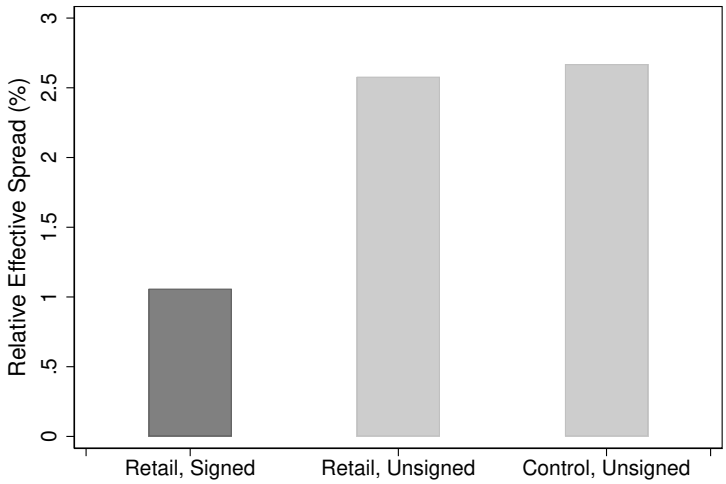


Figure 3. True Effective and Quoted Spreads for Option and Stock Retail Trades
The figure compares signed *unadjusted* relative effective spreads and relative quoted spreads of retail trades between options and stocks.

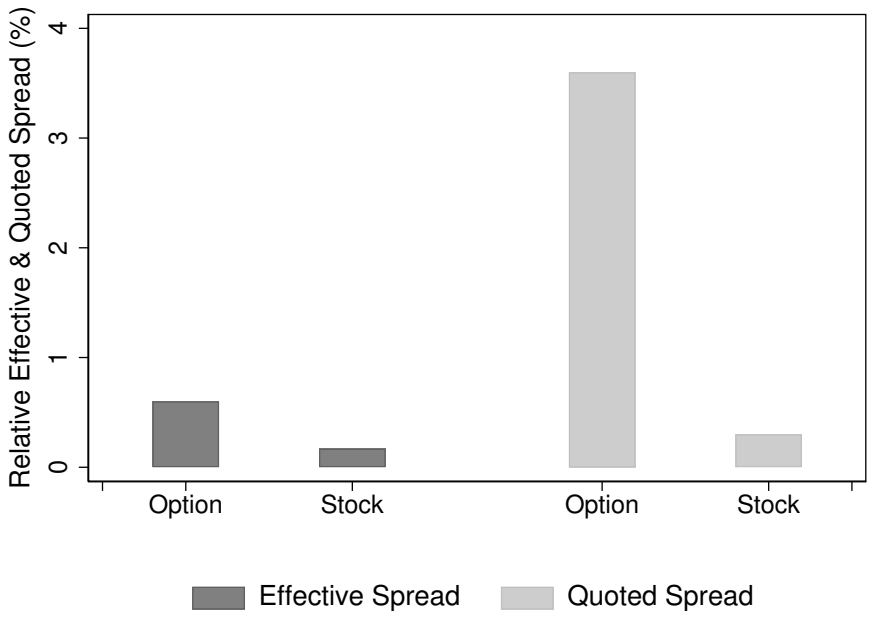


Figure 4. Trade Price Distribution Relative to Quoted Spread.
The figure shows the distribution of trade prices of retail option trades relative to the quoted bid-ask spread. The normalized transaction price is defined as the actual transaction price minus the corresponding best bid price, divided by the bid-ask spread. I.e., zero (one) denotes trades at the bid (ask) price. Almost all option trades are expected at or within the NBBO.

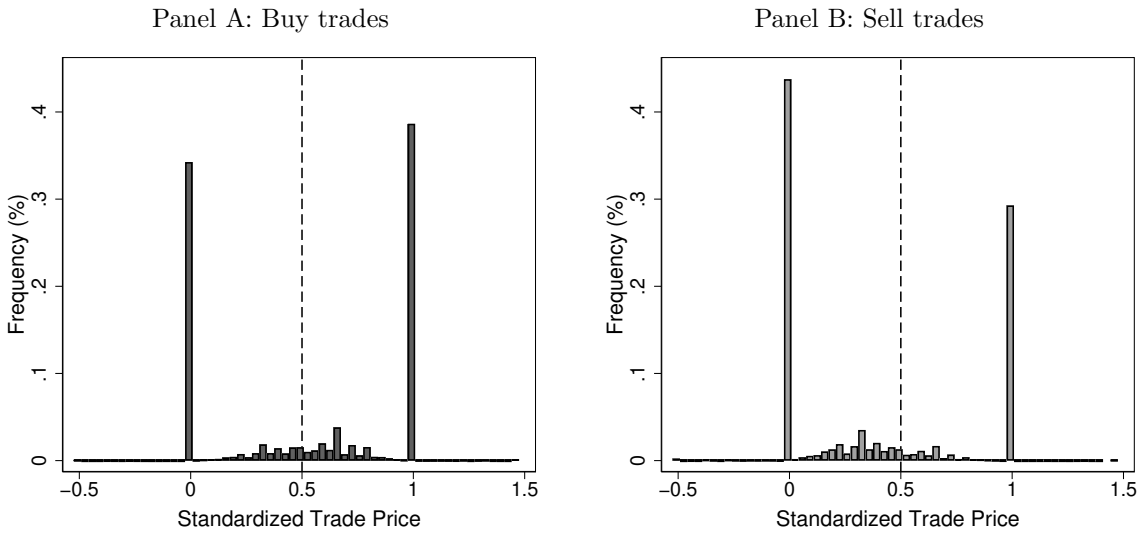


Table 1. Volume Distribution by Order Type and Broker

This table reports the distribution of executed volume by order type (non-marketable limit, market, marketable limit, and other) and retail brokers, based on Form 606 monthly reports from 2020 to 2022. Selected brokers account for 88.4% and 92.3% executed retail volume on options and stocks, respectively. Non-marketable limit orders represent liquidity-providing orders, while market and marketable limit orders represent liquidity-taking orders. The "Other" category includes order types such as immediate-or-cancel orders, stop orders, etc. (see SEC Rule 11Ac1-5 for details) that are not liquidity-providing. For each broker and asset class, the share of trading volume receiving payment associated with different order type as well as the broker's market share in the overall PFOF receiving volume are calculated monthly. The table reports broker-specific averages across months. The row "Total" reports the weighted averages calculated across all brokers and months in each asset class.

	Options					Stocks				
		Order type (%)					Order type (%)			
Broker	Average weight (%)	Non-marketable limit	Market	Marketable limit	Other	Average weight (%)	Non-marketable limit	Market	Marketable limit	Other
Apex	1.1	24.8	5.2	34.5	37.1	3.4	15.3	30.6	42.6	14.7
Charles Schwab	9.5	30.5	26.4	19.4	23.6	12.9	18.9	56.7	18.4	8.7
E*TRADE	12.4	27.4	27.2	21.1	24.4	12.3	17.8	42.4	27.7	15.4
Fidelity	7.3	39.4	41.2	23.4	21.3	-	-	-	-	-
Interactive Brokers	7.4	55.0	0.2	38.8	46.2	-	-	-	-	-
Robinhood	28.0	52.5	0.0	44.2	3.2	19.2	10.5	38.1	32.6	18.7
TD Ameritrade	14.8	32.8	9.3	30.0	27.9	13.2	17.8	36.1	33.1	12.9
TD Clearing	15.0	40.7	13.8	34.2	11.3	34.8	17.0	49.3	23.0	10.8
Vanguard	0.2	46.1	12.5	36.8	4.6	-	-	-	-	-
Webull	4.8	41.3	5.4	47.2	6.1	5.6	27.3	19.2	33.0	21.4
Total		41.2	12.7	33.7	17.7		17.0	43.9	27.7	13.8

Table 2. Trade Summary Statistics.

This table reports summary statistics for option and stock trades. Panel A summarizes 451,299 retail option trades. Panel B details 608,083 retail stock trades. Statistics include the total count of trades, mean, standard deviation, and percentiles (1st, 5th, 25th, 50th, 75th, 95th, 99th) to capture distributional characteristics. Key variables are defined as follows: Trade Price reflects the per-contract execution price (options) or per-share price (stocks), in dollars. Trade Size measures the number of contracts (options) or shares (stocks) per trade, while Trade Value calculates the total dollar value of the trade. SLAN is an indicator of whether the trade occurred in a single-leg price improvement auction. Exchanges at NBBO count the number of exchanges quoting the NBBO price when the trade is executed. Moneyness compares an option's strike price to its underlying stock price: for calls, values below one indicate in-the-money (ITM) status, while for puts, values above one denote ITM. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

Panel A: Option Retail Trades

				Percentiles						
Variable	Count	Mean	St Dev.	1	5	25	50	75	95	99
Trade Price	451,299	4.20	8.38	0.15	0.29	0.89	1.78	3.66	17.00	43.45
Underlying Price	451,299	407.68	554.01	6.79	21.41	127.58	318.06	422.29	1033.74	3352.34
Trade Size (shares)	451,299	327.5	1163.8	100.0	100	100	100	200	1000	4000
Trade Value ($)	451,299	1056.2	4355.0	18	39	120	265	700	3700	12675
SLAN	451,299	0.27	0.45	0	0	0	0	1	1	1
# Exchanges at NBBO	451,299	4.45	4.29	1	1	1	2	7	14	16
Moneyness Call	265,099	0.938	2.637	0.631	0.836	0.962	0.990	0.999	1.015	1.116
Moneyness Put	186,193	0.974	0.078	0.704	0.871	0.972	0.992	0.999	1.009	1.074
Days to expiration	451,299	10.7	42.9	0	0	1	2	7	38	158
Hour of Day	451,294	11.00	1.94	9	9	9	10	12	15	15

Pabel B: Stock Retail Trades

				Percentiles						
Variable	Count	Mean	St Dev.	1	5	25	50	75	95	99
Trade Price	608,083	75.6	167.3	1.25	2.32	5.46	12.85	58.79	387.00	847.00
Trade Size	403,599	292.8	838.0	1	2	25	100	200	1000	3500
Trade Value	403,599	6699.06	18540.46	11	58	405	1472	4999	28995	93540
Hour of Day	608,083	11.3	1.9	9	9	10	11	13	15	15

Table 3. Retail Trading Costs in Options.

This table reports relative bid-ask spreads for retail and control sample option trades. True effective spreads use verified trade direction and are computed as twice the percentage difference between the execution price and pre-trade midquote. The unadjusted version includes cases where retail limit orders set the NBBO, while the adjusted version removes this mechanical effect by using the next best quote. Conventional effective spreads follow standard methodology using inferred trade direction and are always non-negative. For each spread measure, we report the number of observations, mean, standard deviation, and key percentiles of the distribution. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

				Percentiles						
Retail Sample Spreads (%)	Observations	Mean	S.D.	1	5	25	50	75	95	99
True Effective	451,299	1.07	4.88	−8.81	−3.28	−0.38	0.66	1.88	6.74	16.62
True Effective Unadjusted	451,299	0.60	5.12	−12.06	−4.65	−0.94	0.57	1.77	6.45	15.38
Conventional Effective	451,299	2.59	4.44	0.00	0.25	0.72	1.38	2.82	8.40	20.00
Conventional Quoted	451,299	3.62	5.96	0.26	0.43	1.02	1.91	3.92	11.76	28.35
Control Sample Spreads (%)										
Conventional Effective	4,178,910	2.68	4.77	0.00	0.20	0.66	1.36	2.90	8.70	21.69
Conventional Quoted	4,178,910	3.59	6.18	0.20	0.38	0.96	1.83	3.87	11.76	28.57

Table 4. Retail Trading Costs in Stocks.

This table reports relative bid-ask spreads for retail stock trades. True effective spreads use verified trade direction and are computed as twice the percentage difference between the execution price and pre-trade midquote. These can be negative when retail traders supply liquidity. Conventional effective spreads follow standard methodology using inferred trade direction and are always non-negative. For each spread measure, we report the number of observations, mean, standard deviation, and key percentiles of the distribution. The sample includes equity trades in the 100 stocks with most retail trades. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

				Percentiles						
Retail Sample Spreads (%)	Observations	Mean	S.D.	1	5	25	50	75	95	99
True Effective	607,922	0.17	45.76	−2.37	−1.46	−0.26	0.05	0.39	1.57	2.66
Conventional Quoted	607,922	0.30	1.34	0.00	0.01	0.04	0.16	0.36	0.83	1.59

Table 5. Retail Trading Costs in Options: Subsample Analysis.

This table reports on the cross-sectional variation in the trading costs and execution quality of retail option trades. Trading cost; i.e., *adjusted* signed effective spread, on each retail trade is the product of the trade direction and the difference between execution price and the quote midpoint, divided by the quote midpoint, multiplied by 2 and scaled by 100. Execution quality, i.e., the effective-to-quoted spread (E/Q) ratio, divides the signed effective spread by quoted spread. Following indicator variables are used as independent variables: "Early" equals 1 for trades occurring from January, 2020 through June, 2021 but equals 0 otherwise; "Top-10 Ticker" equals 1 if a trade is associated with the 10 underlying tickers whose option contracts are most frequently traded in by retail investors in a given month and equals 0 otherwise; "ATM" equals 1 if moneyness (defined as underlying price divided by strike price for call options and as strike price divided by underlying price for put options) is between 0.98 and 1.02 and equals 0 otherwise; "OTM" equals 1 if moneyness is lass than 0.95 and equals 0 otherwise; "0DTE" equals 1 if the trade occurs on the contracts expiration date and equals 0 otherwise; 'Buy trade" equals 1 if the trade is attributable to a retail buyer and equals 0 otherwise; "Call option" equals 1 if the contract is a call option and 0 if it is put; "PFOF" equals 1 if the trade occurs on an exchange allowing PFOF and equals 0 otherwise; and "SLAN" equals 1 if trade is executed as single-legged auction transaction and equals 0 otherwise. Specifications control for different combinations of underlying ticker, date, and trader fixed effects. Standard errors are clustered by underlying ticker and date, with t-statistics reported in brackets and symbols *, **, ***, reflecting statistical significance given 10%, 5%, and 1% type I error levels, respectively. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

	Panel A: Effective Spread (%)					Panel B: E/Q Ratio				
Early	−0.011	−0.088		−0.00049		−0.035**	−0.036**		−0.00071	
	[−0.15]	[−1.07]		[−0.01]		[−2.00]	[−2.01]		[−0.07]	
Top-10 Ticker	−0.94***	−0.47***	−0.92***	−0.98***	−0.40***	−0.0061	−0.024	−0.015	−0.048***	−0.017
	[−12.98]	[−4.41]	[−12.14]	[−11.78]	[−5.31]	[−0.33]	[−1.12]	[−0.84]	[−2.91]	[−1.04]
ATM	−0.30***	−0.23***	−0.31***	−0.38***	−0.35***	0.026***	0.012	0.024***	−0.026***	−0.037***
	[−5.97]	[−5.67]	[−6.48]	[−7.66]	[−11.52]	[3.74]	[1.58]	[3.24]	[−2.87]	[−5.51]
OTM	0.62***	0.60***	0.63***	0.63***	0.66***	0.013	0.022*	0.011	0.029***	0.041***
	[10.75]	[9.54]	[10.59]	[10.51]	[11.11]	[1.17]	[1.73]	[1.05]	[4.37]	[6.22]
0DTE	0.67***	0.71***	0.72***	0.57***	0.61***	−0.0017	−0.0055	0.0027	−0.019**	−0.031***
	[6.54]	[6.01]	[6.42]	[6.02]	[6.12]	[−0.15]	[−0.53]	[0.15]	[−2.52]	[−2.93]
Buy	−0.37***	−0.37***	−0.37***	−0.35***	−0.35***	−0.053**	−0.053**	−0.053**	−0.047**	−0.047**
	[−4.32]	[−4.32]	[−4.34]	[−4.31]	[−4.31]	[−2.56]	[−2.57]	[−2.55]	[−2.33]	[−2.31]
Call option	0.054**	−0.0020	0.036	0.017	−0.048*	−0.021***	−0.020***	−0.016***	−0.019***	−0.019***
	[2.05]	[−0.07]	[1.33]	[0.81]	[−1.67]	[−4.10]	[−3.23]	[−2.80]	[−3.99]	[−3.46]
PFOF	0.53***	0.52***	0.53***	0.58***	0.59***	0.15***	0.15***	0.15***	0.17***	0.17***
	[10.90]	[11.20]	[10.81]	[10.19]	[10.36]	[4.31]	[4.25]	[4.31]	[5.71]	[5.63]
SLAN	−0.092	−0.13	−0.095	−0.43***	−0.47***	−0.20***	−0.20***	−0.20***	−0.32***	−0.32***
	[−0.67]	[−0.91]	[−0.70]	[−5.58]	[−6.32]	[−3.59]	[−3.51]	[−3.70]	[−6.69]	[−6.78]
Fixed Effects:										
Stock	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Date	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Trader	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Observations	450,811	450,811	450,811	450,811	450,811	450,811	450,811	450,811	450,811	450,811

Table 6. Retail Trading Costs in Options across Trader Types.

This table reports differences between relative effective spreads of signed and unsigned retail trades across trader types. We consider the following groups: traders with a median trade duration lower than one day ("Fast trader"); traders with a median trade size less than \$200 ("Low stakes"); traders with a median trade size greater than \$5,000 ("High stakes"); traders with a median number of trades per month lower than 10 ("Few trades"); and traders with a median number of trades per month greater than 30 ("Many trades"). Signed effective spread is the product of the trade direction and the difference between execution price and the quote midpoint, divided by the quote midpoint, scaled by 100. Unsigned effective spread does not involve the trade direction. Averages and 95% confidence intervals of both quantities are estimates in sub-samples of the following trader characteristics. Specifications control for date fixed effects, and standard errors are clustered by underlying ticker and date, with t-statistics reported in brackets and symbols *, **, ***, reflecting statistical significance given 10%, 5%, and 1% type I error levels, respectively. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

	Fast trader		Low stakes		High stakes		Few trades		Many trades	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Signed	1.104	1.056	0.976	1.371	1.085	0.577	1.063	1.108	1.155	1.014
	[0.914,1.294]	[0.843,1.268]	[0.779,1.173]	[1.127,1.614]	[0.873,1.297]	[0.494,0.659]	[0.863,1.262]	[0.835,1.381]	[0.914,1.395]	[0.831,1.197]
Unsigned	3.42	2.379	2.439	3.174	2.618	2.291	2.563	3.16	2.955	2.402
	[2.849,3.990]	[1.894,2.864]	[1.932,2.946]	[2.542,3.806]	[2.077,3.159]	[1.958,2.625]	[2.044,3.082]	[2.460,3.860]	[2.354,3.556]	[1.916,2.888]
Unsigned/Signed ratio	3.10	2.25	2.50	2.32	2.41	3.97	2.41	2.85	2.56	2.37
Observations	96,474	345,549	341,516	100,507	425,548	16,466	410,050	31,973	163,260	278,763

Table 7. Trading Cost Persistence.

This table shows persistence in retail trading costs. For each investor, we split her trading history into two halves and computed EQ ratio for both periods. Low EQ ratio indicates low execution costs. We then sort traders into portfolios/groups based EQ ratio during the first half of their tenure and report their future EQ ratio and the probability of staying in the same portfolio. A low EQ ratio means low execution costs. Outcome variables underlying EQ ratio are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

Panel A: all trades

Trader EQ Ratio Quintile	Average EQ ratio, 1^{st} half	Average EQ ratio, 2^{nd} half	Prob. of Staying in the Same EQ Ratio Quintile
1, Good	−0.10	0.13	0.51
2	0.22	0.29	0.37
3	0.39	0.40	0.36
4	0.54	0.49	0.37
5, Bad	0.88	0.60	0.52

Panel B: TD trades

Trader EQ Ratio Quintile	Average EQ ratio, 1^{st} half	Average EQ ratio, 2^{nd} half	Prob. of Staying in the Same EQ Ratio Quintile
1, Good	−0.08	0.19	0.55
2	0.22	0.29	0.38
3	0.39	0.41	0.37
4	0.53	0.48	0.35
5, Bad	0.78	0.57	0.51

Panel C: non-TD trades

Trader EQ Ratio Quintile	Average EQ ratio, 1^{st} half	Average EQ ratio, 2^{nd} half	Prob. of Staying in the Same EQ Ratio Quintile
1, Good	−0.11	0.09	0.51
2	0.22	0.28	0.42
3	0.39	0.39	0.35
4	0.55	0.50	0.36
5, Bad	0.95	0.63	0.54

Table 8. Retail Trading Costs in Options by Order Type.

This table reports summary statistics of signed relative effective spreads by order type, decomposing trades conditional on whether adjustment for the effect of aggressive limit orders applies. Panel A, B, and C report statistics for, respectively, all trades, trades reflecting retail marker orders, and trades reflecting retail limit orders. In each panel trades are decomposed based on whether the adjustment accounting for the effect of aggressive limit orders, as described in Subsection 3.4 applies. ATrading-cost measures are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

Panel A: All Retail Trades

				Percentiles						
Trades	Observations	Mean	S.D.	1	5	25	50	75	95	99
All	451,299	1.07	4.88	−8.81	−3.28	−0.38	0.66	1.88	6.74	16.62
Needed Adjustment	95,292	0.54	5.29	−11.57	−3.57	−0.18	0.00	1.01	5.83	17.31
No Adjustment Needed	356,007	1.21	4.76	−8.33	−3.17	−0.41	0.83	2.06	6.90	16.33

Panel B: Retail Trades - Market Orders

				Percentiles						
Trades	Observations	Mean	S.D.	1	5	25	50	75	95	99
All	271,342	2.44	4.60	−0.46	0.00	0.66	1.33	2.74	8.00	19.18
Needed Adjustment	21,055	0.50	5.51	−12.50	−2.80	0.00	0.00	0.84	5.05	15.79
No Adjustment Needed	250,287	2.61	4.48	0.00	0.25	0.75	1.42	2.84	8.33	19.35

Panel C: Retail Trades - Limit Orders

				Percentiles						
Trades	Observations	Mean	S.D.	1	5	25	50	75	95	99
All	179,957	−1.01	4.54	−14.08	−5.88	−1.70	−0.68	0.00	2.67	10.17
Needed Adjustment	74,237	0.55	5.22	−11.32	−3.74	−0.43	0.00	1.05	6.06	17.82
No Adjustment Needed	105,720	−2.11	3.61	−15.58	−6.90	−2.32	−1.16	−0.59	−0.12	0.00

Table 9. Determinants of Order Choice.

This table reports on the cross-sectional determinants of the retail option order type choices. The limit order indicator equals 1 if a buy (sell) retail trade is executed below (above) the quote midpoint and equals 0 otherwise. Each dependent variable is regressed on the following variables: "Depth" measures the cumulative bad- and ask-side depth at the first two levels of order book at the time of trade, in 1,000 contracts; "Volume" is the same-day total option trade volume, in 1,000 contracts, in the underlying security; "Volatility" is the same-day absolute return of the underlying security; "0DTE" is an indicator variable that equals 1 if the trade occurs on the contracts expiration date and equals 0 otherwise; "Moneyness" is the underlying price divided by strike price for call options and as strike price divided by underlying price for put options; "Buy trade" is an indicator variable that equals 1 if the trade is attributable to a retail buyer and equals 0 otherwise. Specifications control for different combinations of underlying symbol, date, and trader fixed effects. Standard errors are clustered by underlying symbol and date, with t-statistics reported in brackets and symbols *, **, ***, reflecting statistical significance given 10%, 5%, and 1% type I error levels, respectively. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

	Dependent variable: Effective Spread				Dependent variable: Limit-order indicator			
Ln(Volume)	−0.38***	−0.41***	−0.29***	−0.38***	−0.027***	−0.017***	−0.014	−0.026***
	[−11.98]	[−11.72]	[−5.34]	[−12.04]	[−11.83]	[−8.40]	[−1.42]	[−8.54]
Depth	0.18***	0.16***	0.16***	0.18***	−0.016***	−0.015***	−0.014***	−0.014***
	[10.39]	[12.70]	[13.83]	[9.94]	[−4.03]	[−6.65]	[−6.54]	[−4.56]
Volatility	2.30***	2.02***	0.99*	2.20***	0.30***	0.24***	0.24***	0.23***
	[4.18]	[4.28]	[1.86]	[3.61]	[4.84]	[5.50]	[3.64]	[3.40]
Buy trade	−0.39***	−0.37***	−0.38***	−0.39***	0.059***	0.054***	0.058***	0.058***
	[−4.15]	[−4.14]	[−4.20]	[−4.18]	[6.20]	[5.74]	[6.19]	[6.14]
0DTE	0.67***	0.59***	0.62***	0.69***	0.014	0.026***	0.0086	0.0063
	[5.72]	[6.03]	[5.65]	[5.04]	[1.51]	[3.72]	[1.00]	[0.63]
Moneyness	−0.016***	−0.014***	−0.010	−0.021***	0.00088***	0.00082***	0.00065***	0.0012***
	[−2.86]	[−2.67]	[−1.61]	[−3.71]	[10.71]	[7.70]	[4.19]	[6.56]
Intercept	6.06***	6.62***	4.89***	6.11***	0.75***	0.61***	0.56***	0.73***
	[13.66]	[13.88]	[6.56]	[14.09]	[21.19]	[21.97]	[4.14]	[18.06]
Fixed Effects:								
Trader	No	Yes	No	No	No	Yes	No	No
Underlying	No	No	Yes	No	No	No	Yes	No
Date	No	No	No	Yes	No	No	No	Yes
Observations	437,979	437,979	437,979	437,979	437,979	437,979	437,979	437,979
Adjusted R-squared	0.021	0.055	0.055	0.024	0.022	0.116	0.033	0.029

Table 10. Retail vs. Control Trades

This table reports on the determinants of retail option trading by comparing retail trades to control trades in the public OPRA data. Each retail trade is matched with five OPRA option trades immediately before and after in the same underlying stock to construct the control sample. We examine three distinct samples: (1) the pooled sample combining retail and control trades, (2) a subsample focused on retail market orders and their corresponding control trades, and (3) a subsample of retail limit orders and their corresponding control trades. The dependent variable is an indicator equal to one for retail trades and zero for control trades. Independent variables include indicators for: SLAN (auction trades), PHLX (trades on PHLX), Single-lot and Round-lot (trade size), 1 Ex@NBBO (one exchange at NBBO), 0DTE (zero-day-to expiration), PFOF (payment for order flow exchanges). We also control effective spreads and underlying symbol, date, and trader fixed effects. Standard errors are clustered by underlying symbol and date, with t-statistics reported in brackets and symbols *, **, ***, reflecting statistical significance given 10%, 5%, and 1% type I error levels, respectively. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

Variable	Share of Trades	All Retail			Retail Market			Retail Limit		
Constant		0.050***	0.049***	0.050***	0.055***	0.053***	0.054***	0.051***	0.049***	0.051***
		[16.24]	[23.90]	[20.75]	[16.52]	[17.01]	[17.87]	[11.95]	[14.83]	[12.84]
SLAN	22.7%	0.015**	0.016**	0.017**	0.019	0.020	0.021	0.012	0.013	0.013
		[2.17]	[2.29]	[2.35]	[1.07]	[1.09]	[1.13]	[0.94]	[0.92]	[1.01]
PHLX	7.2%	0.019***	0.018***	0.019***	0.040***	0.039***	0.039***	−0.0087***	−0.0096***	−0.0090***
		[4.12]	[3.58]	[3.80]	[4.47]	[4.23]	[4.30]	[−3.17]	[−3.79]	[−3.50]
SLAN×PHLX	5.6%	0.052***	0.053***	0.053***	0.042*	0.043*	0.043*	0.069***	0.070***	0.070***
		[3.45]	[3.53]	[3.51]	[1.77]	[1.75]	[1.77]	[16.35]	[18.47]	[17.53]
Single-lot	54.9%	0.065***	0.065***	0.065***	0.072***	0.072***	0.072***	0.059***	0.060***	0.060***
		[22.41]	[25.42]	[23.49]	[24.45]	[26.64]	[25.13]	[13.31]	[16.74]	[14.64]
Round-lot	23.9%	0.035***	0.035***	0.035***	0.034***	0.034***	0.034***	0.040***	0.040***	0.040***
		[13.84]	[14.36]	[14.04]	[13.43]	[13.86]	[13.54]	[9.70]	[10.59]	[10.10]
1 Ex@NBBO	45.0%	−0.0067***	−0.0071***	−0.0069***	−0.035***	−0.035***	−0.035***	0.032***	0.033***	0.033***
		[−6.94]	[−10.39]	[−9.19]	[−5.73]	[−5.91]	[−5.92]	[8.74]	[8.30]	[8.39]
0-DTE	18.1%	0.038***	0.054***	0.041***	0.041***	0.055***	0.043***	0.041***	0.058***	0.043***
		[11.46]	[13.92]	[11.23]	[10.51]	[13.04]	[10.26]	[10.29]	[15.87]	[10.08]
PFOF	35.1%	−0.016***	−0.016***	−0.017***	−0.0036	−0.0033	−0.0043	−0.039***	−0.039***	−0.040***
		[−6.20]	[−6.09]	[−6.53]	[−1.07]	[−0.95]	[−1.25]	[−11.64]	[−11.45]	[−11.68]
Effective Spread (%)	N/A	−0.00035***	−0.00095***	−0.00060***	0.00058*	0.00023	0.00043	−0.0018***	−0.0024***	−0.0020***
		[−2.62]	[−4.45]	[−3.62]	[1.86]	[0.62]	[1.33]	[−11.72]	[−10.06]	[−11.26]
Fixed effects:										
Underlying		No	Yes	No	No	Yes	No	No	Yes	No
Date		No	Yes	No	No	Yes	No	No	Yes	No
Trader		No	No	Yes	No	No	Yes	No	No	Yes
Observations		4,567,772	4,567,772	4,567,772	2,585,244	2,585,244	2,585,244	1,735,799	1,735,799	1,735,799
Adjusted R-squared		0.013	0.015	0.015	0.021	0.022	0.022	0.016	0.017	0.017

A Appendix

Table A.1. Summary of the journal-OPRA merge process.
This table summarizes the number of trades with intraday timestamps matched between trading journal data and OPRA. The first column lists the number of journal trades that can be matched with at least one OPRA trade (by underlying symbol, date, timestamp, strike price, call vs. put indicator, transaction price, and expiration date) and the as well the number of journal trades that cannot be matched with OPRA. Matched trades with missing trade sizes in the journal data or those whose the trade size reported in the journal data differs from that in OPRA are excluded. Remaining journal-to-OPRA matched trades are split into one-to-one matches as well as one-to-many, many-to-one, and many-to-many matches, with the numbers of data rows for each category are reported in the middle column. Only one randomly selected row from each set of duplicates rows corresponding to any of the last three match categories are retained, and the resulting numbers of unique matches corresponding to each category are presented in last column.

Description	Journal data	Raw journal-OPRA merge	Sample without duplicates
Trades matched with OPRA:	746,661	1,323,673	614,980
One journal to one OPRA trade	485,417	485,417	485,417
One journal to many OPRA trades	198,717	747,087	124,701
Many journal to one OPRA trade	22,610	22,612	5,81
Many journal to many OPRA trades	39,917	68,557	4,862
Trades not matched with OPRA	49,238	N/A	N/A
Total - no filter	795,899	1,323,673	614,980
SPX trades	-	-	50,477
Total - with price and other filters	-	-	451,299

Table A.2. Trade Summary Statistics: Control Option Trades.
This table reports summary statistics for 4,178,910 control option trades. Statistics include the total count of trades, mean, standard deviation, and percentiles (1st, 5th, 25th, 50th, 75th, 95th, 99th) to capture distributional characteristics. Key variables are defined as follows: Trade Price reflects the per-contract execution price (options) or per-share price (stocks), in dollars. Trade Size measures the number of contracts (options) or shares (stocks) per trade, while Trade Value calculates the total dollar value of the trade. SLAN is an indicator of whether the trade occurred in a single-leg price improvement auction. Exchanges at NBBO count the number of exchanges quoting the NBBO price when the trade is executed. Moneyness compares an option's strike price to its underlying stock price: for calls, values below one indicate in-the-money (ITM) status, while for puts, values above one denote ITM. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

				Percentiles						
Variable	Count	Mean	St Dev.	1	5	25	50	75	95	99
Trade Price	4,178,910	6.51	21.14	0.14	0.25	0.90	2.05	5.10	24.40	72.80
Underlying Price	4,178,910	403.39	537.85	6.71	21.42	129.91	323.19	422.07	1019.08	3338.50
Trade Size (shares)	4,178,910	538.4	1635.2	100.0	100	100	100	400	2000	6800
Trade Value ($)	4,178,910	2445.6	13291.9	17	39	152	420	1400	8650	33315
SLAN	4,178,910	0.22	0.41	0	0	0	0	0	1	1
# Exchanges at NBBO	4,178,910	4.43	4.32	1	1	1	2	7	14	16
Moneyness Call	2,442,239	0.941	2.024	0.545	0.794	0.951	0.987	0.999	1.039	1.257
Moneyness Put	1,736,628	0.968	0.117	0.590	0.816	0.958	0.989	0.999	1.028	1.185
Days to expiration	4,178,910	21.0	68.6	0	0	1	3	11	86	381
Hour of Day	4,178,863	10.99	1.93	9	9	9	10	12	15	15

Table A.3. Retail Trading Costs in Options: Active Tickers and Brokers Other than TD. This table reports relative bid-ask spreads for retail and control sample option trades.True effective spreads use verified trade direction and are computed as twice the percentage difference between the execution price and pre-trade midquote. The unadjusted version includes cases where retail limit orders set the NBBO, while the adjusted version removes this mechanical effect by using the next best quote. Conventional effective spreads follow standard methodology using inferred trade direction and are always non-negative. For each spread measure, we report the number of observations, mean, standard deviation, and key percentiles of the distribution. Panel A focuses on trades in the ten most actively traded underlying securities, while Pnael B focuses on trades executed by brokers other than TD. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

Panel A: Option trades in top-10 active tickers

				Percentiles						
Retail Sample Spreads (%)	Observations	Mean	S.D.	1	5	25	50	75	95	99
True Effective	319,018	0.77	2.85	−5.41	−2.17	−0.28	0.61	1.52	4.37	8.70
True Effective Unadjusted	319,018	0.58	3.02	−6.40	−2.71	−0.66	0.59	1.50	4.35	8.70
Conventional Effective	319,018	1.75	2.53	0.00	0.23	0.62	1.12	2.02	5.17	10.10
Conventional Quoted	319,018	2.27	3.23	0.24	0.39	0.84	1.46	2.60	6.45	13.63
Control Sample Spreads (%)										
Conventional Effective	2,993,824	1.80	2.83	0.00	0.17	0.55	1.07	2.06	5.71	11.11
Conventional Quoted	2,993,824	2.30	3.55	0.18	0.34	0.78	1.41	2.60	6.90	14.69

Panel B: Option trades executed by brokers other than TD

				Percentiles						
Retail Sample Spreads (%)	Observations	Mean	S.D.	1	5	25	50	75	95	99
True Effective	212,884	1.07	4.91	−9.09	−3.24	−0.29	0.68	1.89	6.70	16.22
True Effective Unadjusted	212,884	0.69	5.13	−11.94	−4.51	−0.83	0.62	1.81	6.45	15.38
Conventional Effective	212,884	2.57	4.44	0.00	0.23	0.70	1.36	2.82	8.40	20.00
Conventional Quoted	212,884	3.70	6.08	0.26	0.43	1.03	1.94	3.98	12.30	28.57
Control Sample Spreads (%)										
Conventional Effective	1,018,581	2.69	4.97	0.00	0.20	0.67	1.36	2.94	8.70	21.84
Conventional Quoted	1,018,581	3.60	6.15	0.20	0.38	0.96	1.85	3.91	11.76	28.57

Table A.4. Retail Trading Costs in Stocks: Active Tickers.

This table reports relative bid-ask spreads for retail stock trades. True effective spreads use verified trade direction and are computed as twice the percentage difference between the execution price and pre-trade midquote. These can be negative when retail traders supply liquidity. Conventional effective spreads follow standard methodology using inferred trade direction and are always non-negative. For each spread measure, we report the number of observations, mean, standard deviation, and key percentiles of the distribution. The sample includes stocks with the most retail option activity. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

				Percentiles						
Retail Sample Spreads (%)	Observations	Mean	S.D.	1	5	25	50	75	95	99
True Effective	156,060	0.00	0.72	−1.84	−1.20	−0.21	0.01	0.22	1.17	1.85
Conventional Quoted	156,060	0.05	0.15	0.00	0.00	0.01	0.02	0.05	0.19	0.55

Table A.5. Retail Trade Summary Statistics and Trading Costs: SPX.
This table reports summary statistics and trading costs for 50,477 option trades associated with SPX. Statistics include the total count of trades, mean, standard deviation, and percentiles (1st, 5th, 25th, 50th, 75th, 95th, 99th) to capture distributional characteristics. Characteristic variables, reported in Panel A, are defined as follows: Trade Price reflects the per-contract execution price (options) or per-share price (stocks), in dollars. Trade Size measures the number of contracts (options) or shares (stocks) per trade, while Trade Value calculates the total dollar value of the trade. SLAN is an indicator of whether the trade occurred in a single-leg price improvement auction. Exchanges at NBBO count the number of exchanges quoting the NBBO price when the trade is executed. Moneyness compares an option's strike price to its underlying stock price: for calls, values below one indicate in-the-money (ITM) status, while for puts, values above one denote ITM. Trading cost measures, reported in Panel B, are defined as follows: True effective spreads use verified trade direction and are computed as twice the percentage difference between the execution price and pre-trade midquote. The unadjusted version includes cases where retail limit orders set the NBBO, while the adjusted version removes this mechanical effect by using the next best quote. Conventional effective spreads follow standard methodology using inferred trade direction and are always non-negative. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

Panel A: Contract and trade characteristics

				Percentiles						
Variable	Count	Mean	St Dev.	1	5	25	50	75	95	99
Trade Price	50,477	8.79	15.22	0.07	0.15	1.17	3.20	9.18	39.06	80.13
Underlying Price	50,477	4021.89	304.29	3254.05	3639.31	3830.83	3965.48	4203.36	4571.93	4703.25
Trade Size (shares)	50,477	304.3	1362.8	100.0	100	100	100	200	1000	2000
Trade Value ($)	50,477	2899.9	10768.0	7	20	144	440	1500	12100	48078
SLAN	50,477	0.09	0.29	0	0	0	0	0	1	1
# Exchanges at NBBO	50,477	1.00	0.00	1	1	1	1	1	1	1
Moneyness Call	23,271	0.990	0.017	0.908	0.970	0.988	0.994	0.998	1.002	1.007
Moneyness Put	27,206	0.977	0.073	0.636	0.907	0.983	0.992	0.997	1.002	1.008
Days to expiration	50,477	5.6	27.3	0	0	0	0	0	15	179
Hour of Day	50,441	11.76	2.09	9	9	10	11	14	15	15

Panel B: Trading costs

				Percentiles						
Retail Sample Spreads (%)	Count	Mean	S.D.	1	5	25	50	75	95	99
True Effective	50,477	9.92	148.42	−237.74	−210.53	−13.33	0.36	152.00	225.81	300.00
True Effective Unadjusted	50,477	2.23	11.88	−22.22	−8.00	−1.14	0.91	3.70	15.38	66.67
Conventional Effective	50,477	5.51	10.78	0.00	0.00	0.99	2.53	5.34	20.00	66.67
Conventional Quoted	50,477	9.63	17.42	0.63	1.05	2.37	4.55	8.70	40.00	66.67

Table A.6. Retail vs. Control Trades: Univariate Analysis

This table reports on the determinants of retail option trading by comparing retail trades to control trades in the public OPRA data. Each retail trade is matched with five OPRA option trades immediately before and after in the same underlying stock to construct the control sample. We examine three distinct samples: (1) the pooled sample combining retail and control trades, (2) a subsample focused on retail market orders and their corresponding control trades, and (3) a subsample of retail limit orders and their corresponding control trades. The dependent variable is an indicator equal to one for retail trades and zero for control trades. Independent variables include indicators for: SLAN (auction trades), PHLX (trades on PHLX), Single-lot and Round-lot (trade size), 1 Ex@NBBO (one exchange at NBBO), 0-DTE (zero-day-to expiration), PFOF (payment for order flow exchanges). Standard errors are clustered by underlying symbol and date, with t-statistics reported in brackets and symbols *, **, ***, reflecting statistical significance given 10%, 5%, and 1% type I error levels, respectively. All outcome variables are winsorized at 0.1% and 99.9% each day. The sample period is form January 2020 to December 2022.

	Panel A: all retail, all control						
Constant	0.093***	0.095***	0.074***	0.10***	0.10***	0.092***	0.098***
	[66.43]	[112.86]	[48.07]	[66.06]	[72.09]	[31.33]	[85.70]
SLAN	0.027***						
	[3.02]						
PHLX		0.055***					
		[9.65]					
Single-lot			0.045***				
			[18.09]				
Round-lot				−0.010***			
				[−3.77]			
1 Ex@NBBO					−0.0061***		
					[−8.97]		
0-DTE						0.036***	
						[9.99]	
PFOF							0.0032
							[0.61]
	Panel B: retail market, corresponding control						
Constant	0.095***	0.099***	0.076***	0.11***	0.12***	0.098***	0.096***
	[19.33]	[58.93]	[54.13]	[84.30]	[28.19]	[34.29]	[24.05]
SLAN	0.042**						
	[1.99]						
PHLX		0.082***					
		[7.50]					
Single-lot			0.053***				
			[18.25]				
Round-lot				−0.016***			
				[−5.23]			
1 Ex@NBBO					−0.037***		
					[−5.12]		
Date-0						0.039***	
						[9.10]	
PFOF							0.024*

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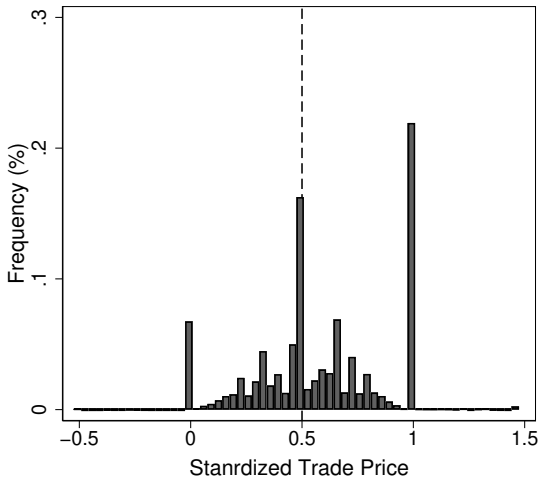
Table A.6 – *continued from previous page*

							[1.95]
	Panel C: retail limit, corresponding control						
Constant	0.10***	0.10***	0.083***	0.10***	0.086***	0.097***	0.11***
	[46.55]	[126.24]	[56.34]	[100.14]	[26.59]	[43.40]	[78.81]
SLAN	0.0059						
	[0.55]						
PHLX		0.016*					
		[1.94]					
Single-lot			0.038***				
			[14.67]				
Round-lot				−0.0027			
				[−0.88]			
1 Ex@NBBO					0.036***		
					[6.68]		
Date-0						0.037***	
						[9.54]	
PFOF							−0.030***
							[−6.68]

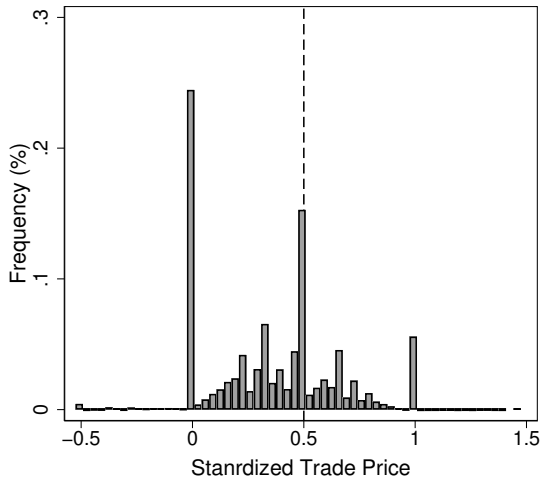
Figure A.1. Normalized Transaction Prices of Retail Option Trades: Conditional on the Number of Exchanges at NBBO.

The figure presents the distribution of execution price within the quoted spread. Normalized transaction price is defined as the actual transaction price minus the corresponding best bid price, divided by the bid-ask spread.

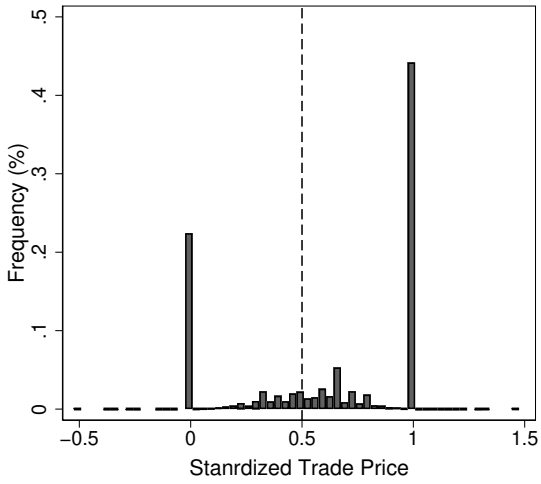
Panel A: Buy trades, one NBBO exchange



Panel B: Sell trades, one NBBO exchange



Panel C: Buy trades, multiple NBBO exchanges



Panel D: Sell trades, multiple NBBO exchanges

