Retail Limit Orders [*]

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Abstract

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Abstract

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JEL Classification: G14, G18, G24

Keywords: Retail investors, market orders, limit orders, broker handling, trading cost.

1. Introduction

Academic evidence suggests that retail traders typically do not have access to the same tools and order routing choices as are available to institutional traders.[1] Since the onset of the COVID-19 pandemic, retail trading in U.S. equity markets has grown substantially, drawing increased academic attention to order handling practices and trading costs of retail orders. Recent research has primarily examined the execution quality of marketable orders placed by retail traders. Retail brokerages generally allow their customers to use limit orders, but these orders have received less attention in empirical studies.[2]

A well-developed theoretical literature examines the trade-offs between marketable and limit orders. Marketable orders are a simple order type that execute immediately at the best available price but pay the bid-ask spread. Limit orders offer the potential for better execution prices but risk not being executed if the market does not reach the specified limit price, resulting in missed trading opportunities (see Handa and Schwartz (1996) and Parlour (1998), among others). Using NYSE audit trail data from 1990-91, Harris and Hasbrouck (1996) find that limit orders placed at or better than the prevailing quote incur lower trading costs compared to marketable orders. Subsequent studies from international markets find similar results.[3] Overall, the evidence suggests limit orders are an important tool in traders' strategies. Notably, these studies are based on the entire order flow in the market, encompassing all types of traders, not just retail traders, because the data do not allow for the identification of retail and non-retail orders separately.

In this study, we focus specifically on retail traders in US equities markets – their use of marketable and limit orders, the execution outcomes of their orders, and how their orders are handled.[4] This focus is

[1] For discussions on the differences in trading resources and brokerage practices between retail and institutional traders, see Harris (2003), Battalio, Corwin, and Jennings (2016), and Boehmer, Jones, Zhang, and Zhang (2021).
[2] For ease of exposition, we use "marketable orders" to refer to market orders and marketable limit orders, and "limit orders" to refer to nonmarketable limit orders in this paper. Nonmarketable limit orders are not executable at the time they are received by the broker based on the opposite National Best Bid or Offer quote, whereas marketable orders (including market and marketable limit) are executable at the time of order receipt.
[3] For example, Biais, Hillion and Spatt (1995) study order choice on the Paris Bourse, Griffiths, Smith, Turnbull and White (2000) on the Toronto Stock Exchange, Ahn, Bae and Chan (2002) on the Hong Kong market, Ranaldo (2004) on the Swiss Stock Exchange, and Bessembinder, Panayides and Venkataraman (2009) on Euronext.
[4] We identify retail orders using a combination of identifiers associated with orders and the brokers who handle these orders in FINRA Order Audit Trail System (OATS) data. Specifically, we classify orders as retail based on the "held" order designation and the "individual" account type, along with a broker classification process that allows us to identify retail order flow. We discuss the data more fully in Section 3.

important for several reasons. First, it is important to understand the execution quality of retail limit orders, as it remains unclear whether they are an attractive choice for retail traders in today's US equity markets, where high frequency trading plays a dominant role.[5] Given the conventional wisdom that retail investors are generally less likely to be sophisticated traders, a limit order trading strategy – which typically requires active monitoring and quickly responding to market conditions – may be less effective in a market where speed offers a significant advantage.[6]

Second, Battalio, Corwin and Jennings (2016) raise concerns that retail traders might not control where their limit orders are routed, and some brokers' routing practices could reduce the chances of these orders being executed. On the other hand, the US regulatory framework has implemented order handling rules and intermarket linkages designed to protect limit orders. These protections can help retail traders obtain better executions and earn compensation for providing liquidity using limit orders.[7]

Third, there are no existing studies that provide a comprehensive analysis of U.S. retail traders' use of marketable and limit orders. This gap in research is likely due to the lack of suitable data to distinguish retail orders from non-retail orders. Public trading databases, such as Trade and Quote (TAQ) data for U.S. equities, do not specifically identify retail trades. While Boehmer, Jones, Zhang, and Zhang (2021, BJZZ) propose a method to classify retail marketable orders in TAQ data, no similar methodology exists for identifying retail limit orders in public data. Recent studies have also raised concerns about the accuracy of the BJZZ classification method.[8]

We analyze the FINRA Order Audit Trail System (OATS) data to understand the benefits and costs of marketable and limit orders for retail traders. The OATS database includes detailed information on orders

[5] Biais, Foucault and Moinas (2015) and Pagnotta and Philippon (2018) describe the current market structure characterized by speed and fragmentation.
[6] Copeland and Galai (1983) highlight the importance of monitoring limit orders, viewing them through an option-like framework.
[7] Examples of limit order protections in the current regulatory system include FINRA Rule 5320, which prohibits market makers from trading ahead of customer orders; SEC Rule 604 and FINRA Rule 6460, which require display of quote matching and improving limit orders; and SEC Rule 611, which prohibits trade-throughs, protecting limit orders at the top of each exchange's limit order book. We discuss the regulation of limit orders in Section 2.2.
[8] Barber, Huang, Jorion, Odean, and Schwarz (2023) note that the BJZZ method may capture only a portion of marketable retail trading. Battalio, Jennings, Saglam, and Wu (2023) further point out that BJZZ identified trades may include non-retail trading.

received by brokers from their clients (henceforth "top orders"), including the identity of the broker, and the venue-specific routing decisions. It also captures venue-specific outcomes, such as executions and traded prices, and the time stamps associated with each routing, modification, execution, or cancellation decision in an order's life cycle. FINRA member firms were required by FINRA rules to report all activity in equities (orders, routes, cancellations and executions) to OATS; as a result, OATS data are more comprehensive and free from the selection bias that can affect data obtained from a subset of industry participants.[9] We study a sample of over 27 million top orders arising from individual account holders of 19 active retail brokers during May 2020.[10] The sample is based on a size-stratified selection of 300 stocks, with 100 each from large, medium and small-cap categories.

Limit orders are a significant portion of retail investors' order flow in our sample, representing 30% of submitted shares, 25.5% of submitted orders, and 18.5% of executed shares in our sample. Limit order usage persists across stock size categories with a slightly higher proportion in small capitalization stocks. We find that retail limit orders incur lower trading costs than retail marketable orders, even after controlling for other key determinants.

Notably, 74% of retail limit orders are placed behind the best quotes (i.e., buy orders priced below the best bid and sell orders priced above the best ask). These orders achieve significantly higher fill rates than previously reported for the overall market and incur lower trading costs than more aggressively priced orders.[11] Additionally, retail limit orders tend to remain open in the market for extended periods, unlike the fleeting limit orders documented in Hasbrouck and Saar (2009). This longer duration increases their likelihood of being filled, consistent with Lo, Mackinlay and Zhang (2002).

This study adds to the literature by providing new evidence on the importance and execution quality of retail limit orders in the US equity markets. The cost advantages of retail limit orders over marketable

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[9] Einav and Levin (2014) and Card, Chetty, Feldstein and Saez (2010) advocate for the use of such administrative data in economic analyses.
[10] We identify retail orders by combining order-specific identifiers with information about the brokers handling the orders. We describe the identification procedure in section 3.
[11] For example, Li, Ye and Zheng (2023) report fill rates lower than 3% on the NYSE. In our sample, even retail limit orders placed away from the NBBO quotes exhibit an average fill rate of 50%.

orders align with theoretical predictions, with limit orders performing better when spreads are wider, volatility is higher, and in smaller stocks. Our results suggest that retail traders can benefit from using limit orders as a way to earn compensation for supplying liquidity. The results on order duration, fill rates, and trading costs indicate that retail limit orders are effective not despite retail traders being slower, but likely *because* they avoid the rapid placements and cancellations that dominate the broader market.

We analyze the trading costs of retail orders using the implementation shortfall (IS) approach outlined in Perold (1988) and used by Harris and Hasbrouck (1996) and Griffiths et al. (2000). The IS measure captures two key components: the transaction cost (effective spread) for the executed portion of the order and the opportunity cost for the unfilled portion. Compared to transaction level databases such as TAQ, the OATS dataset provides detailed order lifecycle information, allowing us to track price movements over the life of an order and calculate opportunity costs of non-execution. Opportunity costs arise when the market price moves away from the limit price, requiring the trader to place a market order after cancelling the limit order. In these cases, the trader incurs both the cost of price drift during the order's lifecycle and the bid-ask spread at the time of cancellation for executing unfilled shares.

To evaluate execution quality, we compare the trading costs of retail limit orders against retail marketable orders, which serve as a natural benchmark since both order types are widely available to retail traders through their brokers. This comparison is particularly relevant given recent research, which shows that retail marketable orders often receive favorable executions, as market makers frequently provide significant price improvement over the best available quotes.[12]

To compare execution quality of retail marketable and limit orders, our main regression specification includes stock-day fixed effects, enabling comparisons within the same stock on the same day. We also present results with broker fixed effects to account for potential differences across brokers, such as routing practices, clientele profile and frictions (e.g., web or app interface quality) that might influence

[12] See, for example, Battalio and Jennings (2023), Brown, Johnson, Kothari and So (2024), Dyhrberg, Shkilko and Werner (2023) and Ernst and Spatt (2022).

limit order usage.[13] We account for order-specific characteristics and intraday market conditions by controlling for order size and the bid-ask spread at the time the order is received. To further account for trading intentions and market conditions, we include a combined stock, five-minute time-interval, trade-direction fixed effect, thus comparing trading costs for marketable and limit orders submitted under similar conditions-specifically buy or sell orders in the same stock within a 5-minute window.

Across all specifications, trading costs of limit orders are approximately 10 basis points lower than for marketable orders; a sizable difference given that the average marketable order IS is 1.1 basis points. We also examine factors from the literature that could affect the cost advantage of limit orders. We find that the limit order cost advantage is larger when quoted spreads are wider (consistent with Cohen, Maier, Schwartz and Whitcomb (1981) and Foucault (1999)) and when realized volatility is higher (consistent with Handa and Schwartz (1996) and Foucault (1999)). In the cross-section, the trading costs of retail limit orders are approximately 20 basis points lower than retail marketable orders in smaller stocks, reflecting the higher compensation for providing liquidity in less liquid markets. We examine limit orders by their price aggressiveness and find that the cost advantage of limit orders is economically small for within-quote and at-quote limit orders. It increases to around five basis points for behind-the-quote limit orders within five times the quoted spread and reaches approximately 22 basis points for orders placed even further behind the quote.

The trading cost advantage of retail limit orders is likely linked to their notably higher fill rate. In large and medium stocks, retail limit orders exhibit a 65% fill rate, and for small stocks, the fill rate is only slightly lower at 60%. Even limit orders placed behind-the-quote more than five times the quoted spread achieve an average fill rate of 50%. These higher fill rates help lower IS by reducing the opportunity costs associated with unfilled shares in limit orders.

Survival analysis highlights order duration as a key factor in explaining these higher fill rates since execution probability increases with time. Using a Kaplan-Meier estimation with execution as the censoring

[13] For example, Fong, Gallagher and Lee (2014) find differences among clients of full service and discount brokers.

event, we examine how cancellation probabilities of limit orders change over time. Unlike the millisecond duration typical for most limit orders in the market, we find that more than 60% of retail limit orders remain open after 10 minutes. The least aggressive orders are the most patient, with more than 50% of these orders remaining open one hour after submission. As a point of comparison, a similar analysis in Hasbrouck and Saar (2009) shows that 60% of all limit orders in their market-wide sample were cancelled within 10 seconds, and 98.4% within 10 minutes. This stark difference highlights how retail limit orders behave differently from broader market trends, staying open much longer and increasing their chances of execution.

Overall, while limit orders require more monitoring, involve setting order parameters, and do not offer the immediacy benefits of marketable orders, our results suggest that they provide an attractive choice for retail traders willing to be patient and supply liquidity. Notably, behind-quote retail limit orders achieve the lowest trading costs, contrasting with earlier studies based on market-wide data, which found that limit orders placed at the prevailing quote typically had lower trading costs. One possible reason for this difference is that previous studies included institutional and professional traders in their analysis of aggregated market data, while we focus specifically on retail traders. Institutional orders are often part of larger trading programs, which can create significant price impact, causing price drift and reducing the execution probability of linked behind-quote limit orders. In contrast, retail traders typically place smaller orders with minimal price impact, making behind-quote orders more effective. Additionally, professional traders, especially high frequency traders, tend to operate on very short time horizons, unlike the longer order durations observed for retail traders in our analysis.

We examine how our sample of retail brokers handle limit and marketable orders. Nearly all retail marketable orders are routed to market makers, who primarily execute these orders in a principal capacity (i.e., acting as the counterparty to the orders received). In contrast, about 11% of retail limit orders are routed to exchanges, with the remaining 89% sent to market makers. Among the limit orders routed to market makers, approximately 31% of the executed shares are filled directly by the market maker on a principal basis, about 64% are executed as riskless principal, where the market maker sources liquidity from other market participants, and about 4% are executed in agency capacity. We find that a higher proportion of principal fills is associated with a statistically lower, but economically similar, IS for retail limit orders.

2. Related Literature and Market Regulation

2.1. Related Literature

A large body of research has studied retail investors from the perspectives of market participation, asset allocation, portfolio diversification and trading behavior (see Campbell (2006) and Gomes, Haliassos, and Ramadorai (2021) for surveys). However, there has been much less research on how retail investors place orders and implement their trading decisions.

Recent studies have primarily focused on the execution quality of U.S. retail marketable orders, highlighting differences in trading costs across brokers (Schwarz, Barber, Huang, Jorion, and Odean (2023)) and the routing of retail orders by brokers to market makers (Dyhrberg, Shkilko and Werner (2023), Huang, Jorion, Lee, and Schwarz (2023), and Ernst, Malenko, Spatt, and Sun (2024)). Dyrhberg et al. (2023) use Rule 605 data, which provides execution quality statistics for marketable orders, while Battalio and Jennings (2023) and Schwarz et al. (2023) analyze proprietary datasets that also focus on marketable orders. In contrast, our dataset includes both marketable and nonmarketable orders arising from individual accounts of 19 active U.S. retail brokerages. This allows us to assess the role of limit orders for retail traders and compare their use to marketable orders.

Kelley and Tetlock (2013) analyze a proprietary trading dataset identifying marketable and nonmarketable orders from two wholesalers between 2003 to 2007. They find that retail limit order imbalances follow negative daily and intraday returns, suggesting that limit orders respond to liquidity shocks, while retail marketable orders trade with momentum and predict news about firm's cash flows. Other studies (e.g., Kaniel, Saar and Titman (2008); Kaniel, Liu, Saar and Titman (2012)) use the NYSE consolidated audit trail data and show that the intensity of retail buying and selling activity predicts future stock returns and earnings. Using detailed Finnish data, Linnainmaa (2010) finds that individual investors' trades tend to have poor post-trade performance, and that the adverse selection associated with pricecontingent limit orders shows up in the data as consistent with behavioral biases attributed to individual investors in the literature. Our study differs by focusing on execution quality outcomes and broker handling across a broad sample of retail marketable and limit orders in the current US equity market structure.

Battalio, Corwin and Jennings (2016) study how retail brokers handle limit orders and show that some brokers route these orders to exchanges that pay rebates for limit orders. Using proprietary data on institutional orders, they find that limit orders routed to such exchanges have worse outcomes compared to orders routed to exchanges that charge fees for limit order executions. Our analysis differs in several important ways. We examine all retail limit orders arising from individual accounts for a broad sample of retail brokers. Our dataset provides a comprehensive view of the order lifecycle, tracking each order from the time it is received by the broker to its final resolution. This allows us to calculate detailed execution quality metrics, including fill rates and implementation shortfalls. We find that retail limit orders achieve higher fill rates than those reported in market-wide statistics and result in lower trading costs compared to retail marketable orders. Additionally, unlike prior research, our data include orders that are routed to exchanges as well as to market makers, allowing us to show that brokers route the majority to market makers, with a significant portion executed by market makers in a principal capacity.

Our analysis is guided by the rich literature on the use of marketable and limit orders in equity markets. Early theoretical models, such as those by Demsetz (1968), Cohen et al. (1981), and Copeland and Galai (1983), highlight the trade-offs between market and limit orders. Parlour and Seppi (2008) provide a comprehensive review of the various models of limit order markets. On the empirical side, studies such as Harris and Hasbrouck (1996) and Griffiths et al. (2000)) find that at-the-quote limit orders are both the most commonly used and the best-performing order type.

We contribute to this literature by examining the execution quality of retail traders' limit orders and comparing them to marketable orders in the current market structure, where the speed of trading may pose challenges for retail traders. Our findings offer a useful comparison to earlier studies. For example, we find that current fill rates for retail limit orders remain comparable to those reported by Harris and Hasbrouck (1996), possibly because retail traders tend to leave their orders open for longer durations.

However, unlike older studies, we find that behind-the-quote orders have the lowest IS and are the most frequently used type among retail limit orders in our sample.

2.2. Regulatory structure around customer limit order display and handling

Retail limit order display and handling is governed by a combination of SEC and FINRA rules. Our analysis shows that brokers route most retail limit orders to market makers. SEC Rule 604 requires market makers to publicly display the full size and price of a customer limit order in an NMS stock under the following conditions: if it would improve the market maker's bid or offer price, or if the customer limit order is priced equal to the market maker's bid or offer or the NBBO and the order represents more than a de minimis size change. FINRA Rule 6460 establishes similar requirements for customer limit orders in OTC Equity Securities. These requirements are designed in part ensure that customer limit orders that would receive priority are exposed to the markets.

The market maker can fulfill this requirement by sending the order immediately to an exchange or another venue that displays the order. A market maker can also fulfill this requirement by submitting principal order linked to or representing the customer order ("representative order) to an exchange or another venue that displays the order, and then filling the customer order at the same price when the representative order executes (a "riskless principal" trade). In our analysis, we find that approximately two-thirds of limit order executions occur on such a riskless principal basis.

Further, FINRA Rule 5320 requires that a FINRA member who accepts and holds a customer order in an equity security cannot execute a trade on the same side of the market for its own account at a price that would satisfy the customer's order without first filling the customer order. If the market maker does trade for its own account at a price that would have satisfied the customer order, it must immediately execute the customer order at the same or better price and up to the size at which it traded for its own account.[14]

In addition, SEC Rule 611 is designed in part to protect the best priced limit orders (referred to as "protected quotations") in NMS stocks at all automated trading centers from being traded through, thus

[14] SEC Rule 604, FINRA Rule 6460 and FINRA Rule 5320 all provide for certain exceptions. See, for example, https://www.finra.org/rules-guidance/rulebooks/finra-rules/5320 for details.

establishing price priority across venues. Customer limit orders, or equivalent displayed limit orders, benefit from this protection.

3. Data and sample description

The primary dataset used in this study is the FINRA OATS database for the month of May 2020.[15] All broker dealers that buy and sell securities on behalf of customers in the United States are required to be registered with the SEC and be members of a registered securities association (currently, FINRA). As FINRA members, they are obliged to report relevant activities to the FINRA audit trail.[16] For each broker-level order ("top order") received from a customer, OATS provides information detailing how the broker handled the top order. The dataset combines a unique broker identifier, the customer ("beneficiary owner") type, the submitted quantity, and the order type, with the audit trail of routes, venues, executions, modifications, and cancellations associated with the order's lifecycle.

Our retail order classification combines identifiers in the data more likely to be associated with retail investors, and further conditions on the brokers who handle the customer orders. We use the beneficiary owner classification field from OATS, which indicates whether an order arises from an account representing institutional, individual, market maker, or proprietary interest.[17] We focus exclusively on orders marked as originating from individual customer accounts.[18] We also consider the "not-held" order handling code in OATS. SEC (2018) notes that not-held orders, where the broker has price and time discretion in handling the order, are typically associated with institutional customers; thus, individual customer orders are more likely to be "held".

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[15] The OATS system has since been replaced by the Consolidated Audit Trail (CAT). Due to this transition, May 2020 is the last month of data available for our analysis. Anand et al. (2021) provide a detailed description of the OATS data. The OATS data used by this study are similar to those underlying the statistics created by FINRA for the tick size pilot program. More details are available at http://www.finra.org/industry/tick-size-pilot-program.

[16] FINRA was responsible for the regulation of 3,435 member firms in 2020 (https://www.finra.org/rules-guidance/guidance/reports-studies/2021-industry-snapshot/firm-data#firms1).

[17] This field can also be marked as "unknown", "null", "error" and "employee".

[18] FINRA rule 4512 (c) defines institutions as a "bank, savings and loan association, insurance company or registered investment company; an investment adviser registered either with the SEC under Section 203 of the Investment Advisers Act or with a state securities commission (or any agency or office performing like functions); or any other person (whether a natural person, corporation, partnership, trust or otherwise) with total assets of at least $50 million." Customer orders that do not meet the criteria of the rule are classified as individuals.

Using this set of orders, we identify 19 large retail brokerage firms that meet the following criteria: (a) a majority of the broker's customer orders are marked as arising from individual accounts; (b) at least 90% of the orders from individual accounts are held orders; and (c) the broker handles at least 100,000 held top orders arising from individual accounts in our sample stocks during May 2020. These criteria result in a final sample of 19 active, retail brokers.[19]

To maintain the anonymity of the regulatory data, our analyses are conducted across the entire sample of 19 firms, not at the level of the brokerage firm or a smaller subgroup of firms. For the median broker in our sample, 99% of the customer (individual plus institutional) orders are marked as arising from individual accounts, and 100% of individual account orders are held orders. Our analysis is based on the sample of held, individual orders received by these 19 brokers.

The stock sample consists of a size-stratified group of 300 exchange-listed stocks traded in May 2020, a recent month when the project was initiated.[20] We focus on common stocks (CRSP share codes 10 and 11) with a share price between \$5 and \$10,000. To select the 300 stocks, we form size terciles based on market capitalization in CRSP at the end of April 2020 and select the largest 100 stocks from each tercile that match with the OATS and TAQ databases.

To construct NBBO quotes, we consider NBBO quotes from the TAQ NBBO and Quote files and remove slow or opening quotes (i.e., those with conditions 'A','B','H','O','R','W'). We additionally remove cancelled quotes, those without prices, quotes with non-positive share quantity, quotes corresponding to locked and crossed markets, and quotes with percentage bid-ask spreads exceeding 10%.

We apply several data filters to refine the sample with three main objectives: ensuring trading costs can be accurately measured (e.g., excluding orders where multiple top orders are merged or orders that have more than one top order); identifying a representative sample of typical retail orders (e.g., limiting to orders

[19] Analogous to our approach, Griffin, Harris and Topaloglu (2003) and Anand et al. (2021) use brokerage firm characteristics to identify trader types.

[20] Market volatility, measured by the VIX, peaked at 83 on March 16, 2020, but declined significantly throughout April. By May 2020, the VIX ranged between 27 to 37, providing a more stable market for our analysis.

below 5,000 shares)[21]; and removing potential data errors (e.g., excluding orders with an execution time two or more seconds before submission). Detailed description of the filters and the number of remaining top orders after applying the filters are provided in the Appendix. Further, we winsorize the execution cost measures at the 0.1 and 99.9 percentile levels.

Our final sample includes over 27 million marketable and limit orders placed through individual accounts held at the identified retail brokers. These orders total more than 4.1 billion shares submitted and over 3.5 billion shares traded. Table 1, Panel A, reports the stock characteristics by size tercile. As expected, large stocks have higher stock prices and higher trading volumes compared to medium and small stocks. The average bid-ask spread at order arrival for large, medium and small stocks are two, nine and 15 basis points, respectively.

Figure 1 presents the proportion of limit orders in the sample, the proportion of shares submitted via limit orders, and the proportion of executed shares traded through limit orders. Table 1, Panels B and C, presents the corresponding numbers. For the full sample, limit orders account for approximately 25.5% of orders, representing 30% of shares submitted and 18.5% of shares traded. These proportions are fairly consistent across large, medium and small stocks. In additional (unreported) results, we find that, unlike the broader U.S. equity market, which features a proliferation of order types (Li, Ye, and Zheng, 2021), retail traders in our sample predominately use marketable and limit orders, which together comprise approximately 90% of all retail orders.[22]

Table 1, Panel B, shows that retail limit orders are larger (average of 182 shares) than marketable orders (average of 145 shares). The median order sizes are smaller but show the same trend – 25 shares for

[21] As a robustness check, we use an alternative threshold of $200,000 consistent with the discussion in SEC (2022). Our inferences are unchanged with this alternative filter.

[22] It is interesting to compare our sample with Linnainmaa (2010), where limit orders comprise 76% of all orders. Linnainmaa (2010) also finds that more than 25% of limit orders remain open for more than a day, whereas in our sample, such orders are less common (approximately 6%). This difference is likely because most US brokers set day orders as the default option, meaning orders automatically expire at the end of the trading day. It may also reflect differences in investor behavior and institutional practices between Finland and the US.

limit orders and 16 shares for marketable orders. Table 1, Panel C shows that our sample is heavily skewed towards the 100 large stocks, which accounts for about 93% of orders and 90% of submitted shares.

4. Execution quality of marketable and limit orders

4.1. Outcomes, univariate results

Table 2 presents execution quality statistics for marketable and limit orders in our sample. Panel A shows results for the full sample, while Panel B presents results by size tercile. The statistics represent average values across all orders within each category.

We present the fill rate, calculated as the filled quantity divided by the submitted quantity for each top order.[23] Marketable orders almost always execute, with an average fill rate close to 100%. In contrast, limit orders have a lower fill rate of 65%. These results align with the market-wide fill rates from previous studies. Harris and Hasbrouck (1996) reported a 44% fill rate in in the early 1990s NYSE data, and Jeria and Sofianos (2008) found 43% fill rates for institutional orders.

However, the fill rates that we find for retail limit orders are significantly higher than the market-wide fill rates of less than 3% reported by Li, Ye and Zheng (2021) for orders on the NYSE. Market-wide fill rates include proprietary and market making orders. A recent analysis by Mackintosh (2020) found that customer orders on Nasdaq had 54% fill rates for displayed at-the-quote orders. Panel B shows that fill rates are consistent across large and medium size terciles, averaging around 65%. For small stocks, the fill rate is slightly lower at 60%, but still relatively high.

Next, we present *Effective spreads*, which are measured for a top order as:

$$\text{\textit{Effective spread}}_i = \frac{P_{1(i)} - P_{0(i)}}{P_{0(i)}} \times D_i, \qquad (1)$$

where $P_{1(i)}$ is the share volume-weighted execution price of the top order, $P_{0(i)}$ is the benchmark price, defined as the NBBO bid-ask quote midpoint when the broker receives the top order from retail client, and

[23] In unreported results, we find that using an alternative fill rate measure which captures the percentage of orders that receive any execution yields almost identical estimates. This is because retail limit orders are typically small and tend to either fill completely or not at all. Less than 0.5% of retail limit orders in our sample receive partial fills.

$D_{(i)}$ is a variable equal to 1 for buy orders and -1 for sell orders (Huang and Stoll (1996)). Table 2, Panel A shows that marketable orders have an average effective spread of 1.04 basis points for the full sample. Panel B breaks this down by stock size terciles, showing averages of 0.7, 3.4 and 7 basis points for large, medium and small stocks. As expected, effective spreads are negative for limit orders, reflecting the cost advantage of liquidity provision, and average negative 20.2 basis points for the full sample. Panel B of Table 2 further shows averages of negative 18.5, negative 39, and negative 52.1 basis points for large, medium and small stocks, respectively.

Effective spreads do not account for the opportunity cost of unexecuted limit orders. If the market price moves away – rising for a buy limit order or falling for a sell limit order – the trader may eventually have to execute the order later, potentially at a less favorable price. The IS approach addresses this by imputing an execution for orders with fill rates below 100%, reflecting the opportunity cost of the unfilled portion of the order (see Perold (1988) and Wagner and Edwards (1993)). The IS approach also assumes that the trader is committed to filling the entire top order (Harris and Hasbrouck (1996), Griffiths et al. (2000)). Following this framework, we calculate the IS for a top order as follows:

$$\textit{Implementation Shortfall}_i = \left[f_i \times \frac{P_{1(i)} - P_{0(i)}}{P_{0(i)}} \times D_i\right] + \left[(1 - f_i) \times \frac{IP_{(i)} - P_{0(i)}}{P_{0(i)}} \times D_i\right], \quad (2)$$

where f_i is the *fill rate* of the top order, $IP_{(i)}$ is the imputed price for the unfilled portion of the order, and all other variables are as previously defined. In equation (2), the first term captures the effective spread from equation (1) for the portion of the order that gets filled, while the second term accounts for the opportunity cost of the unfilled portion.

The literature has used different prices for $IP_{(i)}$ to estimate this opportunity cost, such as the closing price (Keim and Madhavan (1997) and Conrad, Johnson and Wahal (2001)), the volume weighted average price during a window after the order is cancelled (Jeria and Sofianos (2008)), and the opposite quote at the end of the order's life cycle (that is, $IP_{(i)}$ is the ask quote for buy orders and the bid quote for sell orders at the time of the last event in the order's life cycle). The opposite quote method (used in Harris and Hasbrouck (1996) and Handa and Schwartz (1996)) applies the largest opportunity cost for the unfilled portion of the top order as it includes both the price drift during the order's lifecycle and the quoted spread at the time of cancellation.

In our analysis, we use the opposite-side quote at the end of the top order's lifecycle as the imputed price. This approach reflects a simple trading strategy for retail traders, who are likely to cancel a limit order and place a marketable order if the market moves unfavorably. For top orders that expire at the close, we use the closing price on the submission day as the imputed price.[24]

Table 2, Panel A shows that limit orders bear significant opportunity costs due to non-execution. The opportunity costs for unexecuted shares in retail limit orders is approximately 16 basis points. The IS, which accounts for these opportunity costs, is negative eight basis points. As described above, the IS is the weighted average of the effective spreads and the opportunity costs, and, in this analysis, the high fill rates imply lower IS due to the lower effective spreads.

The IS for limit orders is approximately nine basis points lower than marketable orders' IS, which averages 1.1 basis points. Panel B further breaks down these results by stock size, showing that limit orders have lower IS than marketable orders across all size terciles. The trading cost difference is about eight basis points for large stocks, 18 basis points for medium stocks, and 21 basis points for small stocks. This indicates that retail traders benefit the most from using limit orders in small stocks, which typically are associated with wider bid-ask spreads and there is a greater reward for supplying liquidity.

4.2. Outcomes, regression analysis

One possible reason for the higher trading costs of marketable orders is that retail traders tend to use limit orders in certain types of stocks. Figure 1 shows that limit orders account for a higher proportion of submitted shares in smaller stocks. Another possible explanation is that retail traders may use market orders and limit orders under different market conditions. In this section, we analyze execution quality differences while controlling for stock characteristics, order attributes, and market conditions. This more

[24] Results are similar when we use the opposite quote as the imputed price for all orders (including the orders that expire at the close).

detailed regression-based analysis offers two potential interpretations. If differences in execution quality are driven by the types of stocks or conditions where the orders are placed, it suggests that retail traders are choosing marketable or limit orders appropriately for the situation, resulting in similar outcomes once these factors are accounted for. However, if differences persist even after accounting for stocks and market conditions, it could indicate that some retail traders may benefit from being more patient with their trades.

The comparison between marketable and limit orders may be affected by differences in stocks traded, the trading day chosen for placing the orders, and the market conditions at the time of the trade. Table 3 examines the relation between retail order type and execution quality using a regression framework that accounts for these differences based on the following model:

$$IS_i = \beta_1 Marketable_i + \beta'\mathbf{X} + FE + \epsilon_i, \qquad (3)$$

where IS_i represents the implementation shortfall for order i. The key variable of interest, *Marketable*, is equal to one if an order is a marketable order and zero if it is a limit order. **X** is a vector of control variables that includes the log of order size and the arrival percentage NBBO quoted spread. Order size accounts for the well-established relationship between order size and increased execution difficulty. The arrival-time spreads account for variations in market conditions throughout the trading day, which can influence execution quality.

Table 3 reports the regression results with stock-day fixed effects, allowing for a direct comparison of the execution quality of marketable and limit orders within the same stock on the same day. Test statistics are based on standard errors clustered by stock and day to account for potential correlation in trading patterns. In column (1), the positive coefficient on *Marketable* indicates that IS for marketable orders is about 9.4 basis points higher than for limit orders, and this difference is highly statistically significant. Column (2) presents the results with control variables, showing that IS increases with order size and arrival-time spreads. However, the trading cost difference between marketable and limit orders remains largely unchanged, suggesting that these differences are not simply due to order size or market conditions.[25]

Next, we examine whether factors identified in the prior literature influence the execution quality difference between retail marketable and limit orders. For institutional orders, Keim and Madhavan (1995, 1996) found that buy orders are more likely to be informationally motivated than sell orders. This result could be potentially relevant for our analysis if more informed retail traders systematically prefer either marketable or limit orders. To investigate this, we estimate the following model:

$$IS_i = \beta_1 Marketable_i + \beta_2 C_i + \beta_3 Marketable_i * C_i + \beta'\mathbf{X} + FE + \epsilon_i, \quad (4)$$

where C_i in column (3) is represented by an indicator variable *Sell,* which equals one for a sell order and zero for a buy order. The other variables are as described earlier. The coefficient β_2 tests whether there is a difference in execution quality between sell and buy orders, while the coefficient β_3 tests whether the execution cost difference between marketable and limit orders varies depending on order direction. The results in column (3) do not show evidence of buy-sell asymmetry, as both regression coefficients associated with *Sell* variable are statistically insignificant.

In columns (4) and (5) of Table 3, we examine how bid-ask spreads and volatility potentially affect the appeal of marketable and limit orders. Cohen et al. (1981) and Foucault (1999) suggest that limit orders should be more attractive when spreads are wider. Handa and Schwartz (1996), Foucault (1999), and Ahn et al. (2001) suggest that higher volatility makes limit orders more attractive compared to marketable orders. In column (4), C_i represents the arrival percentage NBBO quoted spread, while in column (5), C_i is the stock-day volatility for the previous trading day, measured as the square root of the sum of prior day five-minute squared quote-midpoint returns. Model 5 includes an interaction between *volatility* and *Marketable$_i$*, but does not include volatility directly, as it is subsumed by stock-day fixed effects.

[25] SEC (2022) suggests that market makers may treat limit orders placed between the opposite quote and the quote midpoint similar to marketable orders and trade with these orders. We note that within-quote limit orders are a small part of our sample. However, we repeat our analysis after removing limit orders placed between the quote midpoint and the opposite quote. Our inferences are unaffected by this filter.

In both columns, the interaction coefficients are positive and statistically significant. These results support theoretical predictions, showing that retail limit orders have lower IS than marketable orders when spreads are wider and volatility is higher. In terms of economic significance, a one standard deviation increase in quoted spreads raises the IS of marketable orders relative to limit orders by three basis points. Similarly, a one standard deviation increase in volatility leads to a relative increase in IS of 2.65 basis points for marketable orders.

Lastly, column (6) examines execution quality differences across stock size terciles. The indicator variable *Small-Med* equals one for small or medium stocks and zero for large stocks. The positive and significant interaction coefficient on *Small-Med* and $Marketable_i$, indicates an incremental effect of 11.7 basis points in trading costs. This finding suggests that the cost advantage of retail limit orders over marketable orders is greater in small and medium stocks, consistent with liquidity providers earning greater compensation in less liquid markets.

4.3. Outcomes, robustness analyses

Differences across brokers could influence our results if certain broker resources favor marketable or limit orders (e.g., online trading platforms or app features) or if there are significant differences in the clienteles they serve. Fong et al. (2014) find that the informativeness of retail order flow varies by broker type, while Schwarz et al. (2023) document variations in execution quality for marketable orders across brokers. To account for these differences, we add broker fixed effects to our benchmark stock-day fixed effects model from Table 3, column (2). Table 4, column (1), shows that adding broker fixed effects increases the model's explanatory power from 3.3% to 4.2%, indicating that broker-related factors provide useful information. However, the overall patterns remain the same -- the IS of retail limit orders remains lower, by approximately 11 basis points, than that of retail marketable orders.

Another possible explanation for our results is that more sophisticated retail traders may primarily use limit orders, while less sophisticated traders may favor marketable orders. If limit orders are placed strategically by more sophisticated traders at times when it is more beneficial to do so, this could explain the observed cost advantage of retail limit orders. To test this possibility, we match marketable and limit orders placed on the same side (buy or sell) of the market at similar times, dividing each trading day into five-minute intervals. We construct a fixed effect combining the stock, the five-minute interval for a given day, and the buy/sell trade direction to match marketable and limit orders under similar conditions. The results in Table 4, column (2), show that even with this detailed matching, retail limit order still have an IS that is approximately nine basis points lower than marketable orders. Adding broker fixed effects in column (3) slightly increases the difference to 10 basis points.

To further examine differences in trader sophistication, we analyze five-minute intervals with and without limit orders. Since marketable orders are much more common in our sample, many five-minute periods contain only marketable orders and are without any limit orders. If more sophisticated traders are more likely to use limit orders, then periods containing limit orders might represent less favorable conditions for marketable orders (i.e., marketable orders are less likely to be associated with sophisticated traders in these periods). In contrast, periods without limit orders may include marketable orders from both more sophisticated and less sophisticated traders. Following this logic, we would expect marketable orders to have higher IS in periods that include limit orders compared to those without.

In Table 4, columns (4) and (5), we compare the IS of marketable orders submitted during five-minute intervals that include limit orders with those placed in intervals without limit orders. We use stock-day and stock-day plus broker fixed effects while controlling for order size and arrival-time spreads, with standard errors clustered by stock and day. The results show no significant difference in IS for marketable orders between periods with and without limit orders. This suggests that the mix of more and less sophisticated traders within marketable orders is similar in both types of periods.

4.4. Limit orders, by price aggressiveness

Building on the broader analysis of marketable and limit orders, we examine the placement strategy of retail limit orders by dividing them into four categories, similar to Biais et al. (1995): orders placed within the NBBO quotes; orders placed exactly at the NBBO quote (e.g., buy orders at the best bid); orders placed behind the NBBO but within five times the prevailing spread at the time the broker receives the order; and orders placed even further behind the NBBO quote.

Panel A of Table 5 and Figure 2 presents how retail limit orders are distributed by price aggressiveness, showing that retail traders place their limit orders across the price spectrum. An unexpected finding is that most retail limit orders are placed behind the NBBO quotes, with about 40% within five times the spread and another 34% even further behind. This differs from Harris and Hasbrouck (1996), who found that at-the-quote limit orders were most frequently used in the overall NYSE market during their sample period. Given today's fast-moving markets, the less aggressive placement strategy we document may help retail traders avoid their orders becoming marketable upon arrival at the broker or venue.

To better understand behind-the-quote orders, we examine how close they are to the best quoted price. We find that 50% of orders placed within five times spread are placed within 0.06% of the best bid (for buy orders) and best ask (for sell orders), while 50% of orders placed further behind (more than five times the spread) are within 0.44% of the best quoted price. Similarly, 75% of orders within five times the spread are within 0.12%, while those placed even further behind are within 1.03% of the best quoted price.

To provide more context for far-behind-the-quote orders, we compare their price placement relative to stock volatility. We scale how far behind the quote an order is by using the most recent 30-minute price range as well as by prior day realized volatility, which we calculate as the square root of the sum of squared five-minute returns. Our results show that 50% of orders placed more than five times the spread behind the quote are within 44% of the prior 30-minute price range and 23% of the prior day volatility. 75% of these orders fall within 94% of the 30-minute price range and 50% of prior day volatility. This suggests that retail limit orders placed far-behind-the-quote orders are comparable to recent prices observed in the stock.

We further explore whether retail traders prefer round numbers when setting prices for behind-the-quote limit orders. Prior research, including Harris (1991) and Ikenberry and Weston (2007), suggest that investors tend to favor certain numbers, such as nickels and dimes post-decimalization, leading to price clustering. This effect may be even more pronounced for retail behind-the-quote orders, as retail investors may be more likely to exhibit this behavioral preference and they have greater control over the price of behind-the-quote orders. That is, the pricing for at the quote orders is determined by the current best bid and ask prices, which are likely to be more influenced by professional traders and overall market dynamics. We use at-the-quote limit orders as the benchmark price clustering that exists in the markets and compare behind-the-quote order pricing to see if a round number preference plays a bigger role in these orders.

Figure 3, Panel A plots the proportion of at the quote, behind-the-quote within five times spread, and behind-the-quote more than five times spread orders that are priced in quarter-dollar increments. Consistent with Harris (1991), we find that orders placed at whole numbers are the most common, followed by orders ending in 50 cents. Compared to at-the-quote orders, far behind-the-quote orders are much more likely to be placed at these round values. Notably, about 18% of orders placed within five times the spread and 36% of orders placed more than five times the spread cluster at whole numbers, compared to less than 5% for at-the-quote orders.

Figure 3, Panel B plots clustering at the second decimal place of an order's price. As expected, at-the-quote orders cluster at zero and five, reflecting the round-number preference documented in prior studies. For example, about 20% of at-the-quote orders cluster at nickels (zeros in the plot). This pattern is even stronger for behind-the-quote orders, where 41% of orders within five times the spread and 60% of orders more than five times spread cluster at nickels. These findings suggest that retail traders employ some simple heuristics in setting the price for behind-the-quote orders.

Placing less aggressive limit orders comes with the tradeoff that they are less likely to execute and potentially incur larger opportunity costs. Harris and Hasbrouck (1996) found that limit orders placed at the prevailing quote have lower IS. To investigate whether similar patterns hold for retail traders, we next examine execution quality across categories of price aggressiveness.

Table 5, Panel A, shows that, as expected, fill rates decrease as limit orders become less aggressive. However, fill rates remain relatively high even for limit orders placed behind-the-quote. Orders placed within five times the NBBO spread fill 68.4% of their submitted shares, while those placed further behind the NBBO still achieve 50% fill rates. For limit orders placed further behind the NBBO quotes, the high fill rates increase the contribution of the executed portion of the order, and this portion is associated with significantly negative effective spreads. This also reduces the contribution of the unfilled portion, which incurs opportunity costs. Panel A shows that retail limit orders placed within five times the spread have trading costs about five basis points lower than marketable orders, while those placed further behind achieve trading costs about 21 basis points lower.

Table 5, Panel B, presents regression results that includes stock-day and broker fixed effects. The analysis covers four categories of price aggressiveness, with each column including all marketable orders and the limit orders that fall into a given category. To compare the IS of marketable and limit orders, we use the indicator variable *Marketable*, which equals one for marketable orders and zero for limit orders. Test statistics are calculated with standard errors clustered by stock and day.

In columns (1) and (2), the coefficient on *Marketable* is positive and statistically significant but economically small, indicating a trading cost difference of less than one basis point. This suggests that retail limit orders placed at or within the NBBO achieve execution quality similar to marketable orders. In column (3), the *Marketable* coefficient shows that IS for marketable orders is about five basis points higher than limit orders placed behind the NBBO but within five times the spread. The difference becomes more pronounced in column (4), where the IS for marketable orders is nearly 22 basis points higher than for limit orders placed more than five times the spread behind the NBBO.

As discussed earlier, the execution cost advantage of limit orders is linked to their fill rates. To understand how retail limit orders in our sample obtain high fill rates, we examine order duration in Table 6. One way to improve fill rates is to leave limit orders open for a longer time. Handa and Tiwari (1996) suggest that as market prices fluctuate, the chances of the limit price being reached increases over time. Higher volatility increases the likelihood of execution, and this probability improves as order duration increases. However, keeping an order open longer also comes with a trade-off – if the price drifts further away from the limit order, the opportunity cost of a non-executed order increases.

Panel A of Table 6 presents the average time to execution and order duration for retail orders. As expected, retail marketable orders execute quickly, with an average time difference between order placement and execution of just three seconds. In contrast, retail limit orders remain open much longer. The average duration of limit orders, including both executions and cancellations, is 1,252 seconds, while the average time to execution is 952 seconds. In unreported results, we find that retail limit orders in smaller stocks tend to have longer average duration. Duration also varies inversely with price aggressiveness: for limit orders placed within the NBBO quotes, duration averages 40 seconds; those placed at the NBBO quote average 106 seconds; those placed within five times the spread average 507 seconds; and those placed further behind the NBBO quotes average 3,014 seconds.

Average durations do not account for the truncation that occurs due to executions. Thus, we follow Hasbrouck and Saar (2009) in presenting the cumulative cancellation probabilities of retail limit orders over time in Figure 4, Panel A and Table 6, Panel B. These results are based on survival probabilities using the Kaplan-Meier estimation where an execution of the limit order is treated as a censoring event. The cancellation probabilities are calculated as one minus the survival probability. Across all retail limit orders, 7.4% are cancelled within 10 seconds, 39.2% within 10 minutes, and 56% within one hour. By comparison, Hasbrouck and Saar (2009) highlight the phenomenon of fleeting limit orders in market wide data, showing that 60% of limit orders are canceled within 10 seconds, 98.4% within 10-minutes, and 99.7% within one hour. This comparison shows that retail traders keep their limit orders open for much longer durations than the typical limit order in the broader market, where fleeting orders are common in high frequency strategies.

Additionally, Table 6, Panel B shows that less aggressive limit orders have lower cancellation probabilities. For example, 27% of retail limit orders placed within the NBBO quotes are cancelled within 10 seconds, compared to just 2.5% for orders placed further behind the NBBO quotes. Similarly, 69% of retail limit orders placed within the NBBO quotes are cancelled within 10 minutes, while only 29% of those placed further behind the NBBO quotes are cancelled within the same time frame. These results suggest that retail traders exhibit greater patience with less aggressive limit orders, which leads to higher fill rates compared to market-wide statistics. Figure 4, Panel B plots execution probabilities, calculated using a model where cancellations are the censoring events. The results show that execution probabilities increase significantly over time for the less aggressive retail limit orders.

5. Retail limit order handling

While there is a growing literature on the handling and execution quality of retail marketable orders, relatively little attention has been given to how brokers handle retail limit orders.[26] Table 7, Panel A presents statistics on the routing and execution of both marketable and limit orders for retail brokers in our sample. Our sample focuses on orders routed either to market makers or exchanges, so, the proportion not routed to market makers is directly routed by the brokers to exchanges.

Table 7, Panel A shows that nearly all retail marketable orders - 99.8% of orders and 99.9% of shares – are routed to market makers. 89% of retail limit orders, representing 87% of submitted shares, are also routed to market makers, while the remaining 11% are sent to exchanges. Of the executed shares, market makers execute 99.9% of marketable order shares and about 83% of limit order shares.

Market makers can execute limit orders using liquidity sourced from other venues, including exchanges. Specifically, market makers can execute trades on a Principal or Riskless Principal basis. In Principal trades, the market maker acts as the counterparty to the retail order, taking the traded shares into its own account. In Riskless Principal trades, the market maker first executes an equivalent trade elsewhere (e.g., on an exchange) before filling the retail order at the same price.

The OATS data provide information on these execution types, which we use in our analysis.[27] The last column in Table 7, Panel A shows that market makers execute approximately 90% of marketable shares as Principal trades, with the remaining 10% executed as Riskless Principal trades. For retail limit orders, the pattern is different. About 33% of shares are executed as Principal trades, while the majority, 67%, are

[26] Battalio and Jennings (2023), Brown, Johnson, Kothari and So (2024), Dyhrberg, Shkilko and Werner (2023) and Ernst and Spatt (2022) examine price improvement offered to retail marketable orders by market makers. Schwarz, Barber, Huang, Jorion and Odean (2023), Huang, Jorion, Lee and Schwarz (2023) and Ernst, Malenko, Spatt and Sun (2024) focus on the broker monitoring of market maker price improvement.

[27] FINRA Notice to members 99-65 (https://www.finra.org/rules-guidance/notices/99-65) clarifies the use of Riskless Principal transactions. The guidance notes that, "Because Market Makers generally trade exclusively from a principal account, it is necessary to engage in two separate principal trades: one with the other market participant, and then another directly with the customer."

executed on a Riskless Principal basis.[28,29] Thus, while market makers execute fewer limit orders as Principal trades than marketable orders, principal executions still constitute a substantial portion of retail limit order executions.

We also examine whether the proportion of limit order executions classified as Principal varies by the price aggressiveness of limit orders. Table 7, Panel B, shows that Principal executions are more likely for more aggressive limit orders. Specifically, 36% of executed shares from limit orders placed within the NBBO quote and 41% of shares from at-the-quote limit orders are executed as principal trades. In contrast, the proportion of Principal executions declines to 28% for behind-the-quote orders within five times the spread, and 27% for limit orders further behind the NBBO quotes.

Table 8 presents a regression analysis examining whether the proportion of Principal executions for an order is related to the order's IS. Only executed orders are categorized as Principal or Riskless Principal, while unfilled orders remain unclassified. Therefore, this analysis focuses on the sample of limit orders routed to market makers that result in executions. To the extent that executed orders differ from unexecuted orders, it is challenging to generalize the results for this analysis to all retail limit orders. Further, market makers choose when to act as Principal, which introduces endogeneity. For example, they may prefer trades with lower cost of liquidity provision, or they may fill difficult orders to maintain broker relationships. If market makers selectively act as Principal for orders they favor, then orders routed for potential Riskless Principal execution may have lower fill rates and higher IS. To mitigate these concerns, we compare limit orders within the same price aggressiveness categories, since fill rates and execution outcomes often relate to order aggressiveness. Specifically, we estimate the following model to examine the relationship between principal executions and IS:

[28] These calculations exclude a small fraction of executed shares that are handled on an agency basis by market makers. In our sample, agency trades are mostly restricted to limit orders contributing approximately 4% of all executed shares. For marketable orders, the corresponding proportion is 0.2%. Including agency orders, 31% of shares in limit orders are executed as Principal and 64% as Riskless Principal by market makers. Given the small magnitudes of agency orders, we focus our attention on Principal and Riskless Principal executions in subsequent analysis.

[29] We are unable to calculate similar statistics for order routes since our data only identify executions as Principal or Riskless Principal.

$$IS_i = \beta_1(\frac{P}{P+R})_i + \beta'\mathbf{X} + FE + \epsilon_i, \tag{6}$$

where IS_i is the implementation shortfall for order *i*. The variable of interest, *P/(P+R)*, is the proportion of order *i*'s execution that occurs with the market maker acting as Principal. Other variables are defined as before. We include broker fixed effects and stock-day-aggressiveness fixed effects, allowing us to compare limit orders within the same price aggressiveness category for the same stock on the same day. Additionally, we include stock-day-aggressiveness-buy/sell fixed effects, which further account for order direction.

The results in Table 8 indicate that limit orders with a higher proportion of Principal executions have lower IS. While the estimate is statistically significant, the economic magnitude is small: increasing the proportion of Principal executions 0% to 100% reduces IS costs by approximately 0.34 basis points in model (4). This effect is far smaller than the nine to 10 basis point IS difference observed earlier between marketable and limit orders. It is difficult to isolate the exact mechanism driving this difference, as it is unclear whether market makers improve IS by offering better executions or simply select easier orders to execute. However, two cautious conclusions can be drawn from this analysis. First, Principal executions by market makers do not appear to be associated with higher trading costs. Second, the choice between Principal and Riskless Principal execution has only a minor effect on the trading costs of retail limit orders.

4. Conclusion

We examine the handling and execution quality of retail limit orders. These orders have received less attention in the literature compared to retail marketable orders. Limit orders account for a significant portion of retail order flow, comprising 25.5% of orders and 30% of shares traded. Retail traders use limit orders across stocks of all sizes and levels of price aggressiveness. Unlike market-wide patterns documented in earlier studies, retail limit orders are more often placed behind the best quotes, with a substantial proportion placed far behind the NBBO. This behavior may reflect retail traders' limitations in monitoring markets and responding quickly. Additionally, retail limit orders placed at or near the best quotes may become marketable by the time they reach the market center, leading retail traders to place orders further behind the quotes to avoid immediate execution.

Retail limit orders perform well, achieving an average fill rate of 65%. Even orders placed far behind the quotes fill, on average, 50% of their intended shares. To evaluate execution quality, we use implementation shortfall, which accounts for the opportunity costs of unfilled orders. Our results consistently show that retail limit orders have lower implementation shortfalls than marketable orders, even after controlling for stock characteristics, broker effects, order attributes and market conditions.

Retail limit orders remain open much longer periods than typical market-wide limit orders, with an average duration exceeding 1,200 seconds. Less aggressive orders have even longer durations, averaging more than 3,000 seconds. This suggests that retail traders exhibit greater patience with less aggressively priced limit orders and are rewarded with higher fill rates compared to market-wide statistics.

Our findings suggest that limit orders provide retail trades with an attractive way to reduce trading costs by being patient and supplying liquidity, though they require additional effort to monitor. Customer limit orders benefit from protections under current market rules, including order handling and trade-through regulations, which may contribute to higher execution quality for retail limit orders. Recent regulatory changes may impact how retail marketable orders are handled. For example, the recently adopted revisions to Rule 605 in SEC (2024) extends reporting requirements to broker dealers to improve the transparency of execution quality for internalized retail marketable trades. These changes could improve the execution quality of retail marketable orders and potentially shift the tradeoffs that we identify in this study.

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Figure 1
Nonmarketable Limit Order Statistics

This table reports statistics on retail marketable (market and marketable limit) and nonmarketable limit orders for a size-stratified sample of 300 stocks during in May 2020. We present the percentage of total orders (blue bars), shares submitted (orange bars), and shares executed (gray bars) for the full sample and by stock size tercile.

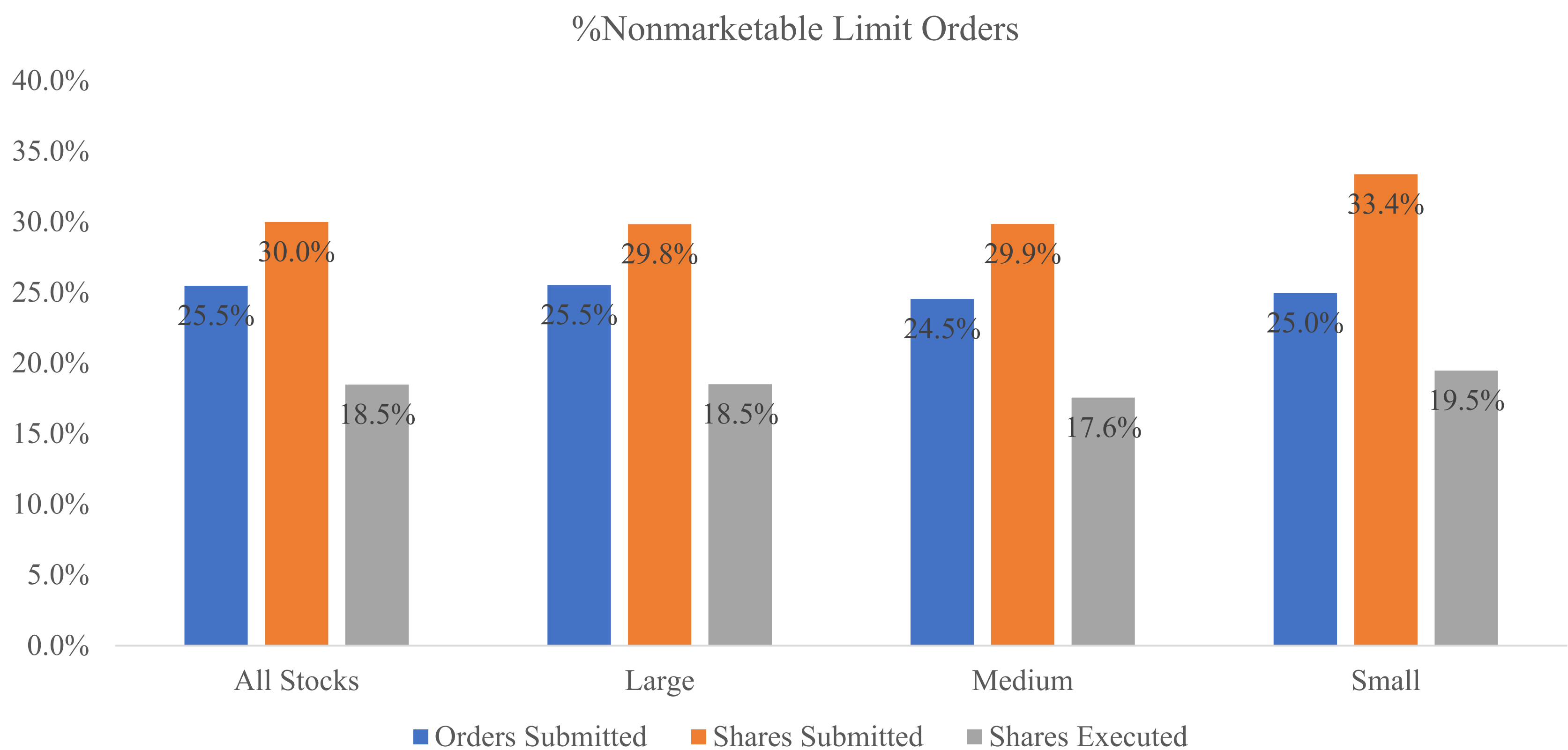


Figure 2
Limit Order Usage by Aggressiveness Level

This figure reports the proportion of limit orders submitted in different aggressiveness categories. We report the proportions of the number of top orders submitted (blue bars), total share quantity submitted (orange bars), and total shares executed (gray bars) for each aggressiveness category. We separate nonmarketable limit orders into: orders with a limit price within the NBBO, at the passive NBBO side price (bid for buy orders, ask for sell orders), behind the passive quote by an amount less than or equal to 5 times the prevailing spread, and behind the passive quote by an amount greater than 5 times the prevailing spread.

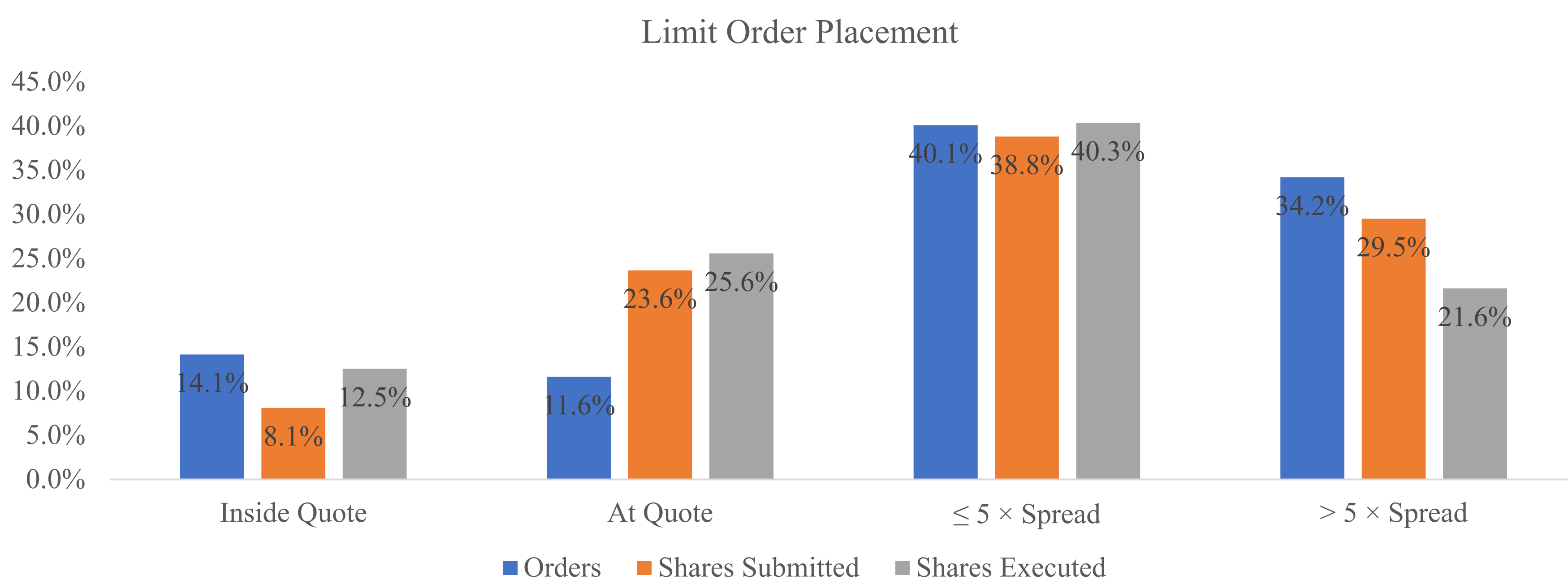
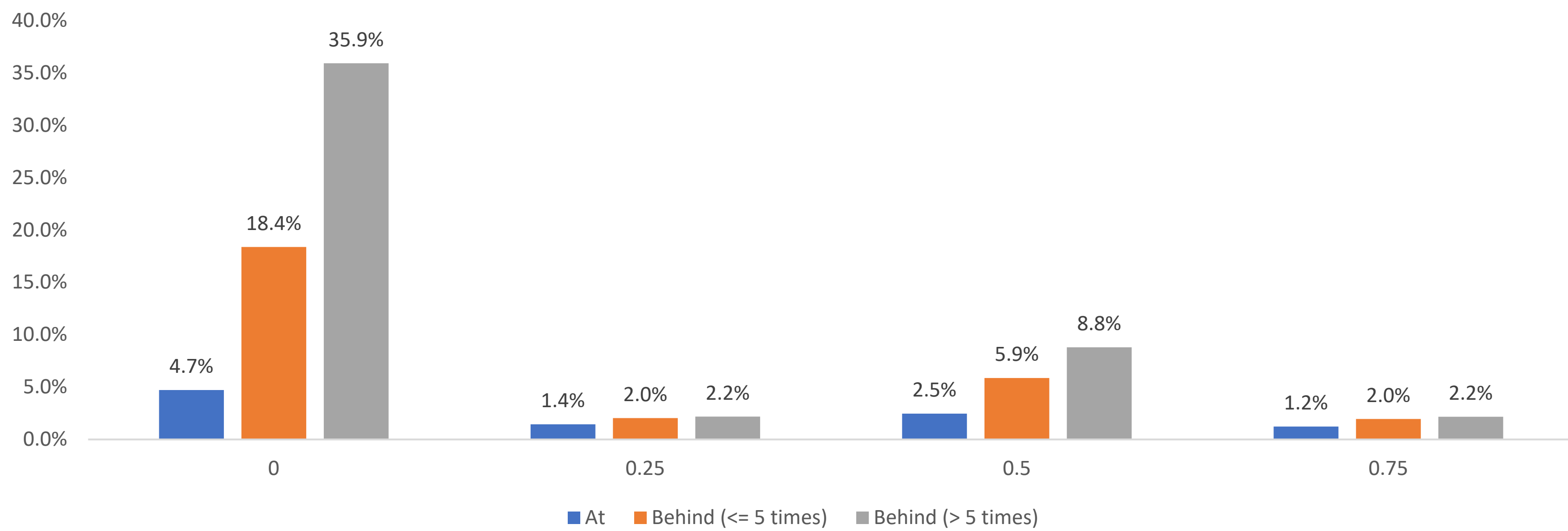


Figure 3
Price clustering of limit orders

This figure reports the clustering of limit orders at different price increments. We report the proportions for at the quote (blue bars), behind the quote within five times spread (orange bars), and behind the quote more than five times quoted spread (gray bars). Figure A presents the proportion of limit orders submitted at quarters. Figure B presents the proportions aggregated by the last digit (second decimal) of the limit order price.

Panel A: Price distribution -- quarters



Panel B: Price distribution – last digit (second decimal)

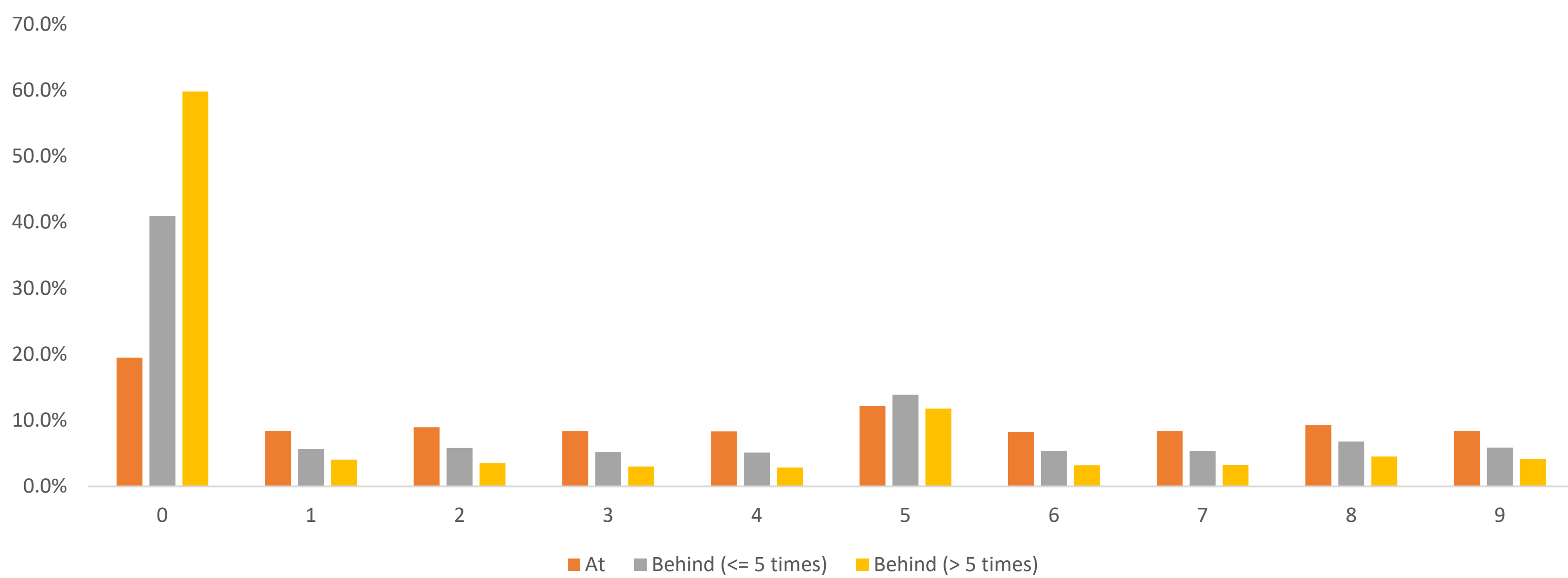
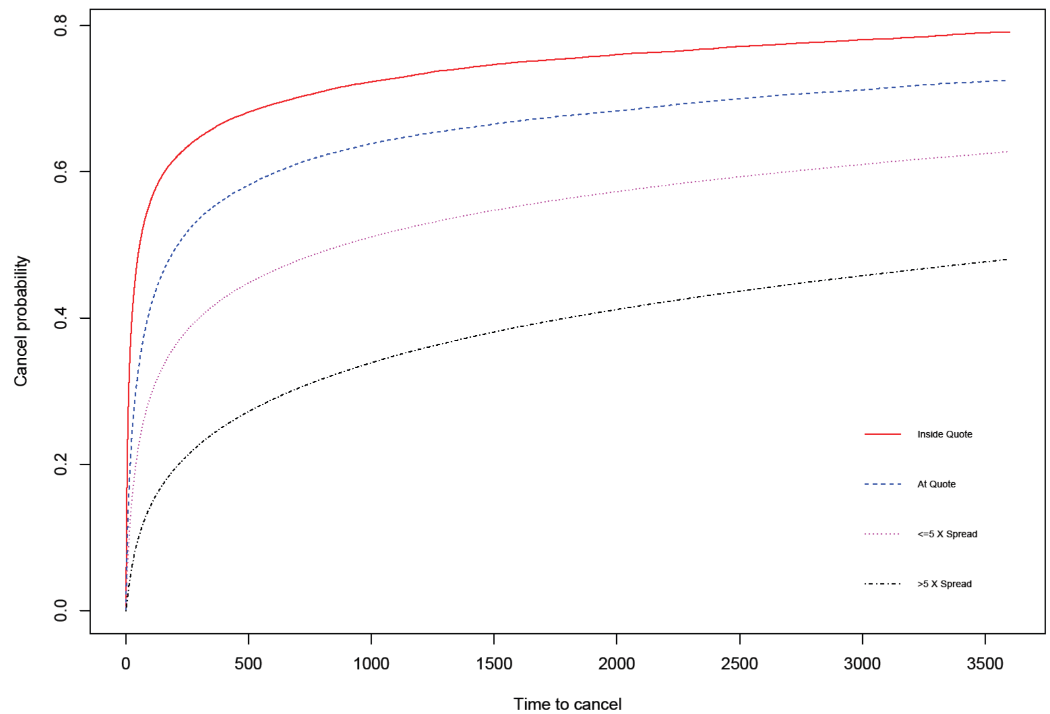


Figure 4
Cumulative Limit Order Cancellation and Execution Probability

This figure uses survival analysis to plot cumulative cancellation probability in Panel A and cumulative execution probabilities in Panel B for limit orders by order aggressiveness categories. The plotted probabilities are one minus the survival probabilities. We present Kaplan-Meier estimates. For cancellation probabilities, execution is the censoring event. For execution probabilities, cancellation is the censoring event. The estimates are based on our limit order sample in May 2020.

Panel A: Cumulative cancellation probability



Panel B: Cumulative execution probability

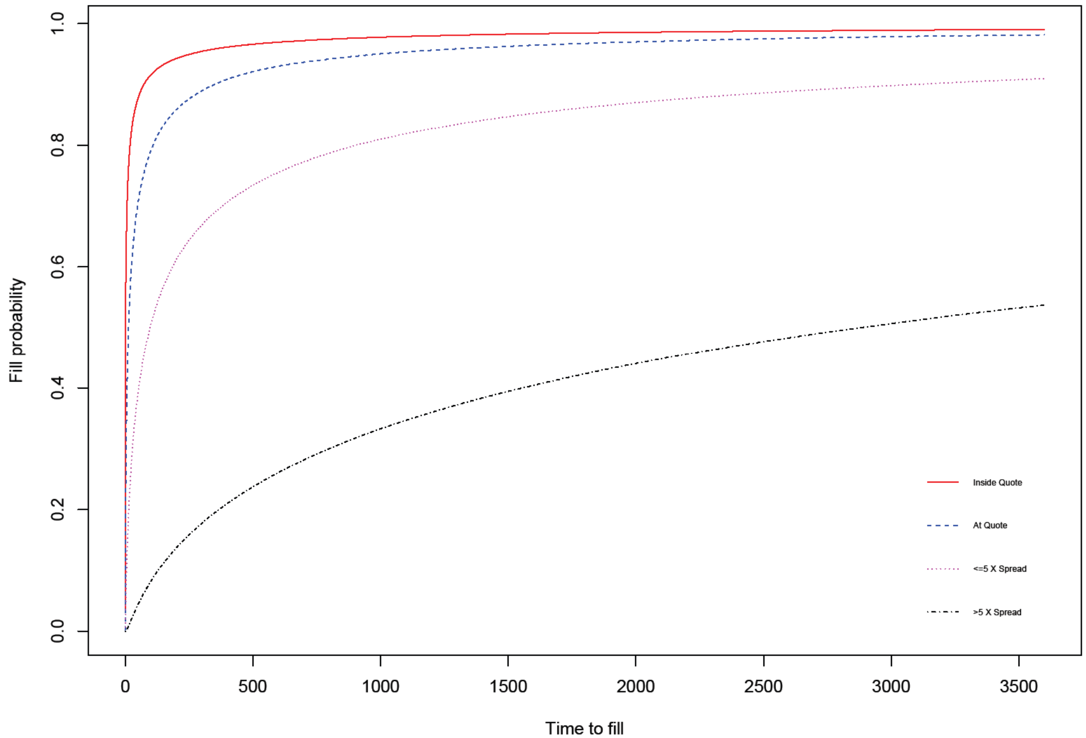


Table 1
Sample Description

This table reports statistics on retail marketable (market and marketable limit) and nonmarketable limit orders for a size-stratified sample of 300 stocks during in May 2020. Panel A presents descriptive statistics for sample firms, grouped by stock size tercile. Panel B presents statistics on marketable and limit orders for the full sample. For each order type, we report the total number of top orders, total share quantity, total shares traded, and the average and median order size. Panel C presents statistics by stock size tercile.

Panel A: Stock Characteristics

Stock Size Tercile	Price	Mkt. Cap. ($1,000's)	Daily Trading Volume	Arrival Spread (bp)
Large	$316.20	$343,304,159.33	28,473,264.48	2.06
Medium	$36.15	$2,515,027.27	7,502,699.53	9.03
Small	$13.38	$502,916.84	3,718,860.75	15.36

Panel B: Order Type Statistics

Order Type	Number of Orders	Total Shares	Total Shares Traded	Average Order Size	Median Order Size
Marketable	20,218,665	2,931,921,376	2,922,492,376	145.01	16.00
Nonmarketable	6,911,935	1,255,834,288	662,703,034	181.69	25.00

Panel C: Order Type Statistics by Stock Size Tercile

Stock Size Tercile	Order Type	Number of Orders	Total Shares	Total Shares Traded	Avg. Order Size	Median Order Size
Large	Marketable	18,779,215	2,632,589,064	2,626,137,451	140.19	15.00
Large	Nonmarketable	6,439,252	1,119,629,026	596,247,199	173.88	25.00
Medium	Marketable	835,497	182,047,703	180,631,887	217.89	25.00
Medium	Nonmarketable	271,775	77,474,482	38,465,901	285.07	50.00
Small	Marketable	603,953	117,284,609	115,723,038	194.19	20.00
Small	Nonmarketable	200,908	58,730,780	27,989,934	292.33	70.00

Table 2
Execution Outcomes, Univariate Statistics

This table reports statistics on execution quality of marketable (market and marketable limit) and nonmarketable orders. For each order type, we report the fill rate (the ratio of executed quantity to top order quantity), effective spread (the percentage difference between the order's volume weighted average execution price and the NBBO midpoint at the time of order arrival at the broker), the opportunity cost for nonmarketable orders and implementation shortfall (IS). IS includes the effective spreads for filled shares of the order and the opportunity cost for the unfilled shares. Opportunity cost is calculated using the opposite NBBO quote price at the end of the order's lifecycle (ask quote for buy orders and bid quote for sell orders). We report execution quality statistics for the full sample of firms in Panel A and by stock size tercile in Panel B.

Panel A: Execution Quality Statistics by Order Type

Order Type	Fill Rate	Effective Spread (bp)	Opportunity Cost (bp)	IS (bp)
Marketable	99.8%	1.04	N/A	1.07
Nonmarketable	65.2%	-20.16	15.92	-8.16

Panel B: Execution Quality Statistics by Order Type and Stock Size Tercile

Stock Size Tercile	Order Type	Fill Rate	Effective Spread (bp)	Opportunity Cost (bp)	IS (bp)
Large	Marketable	99.8%	0.74	-9.31	0.75
Large	Nonmarketable	65.3%	-18.45	13.57	-7.70
Medium	Marketable	99.8%	3.43	-2.93	3.56
Medium	Nonmarketable	65.2%	-38.96	35.93	-15.03
Small	Marketable	99.7%	6.99	8.87	7.59
Small	Nonmarketable	60.0%	-52.05	57.88	-13.43

Table 3
Execution Outcomes, Regression Analysis

This table reports results for regressions comparing implementation shortfall (IS) of marketable and nonmarketable limit orders. IS includes the effective spreads for filled shares of the order and the opportunity cost for the unfilled shares. Opportunity cost is calculated using the opposite NBBO quote price at the end of the order's lifecycle (ask quote for buy orders and bid quote for sell orders). Explanatory variables include Marketable, an indicator variable set to one for marketable orders (market and marketable limit) and zero for limit orders; the natural log of order size (in shares); and the NBBO percentage spread at the time of order arrival. Sell, an indicator variable equal to one for sell orders and equal to zero for buy orders; Volatility, the square root of the prior day sum of five-minute squared stock returns, and Small-Med, an indicator variable equal to one for orders in small and medium stock size terciles and equal to zero otherwise. The regressions include stock-day fixed effects. Standard errors clustered by stock and day are reported in parentheses.

	Dependent variable: Implementation Shortfall (bp)					
	(1)	(2)	(3)	(4)	(5)	(6)
Marketable	9.416***	9.551***	10.271***	7.569***	4.890***	8.746***
	(0.990)	(1.012)	(2.088)	(0.877)	(1.065)	(0.966)
Ln(Order Size)		0.288***	0.282***	0.308***	0.292***	0.299***
		(0.058)	(0.042)	(0.062)	(0.058)	(0.058)
Arrival Spread (bp)		0.268***	0.269***	-0.202***	0.276***	0.287***
		(0.026)	(0.026)	(0.067)	(0.026)	(0.025)
Sell			1.592			
			(3.091)			
Marketable × Sell			-1.805			
			(3.125)			
Marketable × Arrival Spread				0.691***		
				(0.077)		
Marketable × Volatility					2.062***	
					(0.421)	
Marketable × Small-Medium						11.708***
						(1.013)
Stock-Day FE	Y	Y	Y	Y	Y	Y
Observations	27,130,600	27,130,600	27,130,600	27,130,600	27,130,600	27,130,600
Adjusted R^2	0.033	0.034	0.034	0.037	0.036	0.037
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 4
Execution Outcomes, Robustness Tests

This table reports regression results with implementation shortfall (IS) as the dependent variable for marketable and limit orders. IS includes the effective spreads for filled shares of the order and the opportunity cost for the unfilled shares, which is calculated using the opposite NBBO quote price at the end of the order's lifecycle (ask quote for buy orders and bid quote for sell orders). Explanatory variables include Marketable, an indicator variable set to one for marketable orders (market and marketable limit) and zero for limit orders; the natural log of order size (in shares); the NBBO percentage spread at the time of order arrival; and an indicator variable equal to one for 5-minute intervals which only have marketable orders without any submitted nonmarketable limit orders and equal to zero if the interval has both marketable and nonmarketable order submissions. Specifications (4) and (5) compare the execution quality of retail marketable orders submitted during 5-minute periods with submitted nonmarketable limit orders and retail marketable orders submitted during 5-minute periods without submitted nonmarketable limit orders. The regressions include stock-day fixed effects in columns (1), (4) and (5), broker fixed effects in columns (1), (3) and (5), and stock-day-5min-Side fixed effects in columns (2), (3), and (5). Standard errors clustered by stock and day are reported in parentheses.

	Dependent variable: Implementation Shortfall (bp)				
	(1)	(2)	(3)	(4)	(5)
Marketable	10.901***	8.965***	10.237***		
	(1.081)	(0.967)	(1.024)		
Ln(Order Size)	0.298***	0.254***	0.272***	-0.031***	0.061***
	(0.054)	(0.037)	(0.036)	(0.005)	(0.009)
Arrival Spread (bp)	0.263***	0.288***	0.287***	0.473***	0.471***
	(0.026)	(0.017)	(0.016)	(0.016)	(0.016)
Marketable only in 5-min Interval				-0.011	-0.018
				(0.026)	(0.025)
Stock-Day FE	Y	N	N	Y	Y
Stock-Day-5min-Side FE	N	Y	Y	N	N
Broker FE	Y	N	Y	N	Y
Observations	27,130,600	27,130,600	27,130,600	20,218,665	20,218,665
Adjusted R^2	0.042	0.099	0.106	0.159	0.167
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 5
Execution Outcomes by Price Aggressiveness

This table reports statistics on execution quality of marketable orders and limit orders categorized by price aggressiveness. Limit orders are categorized as follows: orders placed within the NBBO quotes; orders placed at the NBBO quotes (e.g., buy orders at the best bid); orders placed behind the quotes but within five times the prevailing NBBO spread at the time the broker receives the order; and orders placed further behind the NBBO quotes. For each order type-category, Panel A reports number of top orders, fill rate (the ratio of executed quantity to top order quantity), effective spread (the percentage difference between the order's volume weighted average execution price and the NBBO midpoint at the time of order arrival at the broker), opportunity cost and implementation shortfall (IS). IS includes the effective spreads for filled shares of the order and the opportunity cost for the unfilled shares. Opportunity cost is calculated using the opposite NBBO quote price at the end of the order's lifecycle (ask quote for buy orders and bid quote for sell orders). Panel B presents regression coefficients with implementation shortfall (IS) as the dependent variable for marketable orders and the specific sample of limit orders within a price aggressiveness category. Each column includes all marketable orders and the limit orders that fall into the specified price aggressiveness category, as labeled. Explanatory variables include Marketable, an indicator variable equal to one for marketable (market and marketable limit) orders and equal to zero for limit orders; natural log of the order size in shares; and the NBBO percentage spread at the time of order arrival. The models include stock-day and broker fixed effects, and standard errors clustered by stock and day are reported in parentheses.

Panel A: Execution Quality Statistics by Price Aggressiveness

Order Type	Orders	Fill Rate	Effective Spread (bp)	Opportunity Cost (bp)	IS (bp)
Marketable	20,218,665	99.8%	1.04	-8.06	1.07
Inside Quote	976,313	83.0%	-0.49	12.55	1.69
At Quote	802,175	76.2%	-3.19	12.95	0.58
≤ 5 × Spread	2,770,720	68.4%	-12.89	16.90	-3.76
> 5 × Spread	2,362,727	50.2%	-54.27	16.17	-20.36

Panel B: Regression Results by Price Aggressiveness				
	Dependent variable: Implementation Shortfall (bp)			
	Inside Quote Limit	At-Quote Limit	≤ 5 x Spread	> 5 x Spread
	(1)	(2)	(3)	(4)
Marketable	0.351***	0.957**	5.384***	22.291***
	(0.072)	(0.379)	(0.857)	(2.476)
Ln(Order Size)	0.070***	0.072***	0.115***	0.216***
	(0.009)	(0.011)	(0.015)	(0.048)
Arrival Spread (bp)	0.444***	0.456***	0.239***	0.402***
	(0.015)	(0.015)	(0.022)	(0.030)
Stock-Day FE	Y	Y	Y	Y
Broker FE	Y	Y	Y	Y
Observations	21,194,978	21,020,840	22,989,385	22,581,392
Adjusted R^2	0.144	0.130	0.041	0.082
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6
Cumulative Limit Order Cancellation Probabilities

This table reports statistics on times to execution, order duration, and uses survival analysis to report cumulative cancellation probabilities over different periods. Panel A reports average volume-weighted time to execution (in seconds) and order duration (in seconds). Panel B reports results for survival analysis. The reported probabilities are one minus the survival probabilities. We present Kaplan-Meier estimates. For cancellation probabilities, execution is the censoring event. The estimates are based on our limit order sample in May 2020.

Panel A: Order Duration and Times to Execution

Order Type	Time to Execution (seconds)	Order Duration (seconds)
Marketable	3.23	6.36
All Limit	951.73	1251.56
Inside Quote	30.04	40.43
At Quote	94.61	106.14
≤ 5 × Spread	484.96	507.00
> 5 × Spread	2784.74	3014.02

Panel B: Cumulative Limit Order Cancellation Probabilities

Time	All	Inside Quote	At Quote	≤ 5 × Spread	> 5 × Spread
5 seconds	4.15%	16.38%	7.64%	4.15%	1.16%
10 seconds	7.35%	26.94%	13.49%	7.72%	2.53%
1 minute	20.15%	50.59%	34.87%	23.84%	10.83%
5 minutes	33.36%	64.70%	53.58%	40.02%	22.69%
10 minutes	39.22%	69.27%	59.77%	46.44%	28.89%
1 hour	56.04%	79.12%	72.54%	62.77%	48.04%
2 hours	64.73%	83.29%	78.08%	70.07%	58.33%

Table 7
Retail Order Handling

This table reports statistics on how retail orders are routed and executed. Panel A reports venue choice statistics for marketable (market and marketable limit), and limit orders routed directly by brokers to exchanges and market makers. We report the proportion of orders routed to market makers. The proportions are reported for number of orders, submitted top order share quantity, and the executed share quantity. We also report the proportion of executed share quantity by market makers in a principal capacity relative to riskless principal. Panel A reports statistics for the full sample and panel B disaggregates by order aggressiveness. Limit orders are categorized as follows: orders placed within the NBBO quotes; orders placed at the NBBO quotes (e.g., buy orders at the best bid); orders placed behind the quotes but within five times the prevailing NBBO spread at the time the broker receives the order; and orders placed further behind the NBBO quotes.

Panel A: Venue Choice for Retail Limit Orders

Order Type	%Market Maker Orders	%Market Maker Shares Submitted	%Market Maker Shares Executed	$\frac{P}{P+R}$
Marketable	99.83%	99.92%	99.92%	89.84%
Nonmarketable	89.05%	86.80%	83.18%	32.70%

Panel B: Venue Choice for Retail Limit Orders by Aggressiveness

Aggressiveness	%Market Maker Orders	%Market Maker Shares Submitted	%Market Maker Shares Executed	$\frac{P}{P+R}$
Inside Quote	90.91%	89.14%	88.39%	36.0%
At Quote	92.37%	91.94%	89.02%	40.7%
$\leq 5 \times$ Spread	90.02%	87.52%	82.70%	28.4%
$> 5 \times$ Spread	86.02%	81.09%	74.16%	26.9%

Table 8
Execution Quality, Principal versus Riskless Principal Executions

This table presents regression results with implementation shortfall (IS) as the dependent variable for retail non-marketable orders executed by market makers on principal or riskless principal basis. IS includes the effective spreads for filled shares of the order and the opportunity cost for the unfilled shares. Opportunity cost is calculated using the opposite NBBO quote price at the end of the order's lifecycle (ask quote for buy orders and bid quote for sell orders). Explanatory variables include the proportion of an executed order that is executed on a principal basis (P/(P+R)); the natural log of order size (in shares); and the NBBO percentage spread at the time of order arrival. The model includes stock-day fixed effects in columns (1) and (2), broker fixed effects in columns (2) and (4), and stock-day-aggressiveness-side fixed effects in columns (3) and (4). Standard errors clustered by stock and day are reported in parentheses.

	Dependent variable: Implementation Shortfall (bp)			
	(1)	(2)	(3)	(4)
$\frac{P}{P+R}$	-0.6062***	-0.2859*	-0.6545***	-0.3375**
	(0.1904)	(0.1638)	(0.1840)	(0.1575)
Ln(Order Size)	0.2242***	0.2945***	0.1862***	0.2657***
	(0.0503)	(0.0424)	(0.0441)	(0.0354)
Arrival Spread (bp)	-1.6941***	-1.6895***	-1.7177***	-1.7132***
	(0.1302)	(0.1288)	(0.1336)	(0.1324)
Stock-Day-Agg FE	Y	Y	N	N
Stock-Day-Agg-Side FE	N	N	Y	Y
Broker FE	N	Y	N	Y
Observations	3,698,981	3,698,981	3,698,981	3,698,981
Adjusted R^2	0.5817	0.5834	0.5915	0.5930
Note:		*p<0.1; **p<0.05; ***p<0.01		

Appendix

The unfiltered sample consists of 46,818,433 orders. We apply several data filters with three main objectives, described in detail below:

1. Filters to accurately measure trading costs and its attribution:

- We remove top orders associated with more than one trading day, more than one top event, more than one stock, and orders marked as merged. We remove top orders without routes to execution venues and orders where a route from a broker to a venue is associated with more than one venue-level new order event. We remove top orders received on non-trading days and orders routed to an execution venue outside of regular trading hours. These filters leave us with 35,997,017 orders.

2. Filters related to identifying a representative sample of retail orders:

- We examine only simple marketable and non-marketable orders. We include marketable orders marked as immediate-or-cancel (IOC). We include orders routed directly to a market maker, directly to an exchange, or initially routed to market maker and subsequently routed by that market maker to an exchange. Requiring a route to a market maker or an exchange eliminates fractional orders since they are executed by the broker itself and not routed out. To ensure results are representative of typical retail investors, we exclude top orders of 5,000 shares or greater. We also remove modified top and venue-level orders, which often involve multiple modifications, likely reflecting sophisticated automated trading strategies. These filters leave us with 27,262,030 orders.

3. Filters related to removing potential outliers and data errors:

- We remove order lifecycles that do not come to a logical end (i.e., cancellation or execution) as these reflect cases where order linkages are missing. Note that this restriction does not remove orders cancelled at (or after) the close since they have a cancellation event. We remove top orders with a fill rate greater than 100% and those with a time-to-execution of less than negative two seconds. We remove limit orders with prices more than \$100 behind the best quotes (e.g., buy orders priced more than \$100 below the best bid). These filters leave us with 27,130,600 orders.