Retail Limit Orders [*]

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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 usually do not have access to the same tools and order routing choices as institutional traders.[1] Since the onset of the COVID-19 pandemic, retail trading in U.S. equity markets has grown substantially, drawing increased attention from academics to order handling and trading costs of retail orders. Recent research has examined the execution quality of marketable orders placed by retail traders. Retail brokerages generally allow their customers to use limit orders to trade, but these orders have received relatively little attention in empirical studies.[2]

A well-developed theoretical literature examines the trade-offs between marketable and limit orders. Marketable orders offer simplicity and execute immediately at the best available price but pay the bid-ask spread. Limit orders offer the potential for better 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), Parlour (1998)). Using NYSE audit trail data from 1990-91, Harris and Hasbrouck (1996) find that limit orders placed at or better than the prevailing quote result in lower trading costs compared to marketable orders. Studies from international markets similarly show that limit orders placed at the prevailing quote tend to have lower trading costs.[3] Overall, the evidence suggests limit orders are an important tool in traders' strategies. Notably, these studies reflect the aggregation of all trader types since the data do not allow a separate analysis of retail and non-retail orders.

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. This focus is important for several reasons. First, understanding the execution quality of retail limit orders is essential,

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[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) using data from the Paris Bourse, Griffiths, Smith, Turnbull and White (2000) using data from the Toronto Stock Exchange, Ahn, Bae and Chan (2002), using Hong Kong market data, Ranaldo (2004), using data from Swiss Stock Exchange, and Bessembinder, Panayides and Venkataraman (2009) using data from Euronext provide relevant evidence on order choice in international markets.

as it remains unclear whether limit orders are an attractive choice for retail traders in the current market structure dominated by high frequency trading strategies. Given the conventional wisdom that retail investors are likely to be less sophisticated traders, a limit order trading strategy, which requires the ability to monitor market conditions and respond quickly, could potentially be less suitable in markets where speed offers a significant advantage.[4]

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.[5]

Third, no existing work provides a comprehensive analysis of U.S. retail traders' use of market and limit orders. The lack of research is likely due to the lack of suitable data to distinguish retail orders from non-retail orders in the market. 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) propose a method (BJZZ) to classify TAQ data trades associated with retail marketable orders, no similar methodology exists for identifying retail limit orders in public data. Recent studies have also noted classification issues with the BJZZ approach.[6]

To understand the tradeoffs faced by retail traders, we study regulatory data on retail orders from a stratified sample of US exchange-listed stocks. The FINRA Order Audit Trail System (OATS) database provides detailed information on orders received by brokers from their clients (henceforth "top orders"),

[4] The importance of monitoring limit orders is emphasized by the option framework for limit orders in Copeland and Galai (1983).
[5] 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.
[6] Recent studies have noted that the BJZZ method may capture only a portion of marketable retail trading (Barber, Huang, Jorion, Odean, and Schwarz (2023)) and may include some non-retail trading (Battalio, Jennings, Saglam, and Wu (2023)).

including the identity of the broker; the venue-specific routing decisions; and the venue-specific outcomes, such as executions, traded prices, and 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 comprehensive and free from the attrition or selection bias that often affect data obtained from a subset of industry participants.[7] We study a sample of over 27 million top orders arising from individual account holders of 19 active retail brokers in a size-stratified sample of 300 stocks (100 each from large, medium and small-cap categories) during May 2020. We identify retail brokers based on their overall activity and the proportion of their orders that are likely to be associated with retail customers.[8]

We find that limit orders are a significant part of retail investors' order flow, accounting for 29.2% of submitted shares, 25.5% of submitted orders, and 18.2% 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, 74.4% 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 limit orders are associated with lower trading costs and exhibit significantly higher fill rates than those reported for the overall market.[9] We find that retail limit orders remain open in the market for long periods relative to fleeting limit orders documented in Hasbrouck and Saar (2009), which increases their fill probabilities (see Lo, Mackinlay and Zhang (2002)).

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[7] Einav and Levin (2014) and Card, Chetty, Feldstein and Saez (2010) advocate for the use of such administrative data in economic analyses.

[8] We classify "held" orders from "individual" accounts associated with our identified brokers as retail orders. The OATS data include fields indicating the beneficiary owner (categorized as individual, institutional, etc.) and handling type ("held" orders or "not-held" orders) for each order. A "not-held" order provides the broker-dealer with price and time discretion in handling the order. SEC (2018) notes that institutional orders are more likely to be handled on a not-held basis. We include a broker in our sample if: (a) most of its customer orders are "individual" (the median is 99% for our sample brokers), (b) at least 90% of these individual orders are "held", and (c) the broker handles at least 100,000 "individual" top orders in our sample of stocks during May 2020.

[9] 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 49.9%.

This study adds to the literature by providing new evidence on the economic relevance and execution quality of retail limit orders. The cost advantages of retail limit orders over marketable orders align with theoretical predictions, with limit orders performing better during periods of wider spreads, higher volatility, and in smaller stocks. We find that limit orders offer retail traders an attractive way to earn compensation for supplying liquidity. The results on order duration, fill rates, and trading costs indicate that the effectiveness of retail limit orders exists, not in spite of retail traders being slower, but likely *because* of them being slow and not following the trend of rapid placements and cancellations that dominate the broader market.

We study 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, Smith, Turnbull and White (2000). Specifically, the IS includes two components: the transaction costs (effective spread) for the executed portion of the order and the opportunity cost for the unfilled portion of the order. Opportunity cost captures scenarios where the market price moves away from the limit price, requiring the trader to place a market order at the time of cancellation. In these cases, the trader incurs the cost of price drift during the order's lifecycle, as well as the bid-ask spread at the time of cancellation for the unfilled shares. We use the trading costs of retail marketable orders as a benchmark to assess the execution quality of retail limit orders. This comparison is relevant because both marketable and limit orders are widely available to retail traders through their brokers. Additionally, recent research shows that retail marketable orders receive favorable executions, as market makers frequently provide significant price improvements.[10]

To compare execution quality of retail marketable and limit orders, our main regression specification uses 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 that might influence limit order usage (e.g., web or app interface quality). We account for order-specific characteristics and intraday market conditions by

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

controlling for order size and the bid-ask spread at the time the order is received. To further account for 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 (i.e., buy or sell orders in the same stock within a 5-minute window).

Across all specifications, we find that trading costs of limit orders are approximately ten basis points lower than for marketable orders – a sizable difference compared to the average marketable order IS of 1.1 basis points. We also examine factors from the literature that could affect the relative performance of these order types, showing that the cost advantage of limit orders is greater when quoted spreads are wider (consistent with Cohen, Maier, Schwartz and Whitcomb (1981)) and when realized volatility is higher (consistent with Handa and Schwartz (1996)). Across stocks, retail limit order trading costs are approximately 20 basis points lower than marketable orders in smaller stocks, consistent with higher compensation due to lower liquidity. When analyzing sub-samples based on price aggressiveness, we find that the cost advantage is economically small for within-quote and at-quote limit orders, around five basis points for behind-the-quote limit orders (within five times quoted spread), and approximately 22 basis points for orders further behind the quote.

The trading cost advantage of retail limit orders is likely to be associated with their notably higher fill rate. For 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 more than five times spread behind the quote achieve an average fill rate of 50%. Survival-analysis highlights order duration as a key factor explaining these higher fill statistics. Unlike the millisecond duration typical for most limit orders in the market, retail limit orders remain open for an average of about 10 minutes. The average duration for the least aggressive category of limit orders is approximately 50 minutes. Higher fill rates contribute to lower IS by reducing the opportunity costs associated with limit orders.

Overall, while limit orders require costly monitoring, involve greater complexity in setting order parameters, and lack the immediacy of marketable orders, our results suggest that limit orders provide an attractive choice for retail traders to earn compensation by providing liquidity. Our findings show that behind-quote retail limit orders achieve the lowest trading costs, contrasting with earlier studies based on aggregated data from all trader types that found limit orders placed at the prevailing quote typically had lower trading costs. A possible explanation is the dominance of institutional and professional traders in the aggregated market data. Institutional orders are often part of larger trading programs that create a significant price impact, leading to 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. Additionally, professional traders, particularly those using high frequency strategies, operate over very short horizons, unlike the longer durations observed for retail traders in our analysis.

We examine how retail brokers handle limit and market orders. Brokers route nearly all retail marketable orders to market makers, who primarily execute these orders in a principal capacity. By contrast, about 11% of retail limit orders are routed to exchanges, with the remaining 89% sent to market makers. Among these, market makers fill approximately 30% of the executed shares on a principal basis, about 66% as riskless principal by sourcing liquidity from other market participants, and approximately 4% 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

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 is relatively less research on how retail investors implement their trading decisions.

Recent studies have focused on the execution quality of retail marketable orders. These studies highlight trading cost differences across brokerages (Schwarz, Barber, Huang, Jorion, and Odean (2023)) and order routing by retail 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. Battalio and Jennings (2023) and

Schwarz et al. (2023) use 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, allowing us to assess the relative importance of limit orders for retail traders compared to marketable orders.

Kelley and Tetlock (2013) examine 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 responding 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)) also find that retail order predict stock returns and earnings, suggesting that retail traders can act as informed participants. The focus of our study differs from these works. While these studies examine retail buying imbalances and their predictive power for returns, our study examines the execution quality outcomes and broker handling for a broad sample of retail marketable and limit orders.

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 where executed limit orders pay a fee. Our analysis differs in several important ways. First, we examine all retail limit orders arising from individual accounts of our sample of retail brokers. Our data include orders that are routed to exchanges as well as to market makers. We find that brokers route the majority of retail limit orders to market makers, with a significant portion executed by market makers in a proprietary capacity. Second, our dataset provides a comprehensive view of the order lifecycle by tracking each order from the moment it is received by the broker to its final resolution. This allows us to calculate detailed execution quality metrics, such as fill rates and implementation shortfalls. Notably, we find that retail limit orders achieve higher fill rates than those reported in market-wide statistics and that their trading costs are lower than those of retail marketable orders.

Our analysis is guided by the rich literature examining 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, Harris and Hasbrouck (1996) examine the performance of orders submitted through the NYSE's electronic (SuperDOT) system during three months in 1990-91. Using the IS approach, they find that at-the-quote limit orders are both the best-performing and the most used order type. Similar findings are reported by Griffiths et al. (2000) on the Toronto Stock Exchange.

We contribute to this literature by focusing on the performance of retail traders' limit orders relative to marketable orders in the current market structure, where the speed of trading may pose challenges for retail traders. Our findings provide an interesting comparison to earlier studies. For example, we observe that current fill rates for retail limit orders remain comparable to those in Harris and Hasbrouck (1996), perhaps because retail traders tend to leave their orders open for longer durations. However, in contrast to 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.

3. Data and sample description

The primary dataset used in this study is the FINRA OATS database for the month of May 2020.[11] Almost every broker-dealer in the United States is required to report audit trail information on equity orders to FINRA.[12] 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,

[11] The OATS system has since been replaced by the Consolidated Audit Trail (CAT). 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.

[12] 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).

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.

We examine 19 large retail brokerage firms. To arrive at this sample of brokers, 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. We focus exclusively on orders marked as originating from individual customers.[13] 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".

Brokers included in our sample 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. 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. In our analysis, we study 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.[14] 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

[13] 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.

[14] 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 environment for our analysis.

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 below 5,000 shares and with clear routing to market makers or exchanges); and removing potential outliers and data errors (e.g., excluding orders with absolute IS over 10%). Detailed description of the filters and the number of remaining top orders after applying the filters are provided in the Appendix.

Our final sample includes over 27 million marketable and limit orders placed by individual account owners through retail brokers, totaling more than four billion shares submitted and more than 3.3 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. Average order arrival bid-ask spreads 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 29.2% of shares submitted and 18.2% of shares traded. These proportions are consistent across large, medium and small stocks. In unreported results, we find that, unlike the broader U.S. equity market where there is 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 their orders.

Table 1, Panel B, shows that retail limit orders are larger on average (164 shares) than marketable orders (136 shares). The median order sizes are smaller but show the same trend – 25 shares for limit orders and 15 shares for marketable orders. Panel C shows that the sample is skewed heavily 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 the execution quality for marketable and limit orders in the full sample. Panel A of Table 2 provides results for the overall sample, while Panel B breaks them down by size terciles. The statistics represent averages across all orders in each category.

We present the fill rate, calculated as the filled quantity divided by the submitted quantity of a top order.[15] Marketable orders almost always execute, with an average fill rate close to 100%. In contrast, limit orders have lower averages, with a fill rate of 65%. These results align with the market-wide fill rates of 44% reported in early 1990s NYSE data by Harris and Hasbrouck (1996) and the 43% fill rates for institutional orders documented by Jeria and Sofianos (2008). Panel B shows that fill rates are consistent across large and medium stock size terciles, at approximately 65%. For small stocks, the fill rate is slightly lower at 60%, but still reasonably high.

We next present *Effective spreads*, which are measured for a top order as:

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

where $P_{1(i)}$ is the share volume-weighted execution price of the top order, $P_{0(i)}$ is the benchmark price (the NBBO bid-ask quote midpoint when the broker receives the top order from the retail client), and $D_{(i)}$ 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' effective spreads average one basis point for the full sample. Panel B further breaks

[15] In unreported results, we find that an alternative measure of fill rate which captures the percentage of orders that receive any execution yields almost identical estimates. This occurs because retail limit orders tend to be small and either get no fill or a 100% fill. Less than 0.5% of retail limit orders in our sample receive partial fills.

this down by stock size terciles, showing averages of 0.74, 3.4 and 6.9 basis points for large, medium and small stocks. As expected, effective spreads are negative for limit orders, averaging negative 20 basis points for the full sample. Panel B of Table 2 shows averages of negative 18, negative 39, and negative 52 basis point 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 from the limit order (e.g., moves higher for a buy limit order or lower for a sell limit order), the trader may eventually have to execute the order 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 assumes that the trader is committed to filling the entire submitted quantity of the top order (Harris and Hasbrouck (1996), Griffiths et al. (2000)). Following this framework, we calculate the IS for the 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 order, and other variables are as previous defined. In equation (2), the first term captures the effective spreads from equation (1) for the filled portion of the order, while the second term accounts for the opportunity cost of the unfilled portion.

The literature has used different prices for $IP_{(i)}$ including the closing price (Keim and Madhavan (1997) and Conrad, Johnson and Wahal (2001)), a volume weighted average price after the order is cancelled (Jeria and Sofianos (2008)), and the opposite quote at the end of the life cycle (i.e., $IP_{(i)}$ is the ask (bid) quote for buy (sell) orders at the time of the last event in the order's life cycle). The opposite quote as the imputed price (used in Harris and Hasbrouck (1996) and Handa and Schwartz (1996)) applies the largest opportunity cost for non-execution as it adds the drift during the order's lifecycle to the quoted spread as the trading cost of the unfilled portion of the order. In our analysis, we use the opposite-side quote at the at the end of the top order's lifecycle as the imputed price. This approach reflects the simplest strategy for retail traders, who are likely to cancel a limit order and replace it with 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.

Table 2, Panel A shows that the average IS of limit orders, which includes the opportunity costs of non-execution, is negative eight basis points, compared to the average effective spread cost of negative 20 basis points. The IS for limit orders is approximately nine basis points lower than the marketable orders IS, which averages 1.1 basis points. Panel B further shows that the average IS for limit orders is lower than that for marketable orders across all size terciles. The trading cost differential 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 more from using limit orders in small stocks, which typically are associated with wider bid-ask spreads and greater rewards for supplying liquidity.

4.2. Outcomes, regression analysis

One possible reason for the higher trading costs of market orders is that retail traders tend to use limit orders in specific types of stocks. Figure 1 shows that limit orders account for a higher proportion of submitted shares in smaller stocks. Another possibility is that retail traders use market orders in different market conditions than limit orders. In this section, we analyze execution quality differences while controlling for stock characteristics, order attributes, and market conditions. This more 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 used, 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 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. The positive coefficient on *Marketable* in column (1) indicates that IS for marketable orders is about nine 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 differential between marketable and limit orders remains largely unchanged.[16]

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) suggest 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, we estimate the following model:

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

[16] 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.

where C_i in column (3) is represented by an indicator variable *Sell* that equals one if order i is a sell order and zero if the order is a buy order. The other variables are as described earlier. The coefficient β_2 tests whether there is an asymmetry in execution quality between sell and buy orders, while the coefficient β_3 tests whether the execution cost difference between marketable and limit orders depends on the 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 two market conditions that could potentially affect the appeal of marketable and limit orders: volatility and bid-ask spreads. Prior studies, such as Handa and Schwartz (1996) and Ahn et al. (2001), suggest that higher volatility makes limit orders more attractive compared to marketable orders. Cohen et al. (1981) posit that the "gravitational pull" of the opposite quote strengthens as bid ask spreads narrow, thus increasing the attractiveness of marketable orders when spreads are narrow. In column (4), C_i represents the arrival percentage NBBO quoted spread, while in column (5), C_i is the stock-day volatility, measured as the sum of five-minute squared quote-midpoint returns. We include the interaction of *volatility* and *Marketable*$_i$, but not volatility itself, as it is subsumed by the stock-day fixed effects in the model.

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 in periods of wider spreads and higher volatility. 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 of 2.1 basis points.

Lastly, column (6) tests 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 11.5 basis points. This suggests that the cost advantages 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 apps) or if there are significant differences in the clienteles they serve. Schwarz et al. (2023) document variations in execution quality for marketable orders across brokers. To account for these differences, we include broker fixed effects in the benchmark stock-day fixed effects model from Table 3, column (2). In Table 4, column (1), the model's explanatory power increases from 3.3% to 4.1%, indicating that broker effects provide useful information. However, the IS of retail limit orders IS remains approximately 11 basis points lower 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 limit order use is optimal, then it may explain the observed cost advantage of retail limit orders. To test this possibility, we match marketable and limit orders by submission 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. The results in Table 4, column (2), show that even with this level of detail, limit order IS is approximately nine basis points lower than that of marketable orders. Adding broker fixed effects in column (3) does not materially change the results.

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, there are many five-minute periods without any limit orders. If more sophisticated traders are more likely to use limit orders, periods containing limit orders might represent times that are relatively less favorable for marketable orders, while periods without limit orders may include a mix of orders from both more and less sophisticated traders. Following this logic, we would expect marketable orders to have higher IS in periods with 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 submitted during 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 order outcomes, 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 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 of Table 5 and Figure 2 presents the distribution of retail limit orders 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 - about 40% are placed within five times the spread, and another 34% are placed even further behind. This differs from the findings in Harris and Hasbrouck (1996), who find that at-the-quote limit orders are most commonly used in the overall NYSE market during their sample period. With fast moving markets, the less aggressive placement strategy we document may be a mechanism for retail traders to ensure that their orders aren't marketable upon arrival at the broker or venue. The result is also consistent with retail traders demanding a bigger premium for their patience and their inability to rapidly cancel and replace limit orders.

However, placing less aggressive limit orders comes with tradeoffs, such as higher opportunity cost if the order is not executed. Harris and Hasbrouck (1996) find that limit orders placed at the prevailing quote have lower IS. To investigate whether similar patterns exist for retail traders, we 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 NBBO quotes. Limit orders placed within five times the spread fill 68.5% of their shares, while those placed further behind still achieve fill rates close to 50%. For limit orders placed further behind the NBBO quotes, the high fill rates increase the contribution of the executed portion, thereby benefiting from significantly negative effective spreads, while reducing the contribution of the unfilled portion, which could otherwise incur higher 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 20 basis points lower.

Table 5, Panel B, presents the regression results with stock-day and broker fixed effects. The analysis is conducted across the four price aggressiveness categories, as indicated in the row labeled 'sample'. Each column includes all marketable orders and the limit orders that fall into the specified price aggressiveness 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, representing a trading cost difference of less than one basis point. This suggests that retail limit orders placed within or at the NBBO quotes achieve execution quality similar to marketable orders. In column (3), the *Marketable* coefficient indicates that IS for marketable orders is about five basis points higher than for limit orders placed behind the quotes within five times the spread. Notably, in column (4), the trading cost difference is much larger, with IS for marketable orders nearly 22 basis points higher than for limit orders placed further behind the NBBO quotes.

To understand how retail limit orders achieve high fill rates, we examine their order duration in Table 6. One way to improve fill rates is to leave the limit order open for a longer time. Handa and Tiwari (1996) argue that fluctuating market prices are more likely to reach the price specified in the limit order as time passes. Volatility increases the likelihood of execution, and this likelihood improves with longer order duration. However, longer order durations can also increase the opportunity costs if the price drifts further away from the limit order.

Panel A of Table 6 presents average times to executions and order durations. We find that retail marketable orders execute quickly, with an average time to execution of just three seconds. In contrast, retail limit orders remain open much longer. The average duration of limit orders, which includes cancellations and executions, is 1,257 seconds, while the average time to execution is 952 seconds. In unreported results, average order duration for retail limit orders is higher for smaller stocks. Duration 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 506 seconds; and those placed further behind the NBBO quotes average 3,014 seconds.

We follow Hasbrouck and Saar (2009) in plotting the cumulative cancellation probability of retail limit orders in Figure 3, Panel A. Table 6, Panel B presents the corresponding numbers. Figure 3 and Table 6 are based on survival probabilities using the Kaplan-Meier estimation where an execution of the limit order is the 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 56.1% within one hour. By comparison, Hasbrouck and Saar (2009) highlight the phenomenon of fleeting limit orders in market wide data, where 60% are canceled within 10 seconds, 98.4% within 10-minutes, and 99.7% within one hour. This comparison highlights that retail traders keep their limit orders open for much longer durations than typical market-wide limit orders, which are often associated with high frequency strategies.

Additionally, Table 6, Panel B shows that cancellation probabilities are lower for less price aggressive limit orders. For example, 27% of retail limit orders placed within the NBBO quotes are canceled within 10 seconds, compared to less than 3% 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 during the same time frame. These results suggest that retail traders exhibit greater patience with less aggressive limit orders, which in turn are rewarded with higher fill rates compared to market-wide statistics. Figure 3, Panel B presents the execution probabilities which are calculated using a model where a cancellation is the censoring event. Execution probabilities increase significantly with time for the least 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.[17] Figure 4 presents statistics on both routing and execution of marketable and limit orders for our broader sample of retail brokers. Table 7, Panel A presents additional statistics on order size, fill rate, and trading costs for retail marketable and limit orders based on their routing. Our sample focuses on orders routed either to market makers or exchanges, so, the proportion not routed to market makers is directly routed by brokers to exchanges.

Figure 4 shows that brokers route nearly all retail marketable orders (99.8% of order and 99.9% of shares) to market makers. In contrast, 89% of retail limit orders accounting for 87% of submitted shares are routed to market makers, with the remaining going to exchanges. The third group of bars in Figure 4 indicate that market makers execute 99.9% of shares from marketable orders and about 83% of shares from limit orders.

Table 7, Panels A and B show differences in order size and costs based on routing. Retail limit orders sent to exchanges are slightly larger, averaging 200 shares, have slightly higher fill rates at 70%, and have marginally lower IS, averaging negative 9.7 basis points. By comparison, retail limit orders routed to market makers average 159 shares, have fill rates of 64.4%, and IS of negative 7.9 basis points.

Comparison of the market maker versus exchange outcomes may not be very meaningful since market makers also source liquidity for limit orders from other venues, including exchanges. Specifically, market makers can execute trades on a Principal or Riskless Principal basis. In Principal trades, the market

[17] 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.

maker acts as the counterparty to the retail order, taking the traded shares into its own account. In Riskless Principal trades, the execution of the retail order is conditional on the market maker first executing an equivalent trade elsewhere at the same price. The OATS data marks these execution types, and we use these classifications in our analysis.[18] The right-most bars in Figure 4 shows that market makers execute approximately 90% of marketable shares on a Principal basis, with the remaining 10% executed as Riskless Principal. For retail limit orders, the pattern is different: about 30% of shares are executed with the market maker acting as Principal, while the majority, 66%, are executed on a Riskless Principal basis.[19] Together, market makers act as Principal for roughly 25% of all shares traded (i.e., 30% of 83% of shares executed by market makers) through retail limit orders.[20] Thus, while market makers do not play as significant a role in executing limit orders as they do for marketable orders, they still execute as Principal a substantial proportion of retail limit orders.

We examine whether the proportion of limit order executions classified as Principal varies by the price aggressiveness of limit orders. Table 7, Panel C, shows that Principal executions are more likely for limit orders placed within the NBBO quote (35% of shares) and at the NBBO quote (39% of shares) compared to orders placed further away, such as within five times the spread (27% of shares) or further behind the quote (25% of shares).

Table 8 presents a regression analysis exploring whether the proportion of Principal executions for an order is associated with the order's IS. This analysis is conducted on the sample of limit orders routed to market makers that result in executions. We acknowledge two shortcomings of this analysis. First, market makers choose when to act as Principal, which introduces endogeneity, as they may prefer easier traders

[18] 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."

[19] A small fraction of executed shares 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%. Given the small magnitudes, we focus our attention on Principal and Riskless Principal executions in our analysis.

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

where the cost of liquidity provision is lower, or they may fill difficult orders to maintain broker relationships. To address this, we control for observable attributes in the regressions. Second, since only executed orders are categorized as Principal or Riskless Principal, unfilled orders remain unclassified. If market makers selectively act as Principal for orders they favor, orders routed for potential Riskless Principal execution may have lower fill rates and higher IS if opportunity costs are included. To mitigate these issues, we compare orders within the same price aggressiveness categories, as fill rates and outcomes are often related to order aggressiveness. Specifically, we estimate the following model to understand the relationship between principal executions and IS costs:

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

where IS_i is the IS 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 described earlier. We include broker fixed effects and stock-day-aggressiveness fixed effects, which allow 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 the direction of the order.

The results in Table 8 indicate that limit orders with a higher proportion of executions classified as Principal 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 0.35 basis points in model (4). This effect is much smaller than the nine to 10 basis point IS difference observed earlier between marketable and limit orders. We cannot isolate the exact mechanism driving this difference. It is unclear whether market makers improve IS costs by offering better executions or simply select easier orders to execute. However, two cautious conclusions can be drawn from this analysis. First, market maker Principal executions do not seem to be associated with higher 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 29.2% of shares traded. Retail traders use limit orders across various stock size categories and price aggressiveness levels. Unlike market-wide findings in earlier studies, retail limit orders are more often placed behind the best quotes, with a substantial proportion placed far behind. This behavior may reflect retail traders' disadvantages in monitoring ability and speed of access, requiring greater compensation for liquidity provision. Additionally, retail orders placed at or near the best quotes may become marketable by the time they reach the market center, prompting retail traders to place orders further behind the quotes.

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 findings 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 are left open for 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. Thus, retail traders exhibit greater patience when using less aggressively priced limit orders and are rewarded with higher fill rates compared to market-wide statistics. The higher fill rates reduce opportunity costs for limit orders.

Our findings suggest that limit orders offer an attractive way for retail traders to earn compensation by 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 and proposed regulatory changes may impact how retail marketable orders are handled. For example, SEC (2022) has proposed Rule 615, which would require retail marketable order internalizations to occur in qualified auctions, with the goal of obtaining greater price improvement. Additionally, the recently adopted revisions to Rule 605 in SEC

(2024) extends the rule to broker dealers to better understand the execution quality of internalized retail marketable trades. These changes could improve the execution quality of retail marketable orders and affect the tradeoffs that we identify in the study.

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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 related to accurately measuring 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 from the sample. 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 only examine simple marketable and non-marketable orders. We allow marketable orders to be marked as immediate-or-cancel (IOC). We examine routed directly to a market maker, routed directly to an exchange, or initially routed to market maker, then subsequently routed by that market maker to an exchange. To ensure that the 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 from the sample as these include orders that are modified many times, likely reflecting more sophisticated automated order submission strategies. These filters leave us with 27,707,096 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). We remove top orders with a fill rate greater than 100%, absolute value of implementation shortfall be less or equal to 10%, and time-to-execution of less than negative 2 seconds. These filters leave us with 27,082,717 orders.

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.

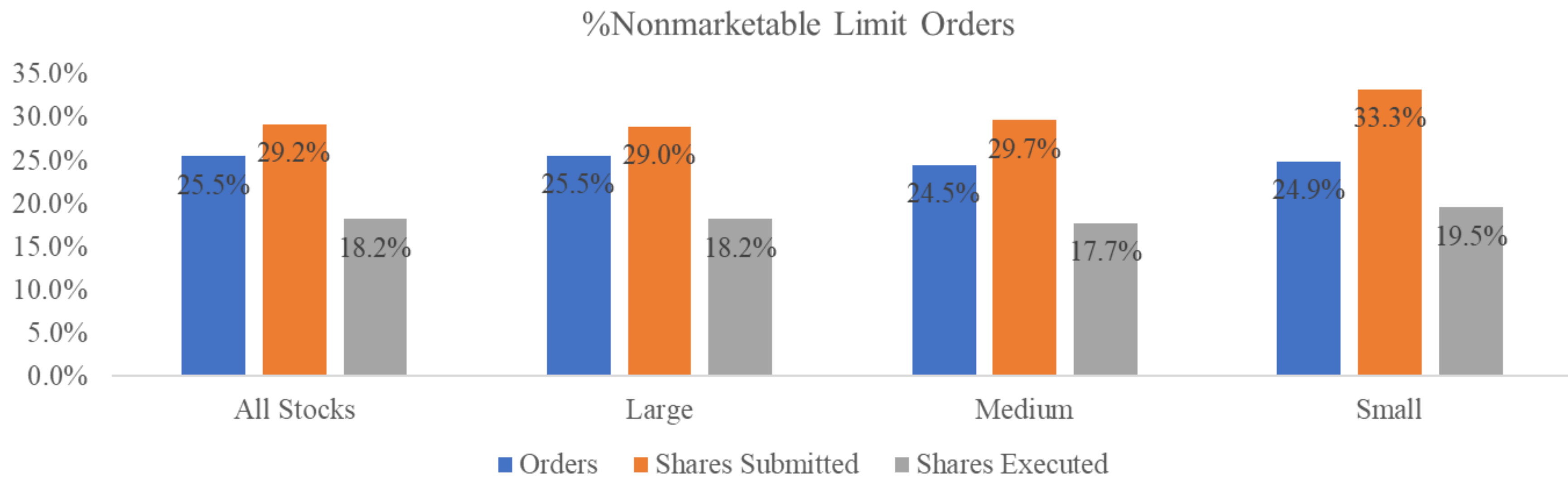


Figure 2
Limit Order Usage by Aggressiveness Level

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 for each aggressiveness category (gray bars). 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.

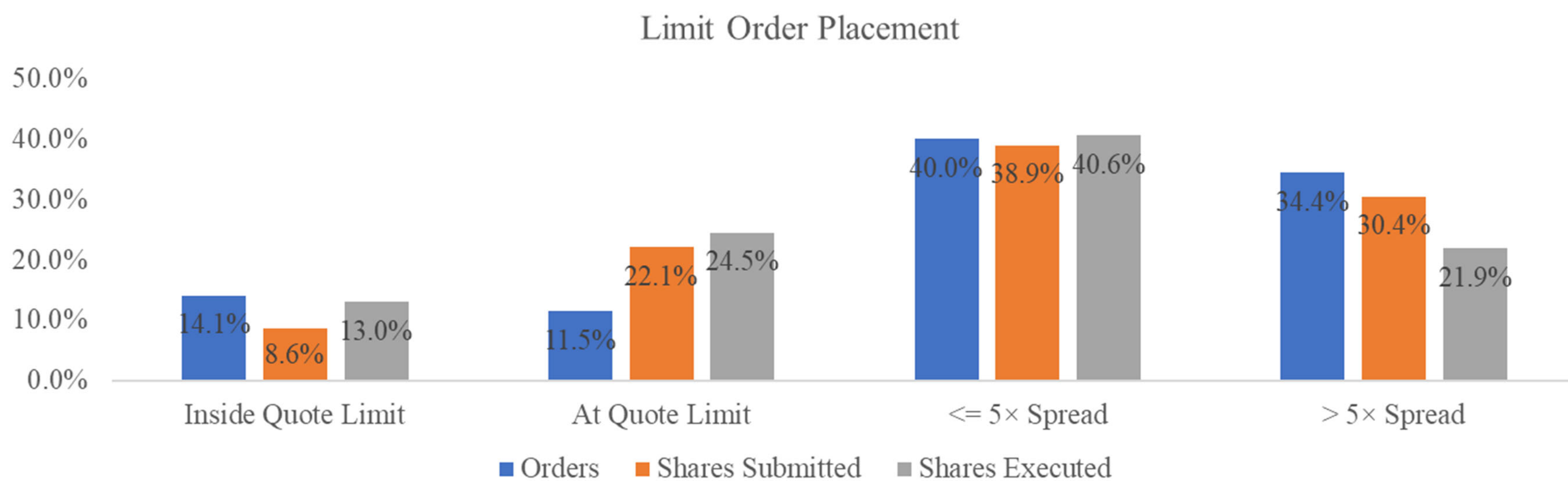
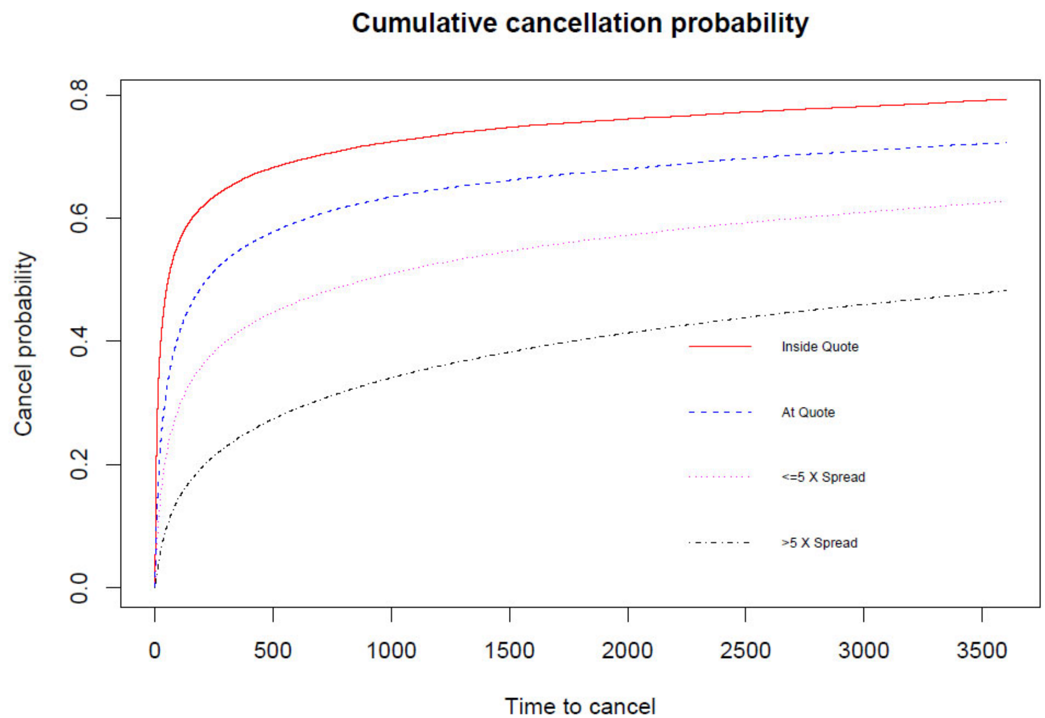


Figure 3
Cumulative Limit Order Cancellation and Execution Probability

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.



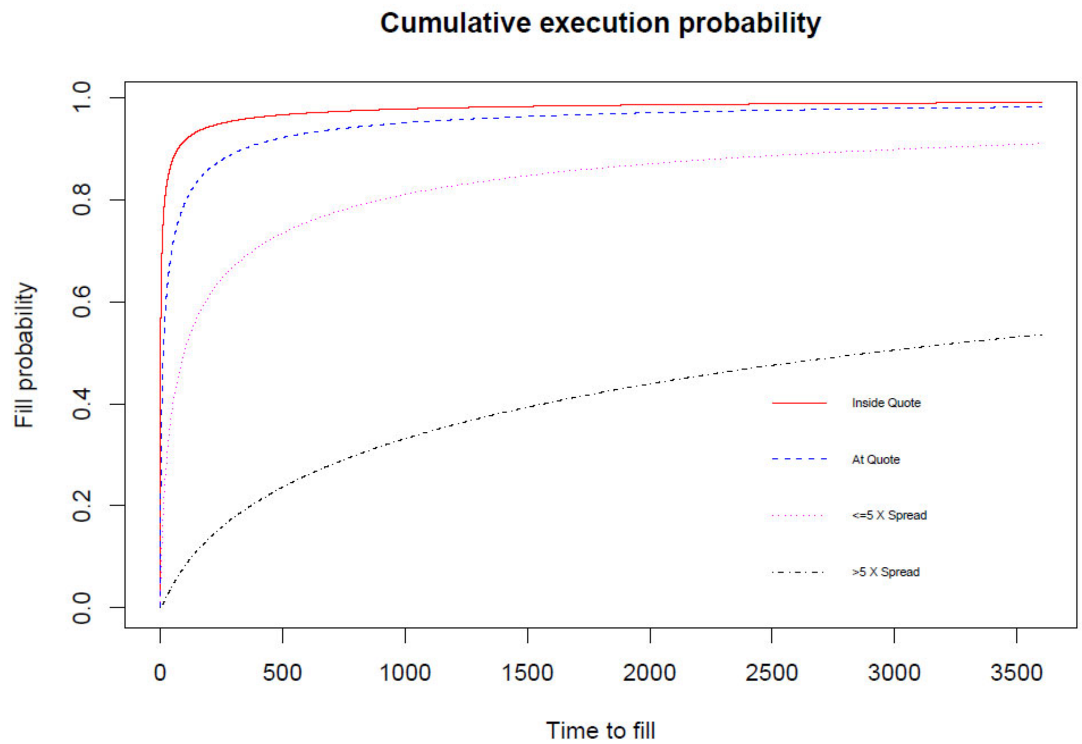

Cumulative execution probability
Fill probability
0.0
0.2
0.4
0.6
0.8
1.0
0
500
1000
1500
2000
2500
3000
3500
Time to fill
Inside Quote
At Quote
<=5 X Spread
>5 X Spread

Figure 4
Retail Order Handling

This figure reports statistics for retail order handling of marketable (blue bars) and nonmarketable limit (orange bars). The first group of bars reports the proportion of orders routed to market makers. The second group of bars reports the share quantity routed to market makers. The third group of bars reports the proportion of shares executed at market makers. The fourth group of bars reports the proportion of shares executed at market makers in a principal capacity.

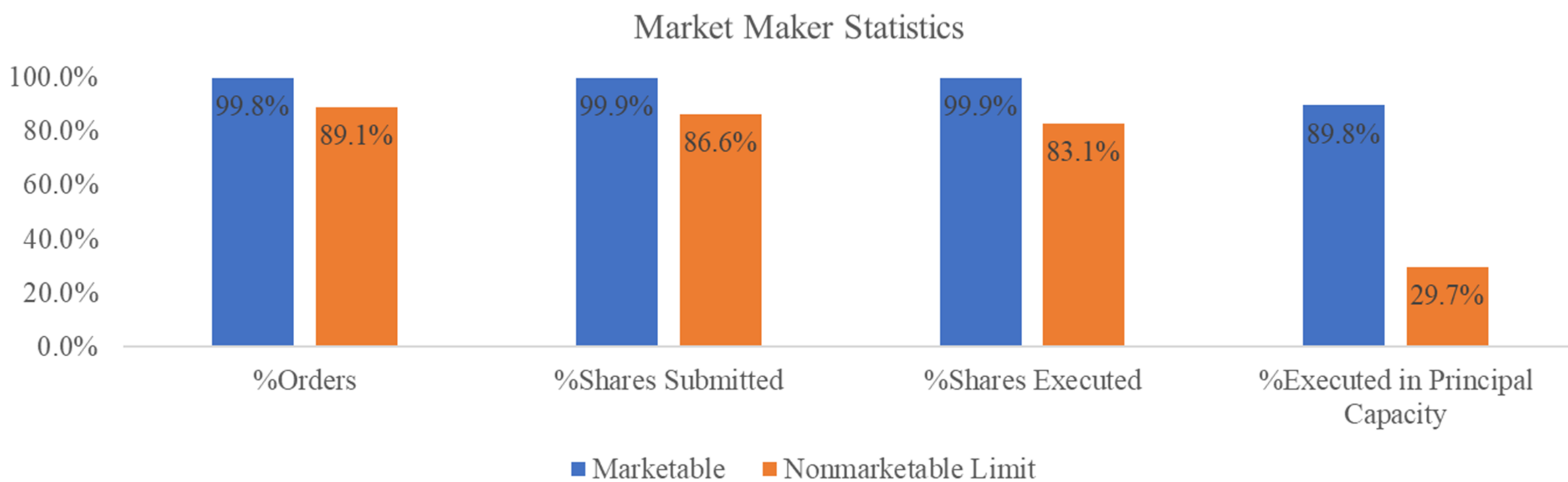


Table 1
Sample Description

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	$317	$343,827,239	28,369,430	2.05
Medium	$36	$2,515,359	7,486,976	9.04
Small	$13	$502,815	3,716,032	15.36

Panel B: Order Type Statistics

Order Type	Number of Orders	Total Shares	Total Shares Traded	Avg. Order Size	Med. Order Size
Marketable	20,180,821	2,742,794,536	2,734,812,002	136	15
Nonmarketable Limit	6,901,896	1,130,341,522	609,165,609	164	25

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	Med. Order Size
Large	Marketable	18,747,296	2,472,998,358	2,467,331,551	132	15
Large	Nonmarketable Limit	6,432,701	1,008,268,407	548,683,628	157	25
Medium	Marketable	831,718	163,167,394	162,065,915	196	25
Medium	Nonmarketable Limit	269,980	68,924,213	34,873,414	255	50
Small	Marketable	601,807	106,628,784	105,414,536	177	20
Small	Nonmarketable Limit	199,215	53,148,902	25,608,567	267	68

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), and implementation shortfall (IS). IS includes the effective spread cost for filled shares of the order and the opportunity cost for the unfilled shares, 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 statistics by stock size tercile in Panel B.

Panel A: Execution Quality Statistics by Order Type

Order Type	Fill Rate	Effective Spread (bp)	Shortfall (bp)
Marketable	99.8%	1.04	1.06
Nonmarketable Limit	65.1%	-20.15	-8.06

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

Stock Size Tercile	Order Type	Fill Rate	Effective Spread (bp)	Shortfall (bp)
Large	Marketable	99.8%	0.74	0.74
Large	Nonmarketable Limit	65.2%	-18.45	-7.62
Medium	Marketable	99.8%	3.42	3.55
Medium	Nonmarketable Limit	65.3%	-38.93	-14.70
Small	Marketable	99.7%	6.97	7.56
Small	Nonmarketable Limit	60.3%	-51.83	-13.30

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 spread cost for filled shares of the order and the opportunity cost for the unfilled shares, 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 daily 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, and standard errors clustered by stock and day are reported in parentheses.

	Dependent variable:					
	IS (bp)					
	(1)	(2)	(3)	(4)	(5)	(6)
Marketable	9.317^{***}	9.444^{***}	10.270^{***}	7.483^{***}	8.313^{***}	8.656^{***}
	(0.999)	(1.020)	(2.099)	(0.880)	(0.993)	(0.976)
Ln(Order Size)		0.276^{***}	0.268^{***}	0.295^{***}	0.282^{***}	0.286^{***}
		(0.058)	(0.042)	(0.061)	(0.057)	(0.058)
Arrival Spread (bp)		0.266^{***}	0.266^{***}	-0.202^{***}	0.272^{***}	0.284^{***}
		(0.025)	(0.025)	(0.069)	(0.025)	(0.025)
Sell			1.864			
			(3.094)			
Marketable × Sell			-2.075			
			(3.128)			
Marketable × Arrival Spread				0.686^{***}		
				(0.080)		
Marketable × Volatility					0.090^{***}	
					(0.024)	
Marketable × Small-Med						11.513^{***}
						(1.107)
Stock-Day FE	Y	Y	Y	Y	Y	Y
Observations	27,082,717	27,082,717	27,082,717	27,082,717	27,082,717	27,082,717
Adjusted R^2	0.032	0.033	0.034	0.036	0.034	0.036

*p**p***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 spread cost for filled shares of the order and the opportunity cost for the unfilled shares, 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; and an indicator variable equal to one for marketable orders during 5-minute intervals without submitted nonmarketable limit orders and equal to zero otherwise. 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 includes 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:				
			IS (bp)		
	(1)	(2)	(3)	(4)	(5)
Marketable	10.796***	8.865***	10.139***		
	(1.088)	(0.975)	(1.031)		
Ln(Order Size)	0.290***	0.242***	0.263***	-0.035***	0.057***
	(0.053)	(0.037)	(0.036)	(0.006)	(0.009)
Arrival Spread (bp)	0.260***	0.291***	0.290***	0.473***	0.471***
	(0.025)	(0.017)	(0.017)	(0.016)	(0.016)
Marketable Order in 5-min Interval				-0.006	-0.014
				(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	27,082,717	27,082,717	27,082,717	20,180,821	20,180,821
Adjusted R^2	0.041	0.098	0.105	0.158	0.167

*p**p***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), and implementation shortfall (IS). IS includes the effective spread cost for filled shares of the order and the opportunity cost for the unfilled shares, 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 limit orders categorized by price aggressiveness. Each column includes all marketable orders and the limit orders that fall into the specified price aggressiveness category, as labeled in row 'Sample.' 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)	Shortfall (bp)
Marketable	20,180,821	99.8%	1.04	1.06
Inside Quote Limit	975,407	83.0%	-0.49	1.68
At Quote Limit	792,732	76.6%	-3.17	0.53
<= 5× Spread	2,761,048	68.5%	-12.87	-3.74
> 5× Spread	2,372,709	49.9%	-54.23	-19.97

Panel B:

	Dependent variable:			
	Shortfall (bp)			
	(1)	(2)	(3)	(4)
Marketable	0.352***	0.982**	5.359***	21.928***
	(0.073)	(0.403)	(0.857)	(2.466)
Ln(Order Size)	0.066***	0.067***	0.111***	0.210***
	(0.009)	(0.010)	(0.015)	(0.048)
Arrival Spread (bp)	0.443***	0.456***	0.238***	0.401***
	(0.014)	(0.015)	(0.022)	(0.030)
Sample	Inside Quote Limit	At-Quote Limit	≤ 5 × Spread	> 5 × Spread
Stock-Day FE	Y	Y	Y	Y
Broker FE	Y	Y	Y	Y
Observations	21,156,228	20,973,553	22,941,869	22,553,530
Adjusted R^2	0.143	0.130	0.040	0.079

*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. For execution probabilities, cancellation 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	6
All Limit	952	1257
Inside Quote Limit	30	40
At Quote Limit	94	106
<= 5× Spread	485	506
> 5× Spread	2785	3014

Panel B: Cumulative Limit Order Cancellation Probabilities

	Nonmarketable Limit Order Type				
Time	All Orders	Inside Quote	At Quote	≤ 5 × Spread	> 5 × Spread
5 seconds	4.2%	16.4%	7.5%	4.1%	1.3%
10 seconds	7.4%	27.0%	13.3%	7.7%	2.7%
1 minute	20.1%	50.6%	34.5%	23.8%	11.0%
5 minutes	33.3%	64.8%	53.2%	40.0%	22.9%
10 minutes	39.2%	69.3%	59.4%	46.4%	29.1%
1 hour	56.1%	79.2%	72.2%	62.7%	48.2%
2 hours	64.8%	83.4%	77.8%	70.0%	58.5%

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 order statistics including the total submitted top order share quantity, the average top order share execution size, the total executed share quantity, total executed share quantity by market makers in a principal capacity, and the total executed share quantity by market makers in a riskless principal capacity. Execution quality statistics in Panels B and D include 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), and implementation shortfall (IS). We report statistics for the full sample of firms in Panel A and B and statistics by order type and price aggressiveness categories of limit orders in Panel C and D. 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	Routed To	Number of Orders	Total Shares	Shares Traded	Avg. Order Size	Shares Traded (P)	Shares Traded (R)
Marketable	Market Maker	20,146,532	2,740,627,158	2,732,661,711	136	2,453,337,336	273,720,444
Marketable	Exchange	34,289	2,167,378	2,150,291	63	-	-
Nonmarketable Limit	Market Maker	6,146,156	978,976,654	505,956,149	159	150,301,664	332,789,599
Nonmarketable Limit	Exchange	755,740	151,364,868	103,209,460	200	-	-

Panel B: Execution Quality Statistics

Order Type	Routed To	Fill Rate	Effective Spread (bp)	Shortfall (bp)
Marketable	Market Maker	99.8%	1.03	1.06
Marketable	Exchange	99.9%	1.61	1.65
Nonmarketable Limit	Market Maker	64.4%	-19.56	-7.87
Nonmarketable Limit	Exchange	70.4%	-24.58	-9.65

Panel C: Venue Choice for Retail Limit Orders by Aggressiveness								
Routed to	Aggressiveness	Number of Orders	Total Shares	Shares Traded	Avg. Order Size	Shares Traded (P)	Shares Traded (R)	P/(P+R)
Market Maker	within quotes	886,771	86,337,160	70,194,207	97	24,557,654	44,871,187	35.4%
Market Maker	at quote	732,231	229,524,500	132,350,472	313	51,151,330	80,580,836	38.8%
Market Maker	≤ 5 ×Spread	2,485,604	384,041,838	204,396,981	155	53,140,477	144,157,454	26.9%
Market Maker	> 5 ×Spread	2,041,550	279,073,156	99,014,489	137	21,452,203	63,180,122	25.3%
Exchange	within quotes	88,636	10,591,355	9,276,144	119	-	-	
Exchange	at quote	60,501	20,203,799	16,644,255	334	-	-	
Exchange	≤ 5 ×Spread	275,444	55,806,144	42,818,768	203	-	-	
Exchange	> 5 ×Spread	331,159	64,763,570	34,470,293	196	-	-	

Panel D: Execution Quality by Aggressiveness				
Routed to	Aggressiveness	Fill Rate	Effective Spread (bp)	Shortfall (bp)
Market Maker	within quotes	82.2%	-0.47	1.72
Market Maker	at quote	75.6%	-3.19	0.60
Market Maker	≤ 5 ×Spread	67.3%	-12.87	-3.62
Market Maker	> 5 ×Spread	49.3%	-53.88	-20.24
Exchange	within quotes	91.6%	-0.74	1.29
Exchange	at quote	88.8%	-2.95	-0.35
Exchange	≤ 5 ×Spread	79.2%	-12.89	-4.80
Exchange	> 5 ×Spread	54.1%	-56.15	-18.30

Table 8
Execution Quality, Principal vs Riskless Principal Executions

This table presents regression coefficients 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 spread cost for filled shares of the order and the opportunity cost for the unfilled shares, 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:			
	IS (bp)			
	(1)	(2)	(3)	(4)
$\frac{P}{P+R}$	-0.6170^{***}	-0.2951^{*}	-0.6653^{***}	-0.3465^{**}
	(0.1898)	(0.1626)	(0.1841)	(0.1569)
Ln(Order Size)	0.2217^{***}	0.2919^{***}	0.1834^{***}	0.2631^{***}
	(0.0505)	(0.0423)	(0.0444)	(0.0353)
Arrival Spread (bp)	-1.6940^{***}	-1.6895^{***}	-1.7176^{***}	-1.7132^{***}
	(0.1304)	(0.1290)	(0.1338)	(0.1326)
Stock-Day-Agg FE	Y	Y	N	N
Stock-Day-Agg-Side FE	N	N	Y	Y
Broker FE	N	Y	N	Y
Observations	3,689,382	3,689,382	3,689,382	3,689,382
Adjusted R^2	0.5813	0.5830	0.5911	0.5926

*p **p ***p<0.01