Via Electronic Submission

Securities and Exchange Commission
100 F Street, NE
Washington, DC 20549-1090
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Re: File No. S7-32-22: Regulation Best Execution

In the attached paper entitled "Who Is Minding the Store? Order Routing and Competition in Retail Trade Execution," we examine competition among wholesalers, to which brokers route orders from their retail investors.

Rather than relying on public disclosures that are aggregated at a high level, we can perform analyses on these interactions using data from an almost two-year long experiment where we placed our own retail trades across several brokerage accounts. Our parallel trades allow us to directly compare execution prices across brokers and venues. In addition, we have direct data on the percentage of order flow routed to each wholesaler and can examine the actual brokers' responses to differences in execution quality.

Importantly, our data allow us to perform *within-broker* analysis. This allows us to control for the characteristics of each broker's order flow, which lead to systematic differences in execution costs across brokers. Additionally, another important advantage of our approach lies in the randomization of trading times across a diverse range of stocks. By systematically placing trades at varied times throughout the day and rotating these times across stocks, we can mitigate measurement biases that could arise from potential strategic behaviors of wholesalers.

In summary, our findings are inconsistent with perfect competition. We find that each broker's wholesaler execution prices have substantial dispersion and are persistent over time. However, most brokers do not adjust their routing even when they are sending more of our orders to higher-cost wholesalers. We also observe that the entry of a new wholesaler improves other wholesalers' execution quality. Finally, we present a stylized model that illustrates how brokers' limited response to execution allows wholesalers to exercise some market power.

Our results show that more active routing could potentially lead to better execution for retail customers. One way to achieve this is through stronger, more specific best execution requirements that require better justification for not modifying routing arrangements when material differences in execution quality exist across markets. With that said, it is unclear whether more active routing across wholesalers would be counterproductive and lead to lower overall execution quality.

Sincerely,

Xing Huang, Philippe Jorion, and Christopher Schwarz

Who Is Minding the Store? Order Routing and Competition in Retail Trade Execution

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November 19, 2023

Abstract

Using 150,000 actual trades, we examine competition among wholesalers, to which brokers route orders from their retail investors. We find that each broker's wholesaler execution prices have substantial dispersion and are persistent. However, most brokers do not adjust their routing even when they are sending more orders to higher-cost wholesalers. We also observe that the entry of a new wholesaler improves other wholesalers' execution quality. Finally, we present a stylized model that illustrates how brokers' limited response to execution allows wholesalers to exercise their market power. Overall, our findings are inconsistent with perfect competition.

JEL Classifications: G12, G14, G50
Keywords: retail trading, execution quality, order routing, competition, bid/ask spread, market microstructure, broker-dealers, wholesalers

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1. Introduction

Retail investors' access to U.S. equity markets has vastly improved over the last few decades. As markets started to automate in the mid-1990s, investors benefited from a major reductions in trading costs. This period also witnessed major structural changes in market design, in particular Regulation NMS (SEC (2005)), which ultimately mostly delegated retail trading to specialized OTC market-makers, known as "wholesalers." After retail trading volumes exploded in late 2019 due to brokers going commission-free, the current market structure has come under scrutiny. This attention culminated in four Securities and Exchange Commission (SEC) proposals in late 2022 whose goal is to further decrease trading costs for retail investors by increasing competition among market makers.

In this paper, we examine the competitiveness of the wholesaler marketplace where retail trades are executed. On the one hand, there are concerns that the wholesaler market is too concentrated, with only four large players.[1] On the other hand, the current market structure is already designed to be competitive. Retail brokers are expected to enforce competition across wholesalers. Indeed, under their legal duty of "best execution," brokers should monitor the quality of execution by wholesalers and act accordingly. Furthermore, their routing decisions should ensure that "order flow is directed to markets providing the most beneficial terms for their customers' orders."[2] Given this market design, one might argue that wholesalers compete in Bertrand fashion such that perfect competition may be obtained even with two competitors. The goal of this paper is to contribute to this debate on competition among wholesalers by providing empirical evidence and economic insights.

[1] See for instance Hu and Murphy (2022) .
[2] FINRA (2014).

We provide a unique window into the analysis of competition in the wholesaler market by observing granular data on interactions between broker routing and wholesaler execution. Rather than relying on public disclosures that are aggregated at a high level, we are able to perform analyses on these interactions using data from an almost two-year long experiment where we placed our own retail trades across 10 brokerage accounts.[3] Our parallel trades allow us to directly compare execution prices across brokers and venues over this large sample. In addition, this provides direct data on the percentage of order flow routed to each wholesaler, as well as the brokers' responses to differences in execution quality.

Importantly, our data allow us to perform *within-broker* analysis. As shown by Schwarz et al. (2023), brokers experience substantial variations in average execution, which likely reflect different characteristics (e.g., the so-called "toxicity") of order flows across brokers. Such across-broker variations in execution could obfuscate comparisons across wholesalers when examined through the lens of aggregate-level data provided in public disclosures. Specifically, we measure price execution relative to the average across venues for each broker, based on the effective over quoted (E/Q) spread, which provides a normalized measure of trading cost. A higher E/Q indicates a larger transaction cost for investors since trades are executed closer to the prevailing quoted spread, and is equivalent to lower price improvement (PI).

Another advantage of our approach lies in the randomization of trading time across a diverse range of stocks. We selected a representative sample of the universe of U.S. stocks

[3]We generated a total of approximately 172,000 trades, equivalent to $22.4 million in notional, over the period from December 21, 2021, to May 31, 2023. Our trades are executed through E*Trade, Fidelity, Interactive Brokers (IBKR, with both their Pro and Lite account types), Robinhood, Schwab, and TD Ameritrade. We placed orders at different brokers that were identical in type (market orders), ticker (stock), size (dollars and shares traded), direction (buy or sell), and submission time. All trades were intraday, i.e., we bought equities after the market opened and then sold them within 30 minutes, with trading spread out throughout the day.

stratified by key dimensions: market capitalization, price, liquidity, and volatility. By systematically placing trades at varied times throughout the day and rotating these times across stocks, we can mitigate the selection bias that that could arise from potential strategic behaviors of wholesalers.[4]

We observe widely varying practices for stock routing. Approximately two-thirds of our brokers route stocks to wholesalers using what we call a "proportional" method. These brokers simply take a "slice" of their aggregate order flow and send it to each wholesaler; the only variation across wholesalers is the dollar size of their slice. The remaining one-third of brokers use what we call a "selective" routing method ("smart-routing" in industry parlance), where the routing for each stock is selected from wholesaler and stock characteristics.

To examine the competitiveness of retail trade execution, we test implications of the perfect Bertrand competition hypothesis. If the market were perfectly competitive with brokers frictionlessly switching across wholesalers based on their execution, the order flow would only go to the wholesaler(s) that provides the best execution quality. Thus, we would expect that for a given broker there is no dispersion of execution costs across wholesalers. However, we find that there is substantial dispersion. Moreover, the dispersion is persistent over time, both at the aggregate and stock levels. At the aggregate level, slopes on past price improvement are often close to one, with R-squares over 50%. At the individual stock level, the persistence is more modest with slopes around 0.3 and lower R-squares (around 8%).

Despite this predictability, a majority of our brokers do not seem to change their routing based on past execution. In fact, only one does so at a statistically significant level. One

[4]Wholesalers might tailor their execution quality based on their understanding of brokers' evaluation metrics. Consequently, using archival or public disclosure data may inadvertently bias the sample towards instances where strategic wholesalers offer superior executions. Our approach with randomized timing on a representative sample could provide a more comprehensive and unbiased view of the market.

possible explanation for the limited response of brokers to past execution quality could be that routing has stabilized at a steady state. If this were the case, we would expect brokers to direct orders in a manner that minimizes costs by sending more orders to wholesalers that provide lower execution costs. Contrary to this prediction, our findings show that the majority of brokers actually route more orders to wholesalers associated with higher average execution costs for our trades.

To illustrate the impact of not changing market share to predictably lower cost wholesalers, we simulate dynamic routing decisions that are based on our prior price execution. Doing so lowers E/Q by 34% when using prior aggregate execution to route all trades and 19% when using stock level prior execution to route trades on a stock-by-stock basis. These changes are more dramatic for proportional brokers, with a drop of 45% using aggregate execution, whereas it is only 10% for selective-routing brokers.

We continue to explore competition by examining the entry of Jane Street as wholesaler for a particular broker in early 2022. This broker is the most responsive broker from our empirical findings, and also has data starting in 2021. Immediately after this entry, we find a significant improvement in aggregate price execution by the other wholesalers at that broker; in addition, they still lost significant market share. This suggests that retail investors at that broker benefited from this increased wholesaler competition.

To collectively explain our findings, we develop a stylized model of order routing that sheds light on the underlying economic intuition. In the model, a broker has two wholesalers to route orders. The broker experiences switching costs, which serve as a modeling device to capture potential frictions that limit the ability or willingness of brokers to respond to dispersion in execution quality. For example, these costs could be for the time and cost of monitoring, limits imposed on maximum or minimum market share, technology limitations, and so forth. Equilibrium outcomes depend on the size of switching costs.

When switching costs are absent or very small, the equilibrium resembles that of Bertrand competition. There is no dispersion among execution costs, since the low-cost wholesaler receives the entire order flow otherwise. All wholesalers offer the same execution, and there is no relation between execution prices and market share. Thus, switching costs, or the broker's limited response to execution that result from them, are essential in understanding the relation between execution prices and market share.

When switching costs are high, wholesalers exercise their market power and raise their execution costs. The rents they extract from the broker (or more precisely, their retail investors) are split according to their market share. The wholesaler with larger market share charges higher costs than the other wholesaler. Thus, this explains the puzzling pattern of brokers routing more orders to higher-cost wholesalers. It is not that brokers route more orders to wholesalers because they are more expensive but rather that wholesalers charge higher prices because brokers route more orders to them.

When switching costs are moderate and the larger wholesaler incurs lower marginal costs when making markets for the broker's order flow, the relation between execution costs and market share can flip. The larger wholesaler has an incentive to charge less because this leads to an even greater market share and higher profits, generating a negative relationship between execution costs and market share.

These results are consistent with our empirical finding that the relation between market share and execution cost is positive for proportional brokers, while it is negative for selective brokers, who tend to respond to prior execution albeit modestly and thus exhibit smaller switching costs than proportional brokers.

Overall, our paper adds significantly to the literature on the broker-wholesaler marketplace. We describe the range of current practices in how brokers route trades to wholesalers. We also document that price improvement is highly persistent over time. We are able to show that a majority of brokers do not react significantly to past price improvement when making routing decisions. This is even if higher execution cost wholesalers have larger market share. We also directly examine competitive changes when a new wholesaler enters the market at one broker. Finally, we present a stylized model to provide economic intuition for our findings. Our results suggest that the marketplace is not perfectly competitive.

Our paper is most closely related to Dyhrberg et al. (2023). The authors use public 605 forms (disclosures of order execution information by market centers) to investigate the competitiveness of the wholesaler marketplace. Their general conclusion is that the wholesaler market is competitive. While we are able to replicate their main empirical finding with our data, we find more mixed results due to the greater detail in our data set, including routing information and execution at the wholesaler-broker levels.

As noted, the SEC has proposed several rules to increase competition in the broker-wholesaler marketplace. These proposals attempt to accomplish this goal through changes in best execution requirements, tick sizes, disclosure, and how orders are executed in the marketplace. The direct implication of our results is that more disclosure would be beneficial for retail investors. Under the proposed disclosure requirements (SEC (2022a)), the 605 forms would be required not only of market centers, but also of retail brokers. This would help investors pick brokers that provide lower execution costs. However, the proposal still does not require disclosing execution costs by broker-wholesaler pair. As we show, this approach would provide more informative measures of wholesaler performance because it controls for broker order-flow characteristics. Such public disclosures would create additional pressure on brokers for better monitoring and execution, creating more competition in this market.

Finally, it is important to note the limitations of our study. Our experiment was based solely on placing small "market" orders for equities during the day; we do not evaluate other types of orders or options trading. Most of our orders are odd-lots, i.e., less than 100 shares, although we also experimented with round lots, with similar results.[5] Even so, it should be noted that odd lots are becoming increasingly important, now accounting for 60% of orders and close to 20% of trading volume.[6] Further, we only examine execution quality in terms of price improvement, while other aspects may be important as well. Lastly, we do not observe the entire order flow of our brokers.

The rest of the paper is organized as follows. Section 2 reviews the current literature on this topic, and describes interactions between brokers and wholesalers. Section 3 describes our self-generated data and descriptive patterns in the routing of individual stocks from brokers to various wholesalers. Next, Section 4 delves into our empirical analysis aimed at evaluating the degree of competitiveness in the wholesaler industry. Section 5 then presents a stylized model explaining our empirical findings. Section 6 concludes.

[5]For example, if some brokers only set allocations at the overall order flow level either due to technological limitations or due to prioritizing one segment (such as trade size) or set of symbols (tickers), then any segment of their flow that is not prioritized will appear to be not monitored since execution within that segment does not impact their routing choices.

[6]See https://www.sec.gov/marketstructure/datavis/ma_overview.html. Currently, the 605 forms do not cover odd lots. So, it is hard to know whether execution quality systematically differs from round lots. Bartlett (2021) uses a regression discontinuity approach, using 2020 data, to show a drop in PI from 45% to 41% for odd lots, implying a slightly worse execution. On the other hand, Fidelity, one of the largest retail brokers, reports that, during 2022Q4, its odd-lot bucket has actually better price improvement, by about 1 ppt. See https://www.fidelity.com/bin-public/060_www_fidelity_com/documents/FIF-FBS-retail-execution-quality-stats.pdf

2. Literature Review and Institutional Background

2.1. Literature Review

Previous work on execution quality has mostly focused on different market environments, market centers, and types of trades. Also, the market environment has drastically changed since the advent of zero commissions in 2019.[7]

A detailed analysis such as ours has not been performed before, owing to a lack of suitable public databases. Traditional trade-level datasets used in academic research, such as the Trade and Quote (TAQ) database, do not identify the broker, nor the wholesaler, nor the trade direction, nor the type of trader (retail or institutional). Our self-generated trades do not suffer from any of these drawbacks. They offer a representative sample of "market" orders, which are most widely used by retail investors.[8]

Other datasets are available, but only at aggregate levels. Under Rule 605, the SEC requires all market centers to publish monthly reports that include information about their average quality of execution on a stock-by-stock basis.[9] The 605 forms, however, have no information about counterparties. Aside from that, Rule 606 requires broker-dealers to publish reports that provide a monthly summary of their routing practices to various venues,

[7]For example, Battalio et al. (2016) and Battalio (2018) use data from 2012 and 2016, respectively, to examine fees and rebates on exchanges, where rebates apply to limit orders.

[8]Schwab (2022), for example (p.10), indicates that about 75% of its equity trades are plain market orders.

[9]For details, see SEC (2005) ("Disclosure of Order Execution Information".) One benefit of these reports is that the filers observed the direction of trades, so that there is no need to use an algorithm to do so. In contrast to a trading experiment, the typical approach in empirical research based on TAQ is to use the Lee and Ready (1991) algorithm or more recently Boehmer et al. (2021). These assign buy (sell) signals from trades executed above (below) the midpoint or based on the amount of subpenny price improvement, respectively. The problem, however, is that these algorithms misclassify many entries at or beyond the midpoint, which systematically understates the extent of price improvement.

detailing fractions of orders as well as PFOFs, both in total dollars and per share.[10] The 606 forms, however, have no information on quality of execution. Overall, these two forms are complementary, but only provide "marginal distributions" about execution and routing, instead of the full joint distribution for which our experiment has a representative sample.

Dyhrberg et al. (2023) provide the first systematic description of the current landscape for retail execution quality. They examine Rule 605 reports from 14 exchanges and the largest 8 wholesalers over the 2019-2022 period. Their first finding is that wholesalers deliver retail trading costs that are lower than those offered by exchanges, leading to savings estimated up to a billion dollars per month.[11]

They also examine competition in the wholesaler market, first by relating market share (not routing data) to prior execution quality. They find that market share for a particular stock i is high when that wholesaler provides better overall execution quality. However, execution quality for stock i has no effect, suggesting that brokers are only focusing on overall execution. They infer that brokers enforce competition by allocating more trades to wholesalers with better execution. Second, they examine the entry of a new wholesaler, Jane Street, which markedly increased its market share around July 2021. They find no change in realized spreads during the quarters after and before that date, concluding that the wholesaler market was already competitive before the entry.

Our regressions of wholesaler market share on prior price improvement find similar results when measured in levels across all our brokers. However, we document that these results are driven by selective-routing brokers as well as the fact that two poorly performing wholesalers

[10]Enhanced disclosure requirements for Rule 606 ("Disclosure of Order Handling Information") were adopted in November 2018. See SEC (2018).

[11]These results echo those in Adams et al. (2021) and Battalio and Jennings (2023).

have low market shares. We also focus on changes, not levels of market shares, and find markedly weaker effects. For proportional-routing brokers, we find the opposite result, i.e., the best wholesalers get lower shares than the worst for our trades.

As to the new entrant, Jane Street entered the market at different times for different brokers. Because the effects are spread over time, this makes it difficult to find changes from aggregated 605 data. In contrast, we have data on individual brokers, which allows us to pick up changes in price execution at the precise time for each broker. Additionally, Form 605 is missing odd-lot trades, which now make up the majority of trades, as indicated previously. Finally, while we conclude that the market is not perfectly competition, we are also certainly not suggesting there is currently no competition. Indeed, retail traders now receive substantially better price improvement from wholesalers than exchanges.

A different perspective is offered by Hu and Murphy (2022), who argue that the wholesaler market is highly concentrated, with two firms, Citadel and Virtu, accounting for about 70% of retail order flow over 2017-2021. Their theoretical model predicts that, in a non-competitive market, spreads should be wider than needed.

Our experiment provides direct evidence on routing and execution patterns between our seven brokers and their wholesalers, which can be used to assess the degree of competitiveness of the wholesaler market.

Indeed, the SEC (2022b) proposed an "Order Competition Rule" (OCR), which attempts to create more competition for retail trades. One concern is the use of Payment for Order Flow (PFOF), where wholesalers pay brokers for their order flow. PFOF could potentially lead to worse execution for retail traders due to its inherent conflict of interest. However, recent research (e.g., Battalio and Jennings (2023), Ernst and Spatt (2023), and Schwarz et al. (2023)) has largely shown that PFOF does not significantly impact price execution for equity trades.

The other concern is the current wholesaler routing model is not optimal and should be replaced by open auctions, where market makers bid on each individual order. This proposed market structure is totally different from the current one; the question is whether it is needed and whether it will indeed lead to better execution.

Ernst and Spatt (2023) provide a systematic comparison of the two models. On the one hand, order-by-order auctions ensure that an incoming retail market order is always routed to the market maker with the best price. However, this may be worse than the typical price in the current routing model, for several reasons. First, the market maker with the most aggressive price is subject to a winner's curse, e.g., because it reveals information about inventory positions. In response, market makers will bid more conservatively, leading to less competition. Worse, market makers may decide not to provide quotes at all, especially for small stocks that are subject to greater adverse selection. This may lead to failed auctions.

On the other hand, under the current routing model, wholesalers evaluate the profitability of the entire order flow that they are committed to trade, enabling the subsidization of say, small or less liquid stocks at the expense of large liquid stocks. In this case, the authors assume that competition is ensured because brokers monitor execution closely and route orders based on each market maker's aggregate performance.

Ernst and Spatt (2023) also provide empirical evidence that is consistent with their conclusions, which is that "retail investor welfare can decrease in a switch to order-by-order trading, especially for volatile or less liquid stocks". We note, however, that their analysis assumes disciplined routing practices. Our paper checks whether this is the case.

Indeed, perfect competition may be difficult to achieve. Competition across wholesalers should be enforced by brokers, who are themselves subject to the scrutiny of retail investors. Best execution rules should be enforced by regulators. Imperfect information, however, makes this difficult. In the current environment, for example, brokers and investors cannot compare execution quality across brokers. In other words, if there is no pressure on brokers from investors to improve execution quality, then brokers might not prioritize applying pressure to wholesalers either.

Addressing this blind spot is the purpose of the recently proposed "Order Execution Disclosure" rule (SEC (2022a)), which would expand the scope of 605 reports to brokers in addition to market centers, and will be discussed in the following section.

2.2. Interactions between Brokers and Wholesalers

Starting in late 2019, almost all retail brokers went commission free, following Robinhood's example in 2015. This was made possible because brokers could route their trades off exchanges, directly to wholesalers. From the brokers' perspective, this setup can not only provide PFOF revenues, but it also helps them fulfill their best execution requirements.

Interestingly, the relation between brokers and wholesalers is rather loose, reflecting the nature of their private arrangements.[12] First, the broker selects a pool of wholesalers that satisfy its due diligence requirements. The broker then sets a level of payment for order flow, which can be zero. It is important to note that the broker typically sets "level", or identical, PFOF rates across wholesalers in order to avoid conflicts of interest in routing decisions. Next, the wholesaler can decide whether to accept or not the broker's orders.

[12] Schwab (2022), for example, provides an overview of order routing practices for U.S. equities.

There are no other contractual obligations: brokers can route orders to any market centers, and wholesalers do not commit to any set price improvement. Notably, brokers receive no indicative quotes, pre-trade, from wholesalers. Also, from the viewpoint of wholesalers, they only see the order flow from each broker in aggregate, i.e., without knowing the identity of the clients placing orders.

The next step is for the broker to send its order flow across venues. Wholesalers then execute the order flow they receive, either internally, i.e., into or from their own inventory, or externally, i.e., pass them along to another venue for execution, with the majority — close to 90% — internalized (SEC (2022b)).

At this point, it is useful to detail the best execution requirements, which apply to both the originating broker and the wholesaler, who acts as "executing" broker. In the U.S., the broker-dealer industry is overseen by the Financial Industry Regulatory Authority (FINRA), which has issued guidance on best execution practices. According to FINRA (2014)'s Rule 5310, a member firm

> "shall use reasonable diligence to ascertain the best market for the subject security and buy or sell in such market so that the resultant price to the customer is as favorable as possible under prevailing market conditions."

In practice, Section .09 requires the originating retail broker to periodically conduct regular and rigorous reviews of the quality of the executions, at least on a quarterly basis. FINRA (2015) also says that this must include both venues currently used by the broker, as well as competing markets.

Reviews are not sufficient, however. In addition:

> "In conducting its regular and rigorous review, a member must determine whether any material differences in execution quality exist among the markets trading the

> security and, if so, modify the member's routing arrangements or justify why it is not modifying its routing arrangements."

Thus, the best execution requirement is for both monitoring the quality of execution and taking action, i.e., changing routing if needed. It should be noted that brokers only observe directly the quality of execution of their *own* orders across wholesalers. They cannot see execution quality for the same trades executed at the same venues for other brokers, which motivates the proposal to expand the disclosure of execution information to brokers (SEC (2022a)).

Brokers can observe stock-level execution reported by market centers in their 605 forms, but these are averaged across all trades and do not include odd lots. Finally, it is important to note that using prior performance to change routing assumes that execution quality is persistent and that changes in order routing will not impact price improvement. We will test the first hypothesis.

Admittedly, different brokers may have different objective functions underlying their routing decisions. Brokers may emphasize different aspects of execution, or may focus on special types of trades, e.g., small market orders. Indeed, different brokers may have different clienteles (e.g., high net worth individuals versus small individual retail traders) that cause the broker to emphasize different types of orders in their routing decisions. In addition, the concept of "best execution" is more holistic than just price improvement (even though this is systematically listed first) and can include additional factors like execution time and fill rates.

From our discussions with the industry, brokers generally provide feedback ("scorecards") on how a wholesaler's price improvement compares to its competitors.[13] If execution is subpar, the broker can advise the wholesaler to provide better price improvement. Of course, brokers also have the option to route more of their orders to different wholesalers.

Practical considerations are also important. For instance, it may be beneficial to keep small allocations to some venues to enable broader and continuous comparisons of execution information. Also, it would be unwise to route all trades to one single venue, even if it had the best execution, because this could lead to less competition in the long run. Reportedly, allocations above 50% would also attract the attention of regulators. Brokers may even be hesitant to route a majority of their orders to one wholesaler in order to diversify against operational issues such as outages. Finally, some wholesalers may not have the technical capabilities to handle multiples of their current trading volumes.

Going into the detail of stock-level routing practices, brokers can follow different approaches. The first is to simply route a certain percentage of their entire order flow over a certain period to a wholesaler, which we refer to as "proportional" routing. Each wholesaler then receives a slice of the broker's order flow, with the same relative weights (or composition) across stocks, perhaps only differing in the share of total volume sent. One benefit of this approach is that, since each wholesaler receives the same composition for the order flow, the broker can compare execution directly at the aggregate level across wholesalers. In addition, discussions with the industry suggest that wholesalers prefer this proportional approach because the order flow is more diversified as well as more predictable over time, making it easier to manage inventory, thus possibly leading to better execution.

[13] Brokers provide anonymized rankings across their wholesalers. Reportedly, this is generally done across trade size segment, e.g., odd-lots, then in "buckets" of 100-499, 500-1999, 2000-4999, and above 5,000 shares.

The second approach is for brokers to route orders on a stock-by-stock basis, which we call "selective" routing, usually described as "smart" routing by the industry. Under this scenario, brokers evaluate execution for each stock individually and increase the fraction of each stock routed to wholesalers that have provided the best execution for that stock. With selective routing, however, different wholesalers would receive different order flow composition, so that evaluating wholesalers on an overall execution level may not be appropriate. So, performance evaluation is more complex under this scenario.

Our data should enable us to address many of these questions, in particular what are the stock routing practices used by brokers, whether execution quality is persistent, and whether routing patterns are influenced by execution quality, all of which are important to evaluate the retail broker-wholesaler marketplace.

3. Data and Descriptive Evidence

3.1. Data

Our main source of data is self-generated, by placing our own parallel trades at several brokerage houses. In summary, we place simultaneous identical trades (i.e., trades in the same stock of the same order size at the same time) across multiple brokerage accounts. An early version of this dataset is used in both Schwarz et al. (2023) and Barber et al. (2023). Further details about the experiment can be found in those manuscripts.

The stocks we traded were selected as a representative sample of the population of U.S. stocks by stratification into 128 bins based on market capitalization, price, liquidity, and volatility using the June 2021 version of the CRSP stock database. To be included, each stock was required to have a price greater than a dollar and a share code of either 10 or 11.[14] One stock was then selected randomly within each bin. Stocks with a share price that drops below one dollar at the end of the week are replaced with others from the same buckets using the latest quarterly version of the CRSP database. In addition, we included four stocks with high retail activity (AMC, Tesla, Nio, and Aurora Cannabis) and some mega-cap stocks (Apple, Bank of America, NVIDIA, ExxonMobil, Google, and Visa.)

During the course of our experiment, we traded stocks at six different brokerages in several accounts. Our trades are executed through E*Trade, Fidelity, Interactive Brokers (IBKR), Robinhood, Schwab, and TD Ameritrade, which is now owned by Schwab. For IBKR, we traded both their Pro and Lite (Free) accounts, which are with and without commissions, respectively. Whenever possible, we use the Application Programming Interface (API) to automatically trade stocks each day. This allows us to process a large number of trades, as well as to ensure that execution times are close to each other. Unfortunately, some prominent brokers, including IBKR Free, Schwab, and Fidelity, do not offer general access to their API. Hence, we had to place trades at these brokers by hand. Trade times are synced to match the trade times at other brokers.

We begin trading each day at 9:40 AM EST, shortly after the opening auction. Our program trades throughout the day, spacing trades out over the course of the day, with the last trades ending at 3:50 PM EST shortly before the market close. Trading times are rotated across stocks to avoid any time-of-day effect. After purchase, the program sells the same number of shares within 30 minutes. Thus, there is little directional exposure during

[14]Stocks less than one dollar are subject to different rules per Regulation NMS. Additionally, some of our brokers will not trade stocks less than one dollar without special approval. Share codes 10 and 11 identify U.S.-based common stocks.

the day and no open positions at the close. Our order target size is $100. We trade full shares only, rounding the number of shares to make the trade size closest to $100, with a minimum size of one share for higher priced stocks. Identical orders are randomized across brokers to avoid giving a systematic time advantage to any broker.[15]

In total, we placed 171,634 trades equivalent to $22.4 million in notional. We supplement our trading data with TAQ, which has a complete record of all trades in U.S. equities. We identified each of our trades and retrieved the matching National Best Bid and Offer (NBBO) generated through WRDS. TAQ also provides a broad classification of trade locations, but most of our trades are off-exchanges and coded as "D." Next, we use return and volume data from CRSP.

Finally, we were able to identify the exact venues for all our trades. We relied on SEC rule 606(b)(1), which requires brokers to provide clients with the exact routing of each of their trades over the last six months. We requested and received this information from all of our brokers. This information is crucial to evaluate routing decisions and wholesaler execution.

In Table 1, we provide summary statistics on order routing for each of our brokerage accounts. The row totals give the total number of trades for that brokerage account, whereas the column totals give the total number of trades sent to that wholesaler across all of our accounts. Panel A shows the total number of trades across brokers and wholesalers, whereas Panel B shows percentages by brokers.

[Insert Table 1 about here]

Most of our commission-free trades are sent to four wholesalers – Citadel, Virtu, Jane

[15]See Schwarz et al. (2023) for a detailed analysis of the experiment's controls and robustness to latency.

Street, and G1X. The rest is sent mostly to Two Sigma (mainly by Robinhood), to UBS which shrunk its market share over this period, and other venues. Routing patterns in the IBKR Pro account are very different, however, with most of the trades sent to IBKR's own Alternative Trading System (ATS) and to exchanges.[16] The routing patterns are also shown in Figure 1.

[Insert Figure 1 about here]

Our data have several advantages over publicly available order routing information. Brokers are required to file SEC Form 606 reports that disclose PFOF information by venue and trade type. They also show the fraction of orders routed to their venues. However, there is no information on the dollar size of the order flows, nor detail about individual stocks, because they are aggregated at the S&P500 and non-S&P500 levels. They are also missing the price improvement for each wholesaler.[17]

The wholesalers used by brokers are required to file SEC Form 605 reports that display detailed execution statistics broken down by stock. Because all trades are aggregated, the data only represent averages across all clients. This hides any differences in execution. Indeed, wholesalers can provide widely different execution across clients, as shown by Schwarz et al. (2023). Also, as noted, odd lots are not reported. The forms can also be used to measure the fraction of trading done for individual stocks by market centers, but these are aggregate

[16] ATSs are computerized systems such as Electronic Communication Networks (ECNs) that automatically match buyers and sellers of securities. A "dark pool" refers to an ATS that is not "lit", meaning that it does not publicly display pre-trade quotations. They are less regulated than exchanges but are still subject to the 1998 Regulation ATS. Both ATSs and wholesalers must also operate as broker-dealers, so are still subject to SEC and FINRA oversight. They generally charge no execution fees or fees that are lower than exchanges.

[17] We compare our trades routing to the 606 data for all of our brokers, except IBKR who does not separate their LITE and PRO accounts. The fit was excellent, with an R-square around 90%. As expected, it was slightly worse for Robinhood, which actively changes routing across stocks and over time. So, our routing sample is representative of the brokers' routing.

numbers as well, which cannot be tied to brokers. Thus, such aggregate data, both at the stock execution level and for venue market share, make it difficult to infer broker routing patterns and execution levels.

Our data directly address these issues. We place the same trades at each broker, so there are no order flow differences. Our trades are largely odd lot trades, which represent the majority of retail stock trading. For each one of our trades, we can precisely trace the routing and execution, and compare them across brokers and wholesalers. Thus, we can directly observe patterns in order flows and check how they react to the quality of execution. This allows us to directly observe the interaction between brokers and wholesalers.

To provide a visual representation of the details in our dataset, Figure 2 plots data for Robinhood and Fidelity as an illustration. In Panels A and C, we report the percentage of our trades sent to each wholesaler over our 18-month trading period. In Panels B and D, we report the effective over quoted (E/Q) spread for each wholesaler, averaged across stocks.

[Insert Figure 2 about here]

Note that E/Q is a traditional measure of transaction cost. For buy trades, for example, the "effective" spread is defined as twice the difference between the execution price and the midpoint; this is then scaled by the (NBBO) quoted spread to give a unitless ratio. This is directly related to price improvement (PI), which in this case is the ask quote minus the execution price, also scaled by NBBO. Indeed, $(E/Q) = 1 - 2$ PI. So, lower E/Q is equivalent to greater price improvement. The graph shows that the average E/Q is around 0.4, which implies PI = 30%.

Our data reveal substantial variation, both over time and in the cross-section, in order routing as well as effective spreads. Such detail far exceeds what is available in public disclosures, which only report aggregate execution statistics and aggregate market shares across wholesalers on a monthly basis.

This said, our data has two limitations. First, most of our orders are odd lot orders that may receive different execution from larger orders.[18] Second, we are only examining market orders for equities. Thus, our results may not generalize to other order types.

3.2. Stock Routing Patterns

We begin our analysis by showing how our brokers route stock trades. As an example, we first compute the percentage of our orders for each stock with more than 100 trades overall that are routed to Citadel. For each broker, we then sort each stock from the lowest to the highest percentage.

We display results in Figure 3 for E*Trade, Fidelity, IBKR Lite, Robinhood, Schwab, and TD Ameritrade, in Panels A to F, respectively. In Panel G, we plot results for IBKR Pro, except for calculating the percentage of orders sent to Citadel we calcuate the percentage sent to its ATS. The horizontal axis corresponds to each of the stocks in our trades. Each entry describes the distribution of trades sent to Citadel for that stock, i.e., with a sequence of 1 (if so) or 0 (or not), showing their average by a circle in the middle of whiskers that represent 95% confidence bands. Red lines indicate that the percentage of orders routed to Citadel is significantly different from the overall average for that broker.

[Insert Figure 3 about here]

[18] Schwarz et al. (2023), however, did place larger trades and trades over 100 shares. They find similar execution compared to their $100 trades. Thus, we would expect orders in larger sizes to be handled similarly.

If brokers were using a "proportional" method to route orders, we should observe that all of our stocks have essentially the same percentage of their orders routed to Citadel, or that the average line should be flat. On the other hand, if many stocks deviate strongly from the average, the broker must be employing a "selective" routing method.

Except for IBKR Pro, the six accounts route between 24% and 37% of their orders to Citadel, on average. Otherwise, the figure suggests that brokers use different methods for routing orders. Four of our brokers use a method close to proportional routing, that is, E*Trade, Fidelity, Schwab, and TD Ameritrade.

The graphs for IBKR Lite and Pro and Robinhood, on the other hand, differ from those in the first group, indicating that these two brokers use selective order routing. Indeed, these two brokers advertise this feature. Robinhood indicates that "[T]his algorithm, known as the smart order router, prioritizes sending your order to a market maker that's likely to give you the best execution, based on historical performance."[19] IBKR also emphasizes its 'SmartRouting' algorithm, which "searches for the best destination price in view of the displayed prices, sizes and accumulated statistical information about the behavior of market centers at the time an order is placed, then immediately seeks to execute that order electronically."[20]

To investigate factors that lead to differences in order routing, we perform a series of logistic regressions. For each broker and wholesaler, we run a model where the dependent variable is set to one if the broker's order was routed to that wholesaler, and zero otherwise. We include variables that may explain routing decisions and can be directly observed by the

[19]See https://robinhood.com/us/en/support/articles/how-robinhood-makes-money/.

[20]See https://www.interactivebrokers.com/lib/cstools/faq/#/content/38448530/.

broker. Following the idea that more trades should be routed to venues that provide lower execution cost, the first variable is the prior calendar month's E/Q ratio for that stock at that venue minus the average E/Q for that same stock across venues, all at the same broker (*Venue Excess E/Q (t-1)*). This variable measures the cost of price execution for this stock traded at this wholesaler relative to other venues. We would expect a negative coefficient with selective routing. The second variable is the percentage of trades that were routed to that venue during the prior calendar month (*Venue % (t-1)*); this controls for persistence in routing decisions.

We also include a number of other control variables. Stock characteristics include the log of the stock price at the time of the trade, the log-volume and both the return and the absolute value of the return on the trade day. We also include the spread at the time of the trade, whether the trade is a buy or sell (1 or 0), and whether the stock is part of the S&P 500 index (1 if so, or 0). The last variable indicates whether our last trade went to the same venue. In all models, we include day fixed effects.[21] We report results in Table 2 for E*Trade, Fidelity, IBKR Lite, Robinhood, Schwab, and TD Ameritrade in Panels A to F, respectively. [22]

[Insert Table 2 about here]

The logistic models lead to the same conclusions as Figure 3 for our brokers. Four of our brokers have nearly proportional routing. The coefficients on prior execution costs are not

[21]Because the number of days that we have traded exceeds the number of stocks, we cannot cluster by stock and include day fixed effects in the same model. We find similar conclusions if we remove the day fixed effects and cluster by stock, or if we include month fixed effects and cluster by stock.

[22]Note that not all wholesalers are present in the panels. This is either because the broker did not send any trades to that venue, or because the number of observations is too small, e.g., for UBS. We chose a cutoff point of at least 100 trades to include venues.

significant. These brokers clearly do not allocate stock-level order flow on the basis of past stock-level execution.

On the other hand, many variables are significant for Robinhood and IBKR Lite. In both cases, a wholesaler is more likely to get an order if the prior month execution on that stock was better than other wholesalers. Order flow is also persistent across time. In many cases, the two brokers' selective-routing systems agree. For example, both are more likely to route trades for stocks with high volumes to Citadel. We find similar results for IBKR Pro. That brokerage account sends orders to different venues (its own ATS, exchanges, and wholesalers) persistently based on prior execution as well.

Interestingly, based on the findings of Schwarz et al. (2023), the three accounts with the lowest overall price improvement are those using selective routing. Other factors, however, may be the primary drivers of the observed differences in execution, such as the toxicity of order flow.[23] Perhaps brokers with more toxic order flows have to work especially hard at improving their execution quality. In any event, the key issue is the quality of actual, not past, trade execution.

4. Competitiveness of Retail Trade Execution

In the prior section, we established the routing patterns of different brokers. In this section, we examine competition of the wholesaler marketplace where our retail trades are

[23]Also, brokers may face conflicts of interests when operating their own ATS that may affect execution quality. Anand et al. (2021) examine institutional brokers that operate their own ATS. They argue that this setup can create potential conflicts of interest. For example, such brokers would avoid paying exchange fees that they typically absorb by using affiliated venues. Also, they benefit from higher volumes on affiliated venues because other participants typically pay fees to their ATS. As a result, such brokers may prefer affiliated ATSs over other venues, even if not optimal for the client. Indeed, these authors report that such trading in affiliated ATSs is associated with lower execution quality.

sent.

4.1. *Price Execution Dispersion and Persistence*

We begin with examining the implications of the perfect Bertrand competition hypothesis. Under this hypothesis, in an ideal scenario of perfect competition, where brokers can frictionlessly switch among wholesalers based on price execution, only those wholesalers offering the highest level of execution quality would attract order flows. This would result in no dispersion in execution costs across wholesalers for a given broker.

To assess the dispersion across wholesalers, we examine whether, for a given broker, the average price execution of each wholesaler significantly deviates from the overall broker average. In Table 3, we present these numbers for each broker-wholesaler pair. We show the average E/Q for each broker, and excess E/Q which represents the deviation of a given wholesaler's execution from the broker's average. These averages are computed over all trades within a month for each pair. We also report time-series statistics based on the Fama and MacBeth (1973) approach using Newey and West (1987) with one lag to control for autocorrelation.

[Insert Table 3 about here]

We observe statistically and economically large differences across wholesalers, even within the Top 4. For both E*Trade, Fidelity, and Schwab, the spread between the best and worst execution cost E/Q is greater than 0.20. TD has the smallest spread, at 0.10, but also the lowest average execution cost.

Additionally, we find the dispersion in price execution is persistent over time, both at the aggregate level, and at the stock level. To measure the overall performance of wholesalers, we first compute the monthly average of E/Q, for each wholesaler at each broker for our trades. We then subtract the average E/Q across wholesalers for that broker to obtain the "excess" E/Q for each wholesaler-pair. To evaluate persistence, we regress this excess E/Q over its average over the last one- and three-month periods. The regression is estimated across all brokers, then separately for proportional and selective-routing brokers, and for each broker individually. Standard errors are clustered by month. We report results in Panels A and B of Table 4.

[**Insert Table 4 about here**]

We find that wholesaler comparative performance is extremely persistent at the aggregate level. Across all brokers, the prior one-month coefficient is 0.74, which is very high and statistically significant. Figure 4 illustrates this very strong relationship and shows that the R-square is very high, above 50%. Using the average execution over the last three months, the slope increases to 0.86. At least, the slope is lower than one, which suggest slow reversion to the broker mean, or mild amelioration of performance over time. These results hold up in our two subgroups of proportional and selective-routing brokers, with similar slope coefficients.

[**Insert Figure 4 about here**]

Of course, brokers can keep track of the entire universe of their trades executed by the various wholesalers and can perform the same analysis in-house. Admittedly, they may have other objectives than the average price improvement across all their trades. Using our representative sample, however, we can also perform the analysis at the broker level. Across our six brokers, we still find high slope coefficients, varying from 0.51 to 0.92 in Panel A. This suggests that excess E/Q across wholesalers is highly predictable at the aggregate level.

Next, we perform the same analysis at the individual stock level. This is useful for a number of reasons. First, this allows us to control for possible tilts in the stocks routed across wholesalers. A broker could send, for example, more stocks with easier price improvement systematically to one wholesaler, which would create artificial persistence in excess E/Q. Even though we found minor effects of stock characteristics on routing in Table 2, this is a useful robustness check. Second, this stock-level analysis is representative of selective routing, where brokers are relying on persistence in price execution at the individual stock level to make routing adjustments.

On the other hand, using data at the stock level is surely noisier than at the aggregate level, leading to estimated coefficients that can be biased downward if the right-hand-side variables are affected by greater errors in the variables.[24] Indeed, actual execution prices surely also reflect transitory movements in stock-level inventory, which create idiosyncratic noise. Due to diversification effects, such transitory deviations are dampened at the total inventory level.

We now calculate excess E/Q as the wholesaler E/Q for a stock at a broker minus the E/Q for that stock across all wholesalers for that broker, both averaged over the month. This is done at each broker individually. We then run the same model as before but at the stock level. Results are shown in Panels C and D of Table 4.

The results are consistent with those at the aggregate level. Across all brokers, subgroups,

[24]This issue is akin to tests of asset pricing models where the right-hand-side variable consists of stock-level historical betas, which are affected by estimation error, reflecting the usual sampling variability. Traditional methodology then groups stocks into portfolios to decrease this error, and thus lower the bias in slope coefficients. See Kim (1995), for example.

and individual brokers, we find that price execution is persistent based on the prior one- and three-month prior price execution. Across all brokers, the slope coefficient is 0.18, and also highly statistically significant. The values of the coefficients, however, are systematically lower than those at the aggregate level in Panels A and B. Also, the R-squares are on the order of eight percent instead of 50 percent. As indicated, the lower coefficients surely reflect the greater degree of noise when evaluating PI at the stock level. All panels indicate that excess E/Q by wholesaler is highly persistent, and thus predictable over time.

Overall, these findings suggest that, for a given broker, there is a substantial and persistent dispersion in price executions across wholesalers.

4.2. Broker Response to Prior Price Improvement

Since the wholesaler's price execution is predictable, brokers can use prior data to make changes to their routing practices to obtain greater price improvement for their customers. In this section, we examine whether brokers use this information to alter their routing decisions over time. We would expect that brokers do change their allocation to wholesalers based on past execution. Indeed, brokers are required, under their best execution obligations, to evaluate the execution quality of execution venues over time, and to act upon this evaluation. As previously mentioned, they reportedly comply with these obligations "by establishing routing allocations based on this historical performance." One would expect that the data supports this assertion. In addition, active routing choices should be an essential practice to maintain competition in the wholesaler market.

4.2.1. Routing Changes and Prior Price Execution

To determine how brokers react to prior execution, we first compute the monthly change in the percentage of orders routed from each broker to each wholesaler, using all trades across all stocks. Next, we regress these changes against the past excess E/Q for that wholesaler at that broker, measured over the prior one- and three-month periods. The regression is estimated across all brokers, then separately for proportional and selective-routing brokers, and finally for each broker individually. For our brokers that use proportional routing, we should observe changes at the overall routing level. For selective-routing brokers, changes should occur at the stock level, perhaps obscuring changes at the overall level. Our models include appropriate brokers dummies and cluster standard errors by month. We report results in Panels A and B of Table 5.

[Insert Table 5 about here]

When pooling all brokers together, we find some evidence that brokers change their routing toward wholesalers that provided better execution the prior month. The slopes are barely statistically significant, but the economic magnitude is quite small. For every 0.01 decline in excess E/Q, there is only approximately a 0.03% increase in the share of orders routed to that wholesaler.

For better economic perspective, recall that E/Q$= +1$ is the worst possible pricing, that E/Q$= 0$ is midpoint pricing, and that E/Q$= -1$ means buying at the bid and selling at the ask. So, if E/Q were to go from $+1$ to -1, which is an extreme move, the wholesaler would only gain 6.2% share. Looking at individual brokers, this result is driven completely by the selective-routing brokers and almost exclusively by Robinhood. Also, note that only the prior month execution has any statistically significant impact on routing changes.[25] To illustrate the differences between the difference between the persistence in dispersion and the lack of routing changes, we plot changes in market share against prior month excess E/Q in Figure 5. Note the slope for proportional brokers is flat while slightly negative for selective brokers.

[**Insert Figure 5 about here**]

Next, we consider stock-by-stock routing as a function of prior stock execution. Brokers with selective routing should be expected to send relatively more trades for individual stocks to wholesalers with better execution for that stock. This is unlike brokers with proportional routing, which only adjust total flows to each wholesaler. The analysis is similar to the previous one, with results reported in Panels C and D of Table 5.

We find similar results. Selective-routing brokers do make changes to their stock routing patterns based on prior execution, while proportional brokers show no response based on the variation in the quality of execution for individual stocks.

Overall, our results are not consistent with perfect competition. Most brokers either do not or cannot make changes to their routing patterns based on prior execution that are likely to improve price execution for our types of trades. Either brokers are poor monitors of price execution by wholesalers, with ineffective follow-up, or the wholesaler market is not competitive and therefore brokers do not feel capable of changing their routing practices.

[25]In untabulated results, we also examine weekly changes on prior week excess E/Q and monthly changes on prior two-month execution. The results are similar to those in Table 5.

4.2.2. Market Share and Prior Price Execution

In contrast, Dyhrberg et al. (2023) conclude that the wholesaler market is competitive, using Form 605. They find that wholesalers with better price execution tend to have a higher percentage of trades routed to them. In other words, they focus on market shares whereas our analyses focus on changes.

For comparison purposes, we also run our analysis using levels instead of changes. Each month, we regress the percentage of our trade (in levels) routed to each wholesaler for each broker against the prior month's excess E/Q for that wholesaler for that broker. Because 96% of our orders are routed to the top four wholesalers, we also present results for the top four wholesalers only, in addition to the full sample. Results are shown in Table 6.

[Insert Table 6 about here]

For the full set of wholesalers, which is the most comparable to these authors' analysis, we indeed match their results. The negative slope indicates that better price execution, or lower cost, is associated with greater market share for wholesalers. For every 0.01 lower excess E/Q, a wholesaler receives 0.3% more share. However, this result is much stronger for our selective-routing brokers than our proportional-routing brokers. Interestingly, only three of our six brokers show significant coefficients with correct negative signs.

Consider next the subsample of "Top 4" wholesalers (Panel B). For all brokers, the slope coefficient is similar to that in the first column. However, results now differ sharply across the two broker groups. While selective-routing brokers still have a very significant negative relation, our proportional brokers now have a positive, significant relation.

To illustrate this point, consider the broker Fidelity. As shown in Panel D of Figure 2, Citadel is, on average, the laggard among the "Top 4" wholesalers for our trades at that broker. Virtu has the best execution, with Jane Street and G1X in between. One would expect a similar ranking of market shares. However, Panel C shows that Citadel receives the most orders, around 40% on average. In fact, the wholesaler shares have been relatively stable over our 13 months of trading. As an aside, it is interesting to note that execution costs for Fidelity have sharply decreased over this period, from an average E/Q of 0.30 to around 0.10, which is a remarkable improvement.

To summarize the evidence across brokers, Figure 6 plots the overall relation between market share and execution costs. Panels A and B break down the sample into proportional and selective brokers, respectively. Selective brokers display the expected negative relation between higher cost and lower shares. In contrast, this relation is positive for proportional brokers.

[**Insert Figure 6 about here**]

In Section 5, we present a model of order routing with switching costs to explain the relation between market share and execution costs.

As discussed previously, best execution certainly has many dimensions, across types of orders, trade sizes, and execution metrics. Our sample focuses on E/Q for our odd-lot market orders. It is possible that Fidelity receives better execution than average from Citadel for non-odd lot orders. Even so, it would be straightforward to establish different routing patterns across trade sizes so that small investors enjoy better execution.

4.2.3. Counterfactual

To see how much using past execution to route orders would potentially improve our execution, we run a counterfactual analysis. We must assume that such rerouting would not alter our trade execution nor the competitive dynamics of the wholesaler market (which is reasonable given the small size of trades.) We use two methods.

The first is based on overall execution. Each month for each broker, we route all of our orders to the wholesaler who had the best execution the prior month. All of our trades are then assigned the average execution for each stock at that broker received from that wholesaler in the current month.

The second is based on stock-by-stock routing. We use the prior month's execution on a stock-by-stock level to reroute our trades to the best wholesaler for that stock during the prior month. Our trades are then assigned the actual execution for each stock at that broker in the current month. We report our results in Table 7 with overall and stock-by-stock execution in Panels A and B, respectively.

[Insert Table 7 about here]

The columns show the original E/Q, the updated E/Q, as well as the absolute and relative difference, for each broker. When using overall execution, the effective spread decreases from an average across brokers of 0.315 to 0.235, which is a major improvement. The percentage improvement averages a drop of 34% across brokers. The changes are statistically significant across all brokers. However, the changes for the proportional-routing brokers are much larger than the selective-routing brokers.

Using stock-by-stock routing creates some improvement as well, but the changes are more muted. This is likely due to the increase in noise that we found previously in our previous stock-by-stock persistence results. These results suggest that routing based on overall execution could in theory achieve better results. In practice, however, this method would create extreme swings in routing fractions that are not realistic. Still, one could modulate the change, by assigning, for example, half the weight on the original and the other half on our updated routing, which would result in half the E/Q improvement reported in the table.

Overall, our results suggest that many brokers are not able to extract the best execution from the wholesaler market. This could be due to monitoring patterns and insufficient pressuring of wholesalers by brokers. For example, retail investors may not know or care about differences in execution across brokers, which does not create pressures for further execution improvement on brokers.[26] Alternatively, brokers may not feel the wholesaler market is competitive enough for them to fully extract best pricing from wholesalers. Regardless of the reason, our results suggest that the wholesaler market is not perfectly competitive and therefore has room for improvement.

4.3. Impact of a New Wholesaler on Price Execution

In the prior section, we find that most brokers do not seem to actively reroute orders across wholesalers to get better execution for their clients. In this section, we examine how the entry of a new competitor impacts the wholesaler market for one of our brokers. Jane Street progressively entered the retail wholesaler market in 2020. Based on Form 606 filings,

[26]For our largely odd-lot orders, even Form 605 has no data on execution. Thus, there is no effective way to evaluate wholesaler performance on odd-lots, even at an aggregate level.

Jane Street became a market center for Fidelity in the second quarter of 2020, for E*Trade in the second quarter of 2021, and for TD Ameritrade in the fourth quarter of 2021. In all cases, market shares increased sharply for Jane Street. Unfortunately, these entrances predate our trading experiment, which starts in early 2022. Otherwise, Dyhrberg et al. (2023) use 605 data to suggest that the entrance of Jane Street did not impact wholesaler execution between the second and fourth quarters of 2021.

However, Jane Street did not become a wholesaler for Robinhood until the first quarter of 2022, which is in our sample. When we started trading, none of our orders were routed to Jane Street. By February 22, 2022, almost a quarter of our trades were routed to Jane Street, as shown in Panel A in Figure 2. During the initial period, Jane Street provided very low trading costs, even negative (Panel B). This amount was not economically sustainable and, once Robinhood started allocating more trades to Jane Street, the trading cost went back to a level comparable to the best wholesalers.

To evaluate more formally the impact of this new entrant, we examine changes in two wholesaler characteristics, i.e., the fraction of orders routed to Robinhood's venues, and the average price improvement across wholesalers, before and after February 23, 2022. If Jane Street increased competition in the marketplace, we should see a lower allocation to other venues, and a decrease in execution costs. Table 8 shows changes in venue routing and price improvement in Panels A and B, respectively.

[Insert Table 8 about here]

We see that the entry of Jane Street significantly impacted the wholesaler market for Robinhood. The allocation to Jane Street went from 3% to 23%, leading to large drops in shares for Virtu, Citadel, and G1X. We also see that, while not always statistically significant, execution costs decreased for all wholesalers after the new entry. Citadel decreased its E/Q cost sharply, from 0.54 to 0.40. For Robinhood overall, the average execution cost decreased from 0.55 to 0.47, which is economically significant. Overall, these results suggest that the wholesaler market benefited from this additional competition.

There are two potential explanations for the observed increase in execution quality at Robinhood. The first is that existing wholesalers raise their execution quality across all trades in response to increased competition. The second is that, as part of its selective-routing system, Robinhood systematically reroutes trades with the worst execution from its existing wholesalers to Jane Street. To investigate this latter explanation, we regress the change in the wholesaler's share in that stock across periods against its initial excess execution cost. If the change was driven by selective-routing decisions, we should see negative, significant coefficients, meaning that higher E/Q should lead to lower share allocations. Table 9 shows the results, which include some stock-level controls.

[Insert Table 9 about here]

The table shows insignificant coefficients in the first row. Thus, routing changes were not driven by the wholesaler's execution quality relative to its peers in the weeks leading up to Jane Street's addition. This suggests that Robinhood used Jane Street's entrance to benefit from better execution across wholesalers.

4.4. Discussions and Implications for 605 Forms

Our results are in contrast to Dyhrberg et al. (2023) who conclude that the entry of Jane Street did not impact execution between the second and fourth quarters of 2021. Several factors could drive the different conclusions. First, our data is more detailed, providing exact execution data for specific stocks routed by a specific broker on a daily basis; in contrast, 605 reports provide stock-level execution statistics for each market center aggregated across all their clients on a monthly basis. Second, we focus on one broker, whereas 605 reports only provide averages across all brokers. This allows us to focus on the effective date of entry for Jane Street, which should be more precise, given that Jane Street's addition to each broker's list of venues happened at different times. Third, almost all of our trades are odd lots, which are not reported on 605 reports. Regardless, at least for odd-lot trades at Robinhood, Jane Street's entry significantly altered order routing and improved price execution.

More generally, it should be emphasized that our within-broker results could not have been picked up by the aggregate 605 forms. Worse, the 605 forms obfuscate within-broker execution quality. As this example demonstrates, Jane Street was added as an executing wholesaler for Robinhood in the first quarter of 2022. Following its entry, Jane Street gained market share at Robinhood because its within-broker execution was better than other wholesalers, which lost market share. Importantly, we note that Robinhood's average execution is worse than that for other brokers, reflecting its client order flow characteristics, i.e., "toxicity."

Next, consider the 605 form for the smallest reported trades, from 100 to 499 shares, which best match Robinhood's retail clients. For Jane Street, this actually shows a worsening of execution quality from January to April 2022. Contrariwise, the 605 form for Virtu shows an improvement in E/Q. In fact, however, we do not observe changes in the within-broker E/Q for Jane Street and Virtu. So, the changes in 605 data almost certainly reflect the addition and subtraction of Robinhood trades, respectively, as opposed to true changes in execution quality.

The conclusion is that changes in the clientele served by wholesalers could create misleading changes in aggregate execution numbers shown in the 605 forms. This demonstrates the superiority of within-broker analysis relative to the aggregate reporting in the 605 forms, and the need for expanding 605 reports to the broker-wholesaler pairs.

5. Model of Order Routing with Switching Costs

Overall, we find empirical evidence that the wholesaler marketplace is not perfectly competitive. While many of our results are intuitive, such as the impact of Jane Street's entry, others are more puzzling. Specially, why would proportional brokers route larger shares of their orders to wholesalers with lower price execution quality? If they were randomly allocating trades, we would expect the relation to be random, not positive. More generally, if price execution is predictable, why do brokers not respond to persistent dispersion across different wholesalers? To provide economic insights into these questions, in this section we develop a stylized model of order routing including brokers' switching costs.

5.1. Setup and Equilibrium

Consider a generic broker, which can route its order flow to two wholesalers X and Y. The size of the order flow is normalized to one. The initial order flow market share of wholesaler X is given by $\sigma \in [0,1]$ with the remaining $1-\sigma$ routed to wholesaler Y. The broker and the two wholesalers are risk neutral. Define p_X and p_Y as the "prices" offered by the wholesalers. Here, these represent the execution costs for the trade, i.e., E/Q, which are charged to the broker's customers.

The broker incurs quadratic switching costs when adjusting the market share. These switching costs are given by $\frac{s}{2}\Delta^2$, where $s \geq 0$ and $\Delta \in [-\sigma, 1-\sigma]$ is the additional market share allocated to wholesaler X. The broker optimally chooses an adjustment of the market share Δ to minimize the sum of the total costs paid to the wholesalers and the switching costs:

$$\min_{\Delta \in [-\sigma, 1-\sigma]} (\sigma + \Delta) p_X + (1 - \sigma - \Delta) p_Y + \frac{s}{2}\Delta^2. \tag{1}$$

Here, switching costs serve as a simple modeling device to capture potential frictions that limit the ability or willingness of brokers to respond to dispersion in execution quality.[27] For example, switching costs could include the time and cost it takes for brokers to monitor wholesalers' performance, managerial/organizational inertia ("nobody gets fired for buying IBM"), the desire/requirement to supply stable order flows to wholesalers, or the lack of technology to implement complex routing, and so on.[28]

Wholesalers incur constant marginal costs to process and make markets for the broker's order flow. These costs may be heterogeneous, denoted by f_X and f_Y for wholesalers X and Y, respectively, where $f_X \leq f_Y$ without loss of generality. Wholesaler X optimally chooses the price p_X, which captures execution costs paid by the broker's customers, to maximize

[27] Switching costs have long been used and studied in the economics literature (see, e.g., Klemperer (1987)).

[28] Many of these costs are likely to be non-linear. In particular, execution performance measures involve numerous metrics for each stock, which typically number more than 10,000. Finding the best routing through optimization is a high-dimensional process, made even more difficult with constraints on market shares. If the broker has limited technology, costs will increase very quickly.

its profits:

$$\max_{p_X} (p_X - f_X)(\sigma + \Delta). \tag{2}$$

Similarly, wholesaler Y chooses the price p_Y to maximize its profits:

$$\max_{p_Y} (p_Y - f_Y)(1 - \sigma - \Delta). \tag{3}$$

A pure-strategy Nash equilibrium is found when (1) the broker optimally chooses its adjustment in the market share, Δ, as a function of the prices charged by the wholesalers; (2) the wholesalers optimally chooses prices, p_X and p_Y, given the broker's strategy and each other's pricing; and (3) the broker's and the two wholesalers' strategies, Δ, p_X, and p_Y, are all consistent. The proposition below fully characterizes equilibrium. The proof is in Appendix A.

Proposition 1 *If switching costs are sufficiently high (i.e., $s > (f_Y - f_X)/(2 - \sigma)$, where $f_Y \geq f_X$), then in equilibrium, the wholesalers charge*

$$p_X = \frac{2f_X + f_Y}{3} + \frac{s(1+\sigma)}{3} \qquad \textit{and} \qquad p_Y = \frac{f_X + 2f_Y}{3} + \frac{s(2-\sigma)}{3}, \tag{4}$$

and the broker adjusts its market share by

$$\Delta = \frac{f_Y - f_X}{3s} + \frac{1 - 2\sigma}{3}. \tag{5}$$

Otherwise ($s \leq (f_Y - f_X)/(2-\sigma)$)*, in equilibrium*

$$p_X = f_Y - s(1-\sigma), \qquad p_Y = f_Y, \qquad \textit{and} \qquad \Delta = 1-\sigma, \tag{6}$$

assuming, for instance, that if $p_X = p_Y$*, wholesaler* X *takes the whole market.*

In the following subsections, we study the properties of the equilibrium characterized in Proposition 1 to connect the theoretical implications with our empirical findings. To clarify economic intuition, we analyze three cases separately: (1) the benchmark case absent switching costs, (2) the case with switching costs and the same marginal costs for the wholesalers, and (3) the case with switching costs and different marginal costs.

5.2. Equilibrium Absent Switching Costs

Suppose the broker incurs no switching cost (i.e., $s = 0$). Then the two wholesalers are in Bertrand competition. When the wholesalers have the same marginal cost, their prices equal the marginal cost ($p_X = p_Y = f_X = f_Y$), resulting in perfect competition even with just two wholesalers, also well known as the "Bertrand paradox." Any dispersion in prices makes the broker shift its entire order flow to the lower-priced wholesaler. Such extremely responsive routing in turn makes the wholesalers compete vigorously with one another, eliminating price dispersion and driving down prices to the marginal cost. In equilibrium, the market is perfectly competitive, and the average price is the marginal cost no matter how the broker routes its order. (For simplicity, we assumed that the broker routes all order flow to wholesaler X.)

However, when the wholesalers have different marginal costs ($f_X < f_Y$), the market is imperfectly competitive. Competition between the two wholesalers drives down prices only to the higher marginal cost ($p_X = p_Y = f_Y$), allowing the low-cost wholesaler (X) to remain profitable.[29]

Note that responsive routing and Bertrand competition alone do not guarantee perfect competition.

Regardless of whether wholesalers have the same marginal cost or not, Bertrand competition implies that the wholesalers charge the same price to the broker in equilibrium. Without price dispersion, of course, there is no relation between prices (or execution costs) and market share. Even if there were wholesalers charging higher prices, we would not observe this in the data because the lowest-price wholesaler should capture a 100% market share anyway. Further, the broker's responsive routing, a requirement for Bertrand competition, is inconsistent with our finding that most brokers do not respond to prior execution costs.

5.3. *Equilibrium When the Wholesalers Have the Same Marginal Cost*

Now, suppose that the broker incurs switching costs (i.e., $s > 0$). Assume, for now, that the two wholesalers have the same marginal cost (i.e., $f_X = f_Y$). The broker finds the optimal adjustment of market share, Δ, by solving Equation (1). The first order condition implies:

$$\Delta = \frac{p_Y - p_X}{s}, \tag{7}$$

[29] Without the assumption that the low-cost wholesaler receives the entire order flow when the prices are equal, there is no pure-strategy Nash equilibrium. Instead, there exist mixed-strategy Nash equilibria, as discussed in Blume (2003).

under some conditions (which are met in equilibrium, see the proof in Appendix A for details). Thus, the broker always moves towards the lower-priced wholesaler (i.e., $\Delta > 0$ if and only if $p_X < p_Y$). But the extent to which it does so depends on and decreases in the switching costs. Higher switching costs make it difficult for the broker to adjust market share drastically even when there is wide price dispersion.

From Proposition 1, in equilibrium, the wholesalers charge:

$$p_X = f_X + \frac{s(1+\sigma)}{3} \qquad \text{and} \qquad p_Y = f_X + \frac{s(2-\sigma)}{3}. \tag{8}$$

As switching costs increase, both wholesalers charge higher prices relative to the marginal cost. The limited ability to adjust market share provides the wholesalers with a scope for exercising their market power.

Further, the extent to which wholesalers extract rents from the broker (or more precisely, from its customers to whom the broker passes down the execution costs) depends on their market share. The wholesaler with larger pre-existing market share (i.e., X if $\sigma > 1/2$ and Y if $\sigma < 1/2$) charges higher prices than the other wholesaler. While the broker does move away from the higher-priced, large wholesaler, that wholesaler remains large after the adjustment.[30] For example, if wholesaler X was initially large with $\sigma = 2/3$, then it remains large after the adjustment with $\Delta = -1/9$ and $\sigma + \Delta = 5/9$, even though p_X is higher, at $p_X = p_Y - s/9$. Thus, there is a positive relation between market share and prices (or execution costs), see Panel A of Figure 7. This is consistent with what we find for proportional brokers in Figure 6.

[30] In equilibrium, $\sigma + \Delta = (1+\sigma)/3$ such that $\sigma + \Delta > 1/2$ if and only if $\sigma > 1/2$.

While the positive relation might initially appear counterintuitive, in that the broker continues routing more order flow to more expensive wholesalers, the intuition becomes clear. It is not that brokers route more order to some wholesalers because they charge higher prices, but rather some wholesalers can charge higher prices because brokers route more orders to them. While brokers can respond by shifting some orders to the smaller wholesaler, in equilibrium, prices are determined such that the expensive, larger wholesaler remains large. In other words, the larger wholesaler can raise prices more than the smaller wholesaler because the change in market share is a relatively smaller portion of their overall profit.

Note that this result does not require that brokers have substantial switching costs. Any switching costs imply that the broker routes more order flows to the more expensive wholesaler.[31]

5.4. Equilibrium When the Wholesalers Have the Different Marginal Costs

In the prior cases, we would find either no relation or a positive relation between execution costs and market share. In this context, the negative relation that we document for selective brokers is puzzling. While selective brokers somewhat respond to execution, their routing behaviors still reflect the presence of strictly positive switching costs.

To understand the negative relation between market share and execution costs, we next allow wholesalers to have different marginal costs (i.e., $f_X < f_Y$), while the broker still incurs switching costs (i.e., $s > 0$).

From Proposition 1, there are two cases. If switching costs are sufficiently high (i.e.,

[31] This is because when $f_X = f_Y$, the second case in Proposition (1) does not apply.

$s > (f_Y - f_X)/(2-\sigma)$), the equilibrium is similar to that obtained when the wholesalers have the same marginal cost.

In Equation (4), the only difference is that prices depend on the weighted average of the marginal costs, where their own marginal cost gets 2/3 of the weight (e.g., $(2f_X + f_Y)/3$). Comparing equilibrium prices, we have

$$p_X < p_Y \qquad \text{if and only if} \qquad s < \frac{f_Y - f_X}{2\sigma - 1} \text{ and } \sigma > \frac{1}{2}. \tag{9}$$

Thus, provided that the lower-cost wholesaler is also the larger wholesaler before the adjustment (i.e., $\sigma > 1/2$) and the switching costs are relatively small (but not too small, as discussed below), the larger wholesaler charges less than the other wholesaler and obtains an even larger market share. The relation between market share and prices is negative, as in Panel B of Figure 7 (Panel C shows how the switching costs affect the signs of the relation).

The larger wholesaler here has two competing incentives. On the one hand it can raise prices to take advantage of its market share and extract larger rents from the broker. On the other hand, it can reduce prices to take advantage of its lower costs and obtain an even larger market share. When the broker's switching costs are relatively small, the incentive to reduce prices outweighs the incentive to raise prices, resulting in the larger wholesaler charging lower prices than the smaller wholesaler in equilibrium.

Notice, this case is the most consistent with our empirical findings that selective brokers, who tend to respond to execution albeit modestly and thus exhibit smaller switching costs than proportional brokers, also exhibit negative relation between market share and execution costs, while proportional brokers generate positive relation between market share and execution costs.

Finally, if switching costs are too small (i.e., $s \leq (f_Y - f_X)/(2-\sigma)$), the equilibrium becomes similar to that with Bertrand competition in Section 5.2, which arises when the broker does not incur any switching costs. The lower-cost wholesaler drives the other wholesaler to zero profits and obtains a 100% market share. Interestingly, switching costs reduce the prices the broker pays because the broker would not shift the entire order flow to the low-cost wholesaler unless it is compensated for the switching costs.

We mention in passing that the difference in switching costs between proportional and selective brokers may be explained by regulatory pressure. Prior literature has shown that large variations in execution costs across brokers likely reflect different characteristics (or toxicity) of order flows (e.g., Schwarz et al. (2023)). Despite the varying degrees of toxicity in order flows, brokers' executions are often benchmarked against the same regulatory standard, such as NBBO. Thus, brokers with more toxic order flows have stronger incentives to improve their execution quality than those with less toxic order flows. If brokers can make costly investments to reduce their switching costs, those with more toxic order flows are likely to have lower switching costs than their counterparts with less toxic order flows. In fact, selective brokers, whose behaviors are consistent with having lower switching costs than proportional brokers, are also the ones with the two highest execution costs, indicating a higher prevalence of more toxic order flows (Table 3).

6. Conclusions

Retail trading has reached record volumes in the last several years, spurred by technological advances as well as the advent of commission-free trading. Even so, the current market structure has attracted the attention of regulators. Many worry about potential conflicts of interest, such as payment for order flow. Others worry about the competitiveness of the wholesaler marketplace given that it has only four large players. These concerns ultimately led the SEC to introduce four proposals aimed at increasing competition in order to improve trading execution.

The counterargument is that the market is functioning well currently, that trading costs have never been lower, and that the proposed market structure changes could actually lead to worse execution for retail traders. In particular, some participants argue that competition across wholesalers is already enforced by retail brokers, who should closely monitor the quality of trade execution and route greater allocations to the most competitive wholesalers, as required by best execution standards.

Using a self-created dataset of over 150,000 trades, our paper provides a unique window into the analysis of competition in the wholesaler market by focusing on actual interactions between broker routing and wholesaler execution.

We first examine routing practices in detail. Routing involves allocations to wholesalers at the aggregate level and/or at the stock level. For stock trades, brokers use one of two routing methods. The first is proportional, where stocks are sent in the same proportions but in potentially different total amounts. The second is selective, where stocks are routed individually to different wholesalers. Competition can be enforced by routing more of either the total dollar amount or individual stock trades to wholesalers with better within-broker execution. We find that most brokers in our sample use proportional stock routing. In addition, a majority of our brokers do not seem to change their routing for our trades based on past performance.

For active routing to be useful, however, execution quality needs to be persistent over time. We verify that prior execution quality by a wholesaler for a given broker can predict future execution quality, at the overall level and on a stock-by-stock basis. Indeed, we provide a hypothetical exercise of increasing routing allocations to venues with better execution quality and show that such practice would lead to significantly higher price improvement for retail investors. If so, it would be easy to increase execution quality within the current market structure. We also find that the introduction of a new wholesaler, Jane Street, caused significant increases in price improvement to Robinhood trades. This can be attributed directly to Jane Street, but also to other wholesalers that responded by improving their execution quality. Finally, we present a stylized model to demonstrate the economic intuition of our model.

Our overall conclusion is that the retail trade wholesaler marketplace is not perfectly competitive. One potential method to improve competition could be through greater disclosure to help facilitate more active routing decisions. Greater disclosure would put more pressure on brokers to manage trading costs actively. While the proposed extension of 605 forms to brokers does represent an improvement, it is still insufficient because it fails to control for broker-specific factors. Further extension of disclosures to each broker-wholesaler pair would allow proper evaluation of execution quality. At the same time, brokers could allocate their trades more actively, yielding better execution for their retail investors and enforcing pricing discipline on existing wholesalers. New entrants may also create more competition, forcing existing wholesalers to improve their execution for the ultimate benefit of retail investors.

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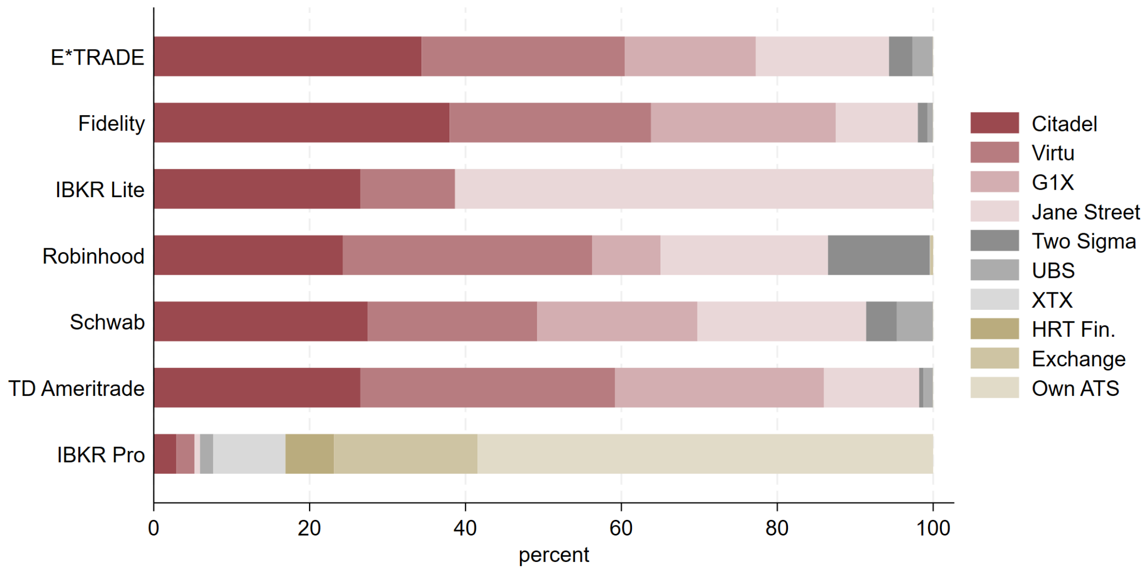


Figure 1: Wholesaler Share by Broker
This figure shows the percent of our orders that went to each wholesaler for each brokerage account. The raw data are in Table 1, Panel B.

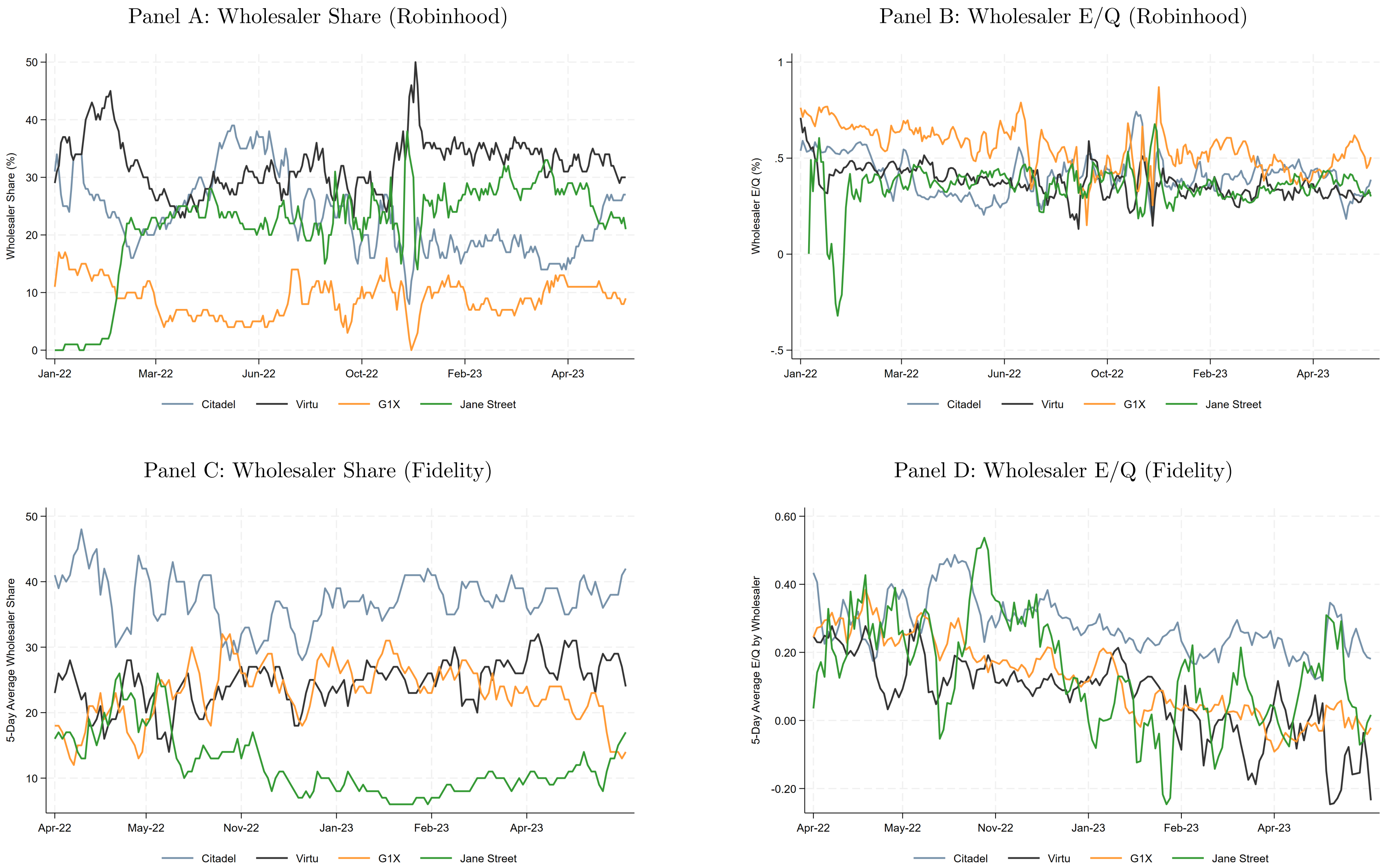


Figure 2: Wholesaler Data: Robinhood and Fidelity
This figure graphs the time series of the fraction of our Robinhood and Filelity orders that go to each wholesaler (Panels A and C) as well as the effective over quoted spread from each wholesaler for these trades (Panels B and D). In both cases, we use a rolling average over the last five trading days.

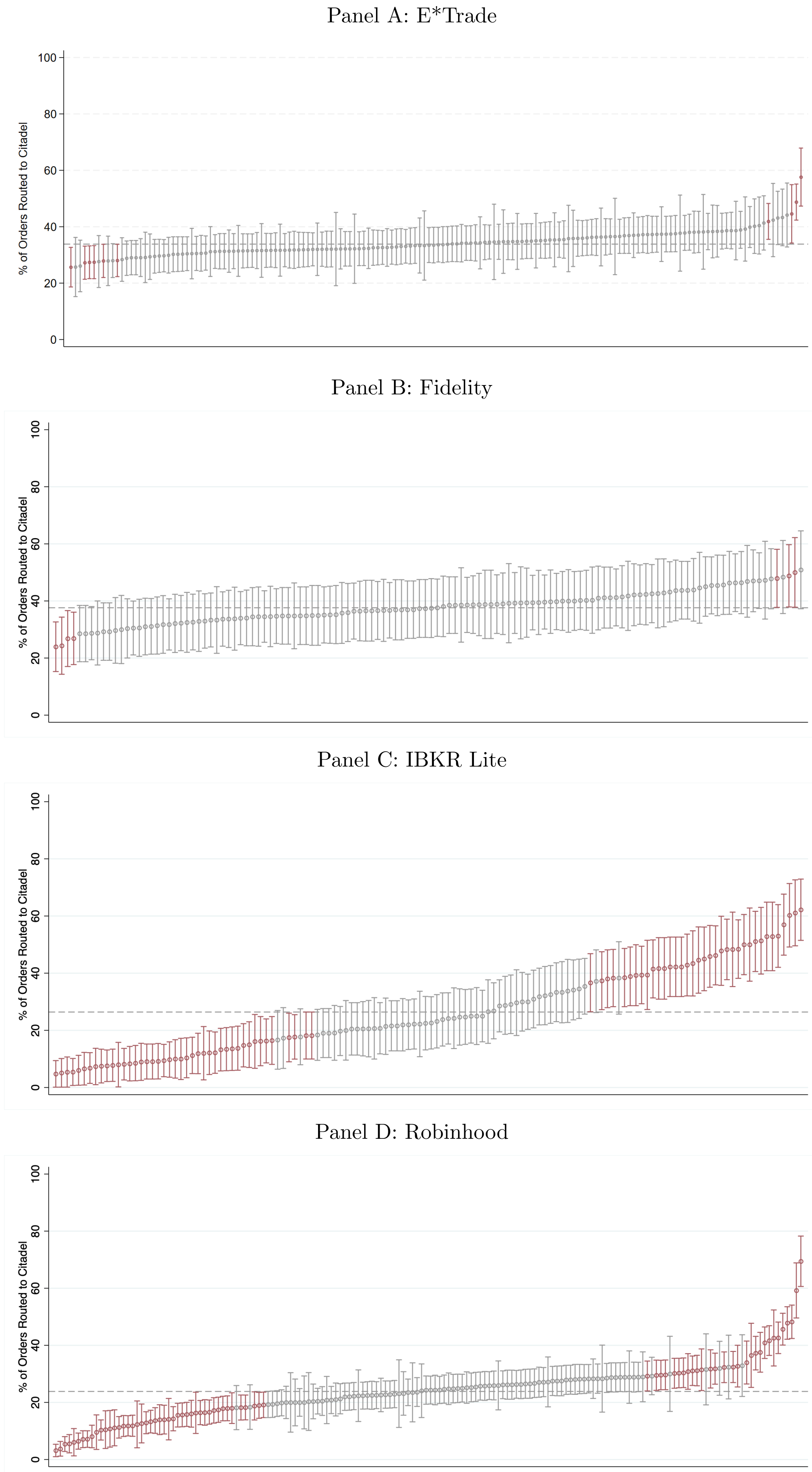
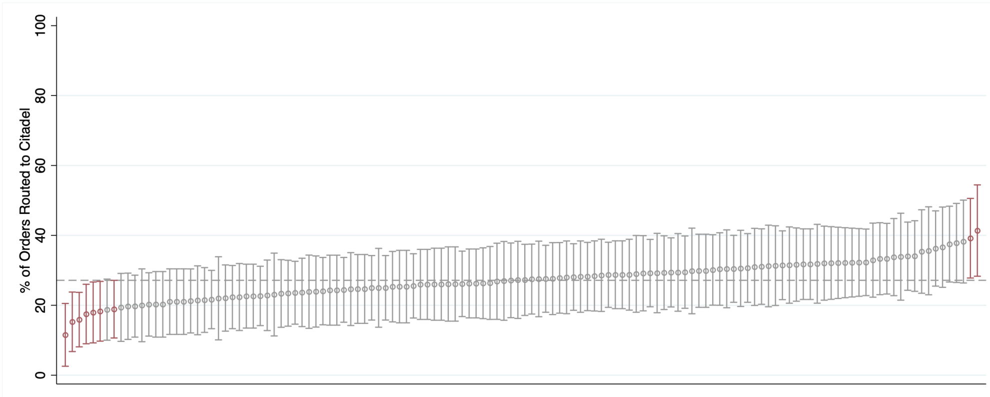
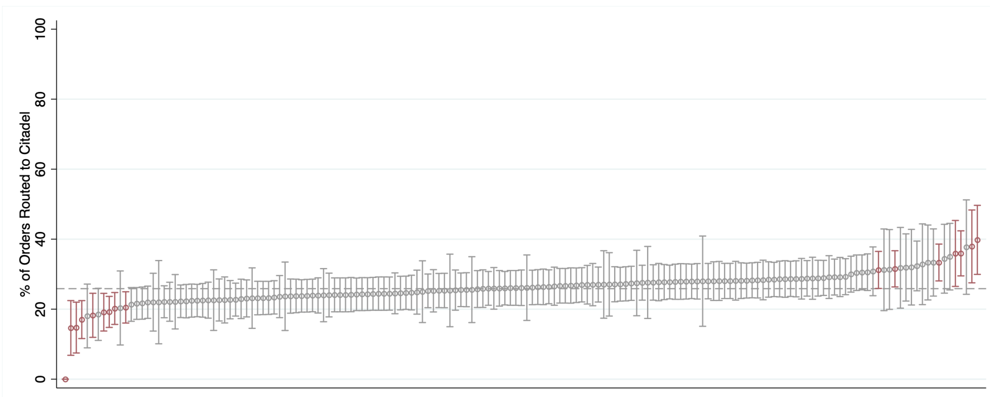


Figure 3: (Continued on the following page.)

Panel E: Schwab



Panel F: TD Ameritrade



Panel G: IBKR Pro

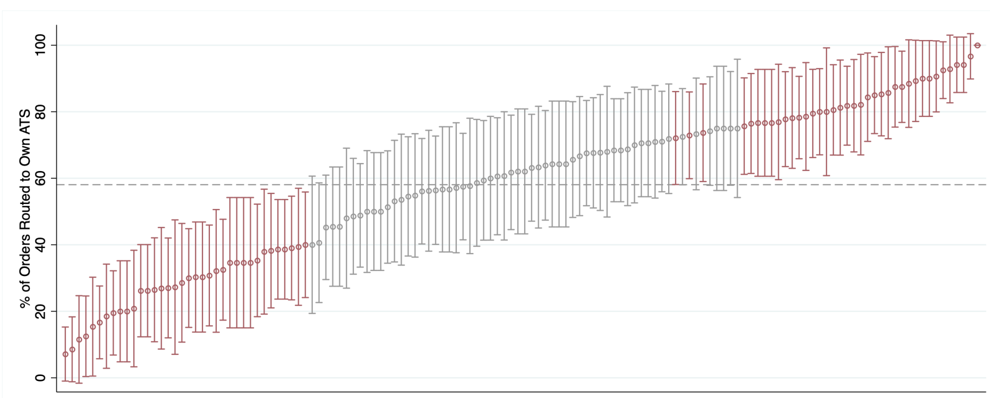


Figure 3: Order Routing Patterns across Individual Stocks
This figure shows the percentage of our orders for each stock that are routed to a specific venue. Panels A to F report order routing for E*Trade, Fidelity, IBKR Lite, Robinhood, Schwab, and TD Ameritrade to Citadel, while Panel G reports order routing for IBKR Pro account to IBKR's own ATS. Each vertical bar represents one stock, with whiskers showing 95% confidence intervals. A stock requires at least 100 trades to be included. If a stock percentage is significantly different from the average at the 5% level, lines are shown in red; otherwise, lines are in black.

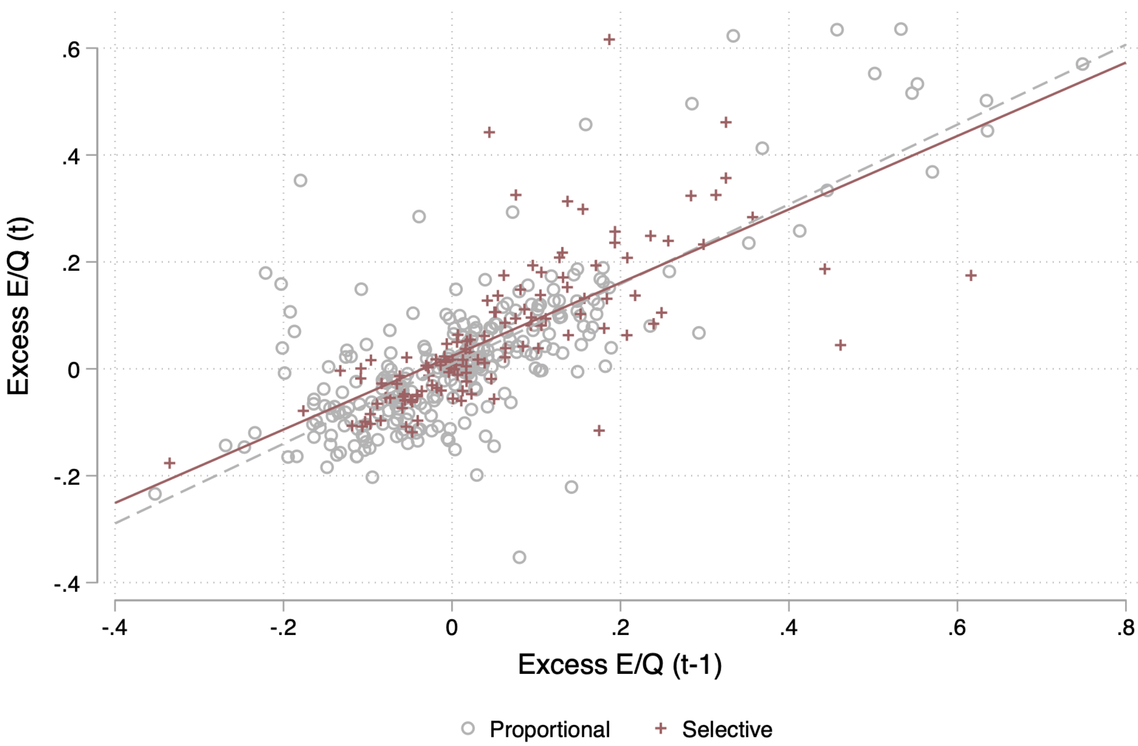


Figure 4: Relation between Current and Prior Month Effective Spreads
This plots, for each broker-wholesaler pair, the excess effective over quoted trade spread (E/Q) for the current month on the vertical axis against that for the prior month. Excess E/Q is computed as the average E/Q for each wholesaler at that broker minus the average for all wholesalers for that broker.

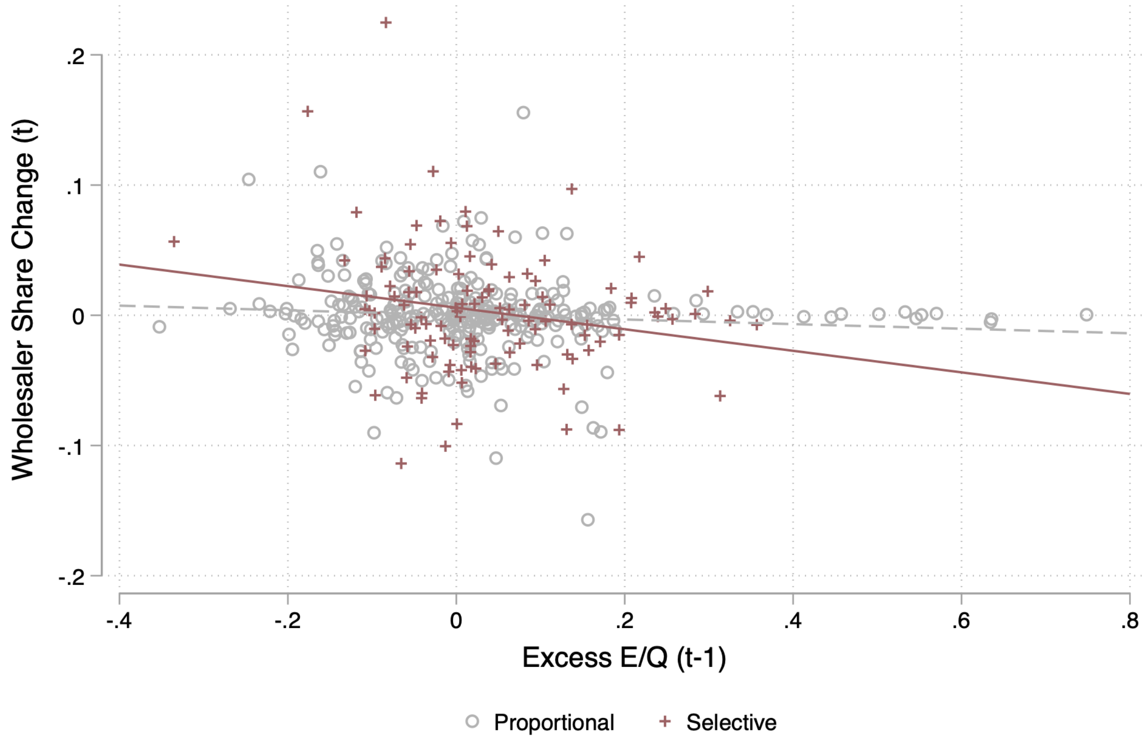
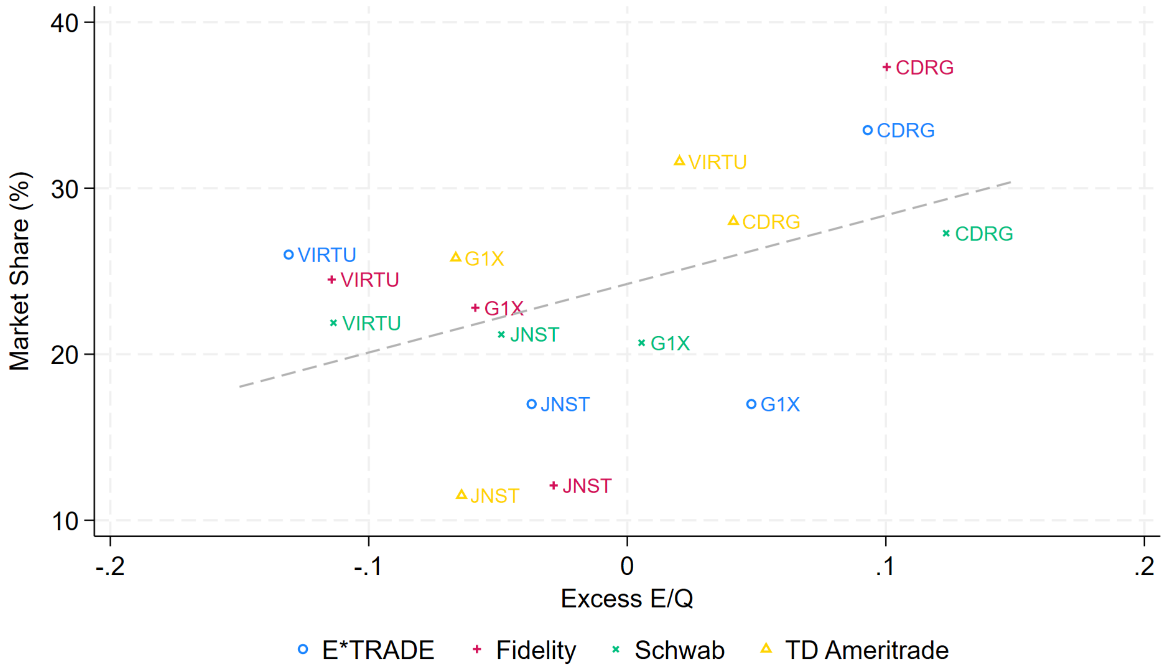


Figure 5: Relation between Market share Changes and Prior Month Effective Spreads

This plots, for each broker-wholesaler pair, the change in wholesaler market share for the current month on the vertical axis against the prior month excess effective over quoted trade spread (E/Q). Excess E/Q is computed as the average E/Q for each wholesaler at that broker minus the average for all wholesalers for that broker.

Panel A: Proportional Brokers



Panel B: Selective Brokers

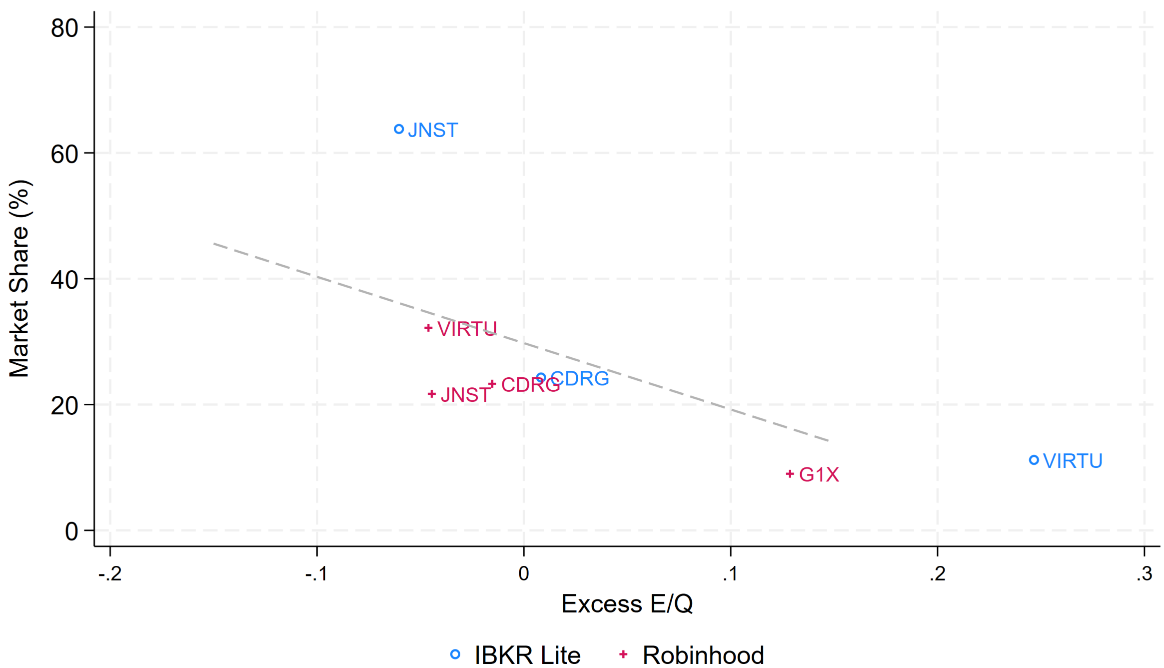


Figure 6: Wholesaler Price Improvement and Share
This figure describes the relation between wholesaler market share and its price improvement as measured by its excess effective over quoted spread. Panel A plots the relation for proportional brokers while Panel B plots the relation for selective brokers.

Table 1: Summary Statistics on Order Routing

This table presents summary statistics on order routing for our trades. We placed parallel trades at six brokers from December 2021 through May 2023. We requested and obtained routing information through SEC rule 606(b)(1). The table reports the number of trades at each broker that go to each wholesaler in Panel A, as well as the percent of orders for each broker in Panel B. Averages in Panel B exclude IBKR Pro.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Broker-Wholesaler Routing Count										
	Citadel	Virtu	Jane Street	G1X	Two Sigma	UBS	Exchange	Other	Own ATS	Total
E*Trade	10,651	8,085	5,286	5,202	919	811	-	-	-	30,954
Fidelity	4,561	3,102	1,262	2,847	148	83	-	226	-	12,229
IBKR Lite	2,834	1,293	6,543	-	-	-	-	42	-	10,712
Robinhood	9,669	12,761	8,568	3,507	5,212	-	150	92	-	39,959
Schwab	3,047	2,410	2,400	2,279	436	512	-	-	-	11,084
TD Ameritrade	11,088	13,660	5,161	11,160	224	497	-	520	-	42,310
IBKR Pro	126	96	31	-	-	71	1,464	-	2,477	4,265
Total	41,976	41,407	29,251	24,995	6,939	1,974	150	880	2,477	150,049

B: Routing Percentages by Broker										
	Citadel	Virtu	Jane Street	G1X	Two Sigma	UBS	Exchange	Other	Own ATS	Total
E*Trade	34%	26%	17%	17%	3%	3%	0%			
Fidelity	37%	25%	10%	23%	1%	1%		2%		
IBKR Lite	26%	12%	61%					0%		
Robinhood	24%	32%	21%	9%	13%		0%	0%		
Schwab	27%	22%	22%	21%	4%	5%				
TD Ameritrade	26%	32%	12%	26%	1%	1%		1%		
IBKR Pro	3%	2%	1%			2%	34%		58%	
Average	29%	25%	24%	16%	4%	2%	0%	1%		

Table 2: Drivers of Routing Decisions

This table examines how brokers route orders to wholesalers, or venues. For each broker, we run a logistic regression where the dependent variable is one if the trade is routed to that wholesaler and zero otherwise. For regressors, we include E/Q (effective over quoted spread) for that stock at that venue in excess of the average for that stock across venues (*Venue Excess E/Q (t-1)*), the percent of orders routed to that wholesaler the previous month (*Venue % (t-1)*), as well as a dummy variable set at one if our last order was routed to that venue (*Prior Same Venue*). We also include a number of stock characteristics including the log of the stock price, the trade date's log volume, return, absolute return, the spread at the time of the trade, and a dummy variable for stocks in the S&P 500 index. Finally, we include a dummy variable reflecting whether the trade was a buy or a sell (*Buy(1/0)*). Models include day fixed effects. **,* represents significance at the 1%, 5% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: E*Trade						
Dep var: the trade is routed to	Citadel	Virtu	G1X	Jane Street	Two Sigma	UBS
Venue Excess E/Q (t-1)	-0.024	-0.016	0.011	0.100*	0.245	-0.027
Venue % (t-1)	0.121	-0.139	0.204	-0.083	2.521**	-9.734**
Log(Price)	0.008	0.026	0.010	0.033*	-0.013	0.025
Log(Volume)	0.013	-0.005	0.007	0.008	0.017	-0.003
Return	0.058	0.042	-0.045	0.159	-0.209	0.078
Abs(Return)	0.057	0.043	-0.046	0.157	-0.219	0.079
Spread	-0.073	0.038	-0.036	0.065	-0.287	-0.052
Buy(1/0)	-0.011	-0.031*	-0.013	0.033	0.065	0.047
SP500	-0.050	-0.080	0.006	-0.083	0.112	0.299
Prior Same Venue	-0.070*	-0.030	0.011	-0.014	-0.440	-0.025
Panel B: Fidelity						
Dep var: the trade is routed to	Citadel	Virtu	G1X	Jane Street	Two Sigma	UBS
Venue Excess E/Q (t-1)	0.084	-0.019	-0.141	0.114		
Venue % (t-1)	-0.031	0.058	0.277	0.400		
Log(Price)	-0.010	0.057	0.002	0.029		
Log(Volume)	0.003	0.011	0.013	-0.065**		
Return	-0.069	0.053	-0.117	0.174		
Abs(Return)	-0.069	0.054	-0.118	0.164		
Spread	-0.003	-0.054	0.065	-0.223		
Buy(1/0)	-0.018	-0.009	-0.002	0.032		
SP500	0.053	-0.109	0.100	0.032		
Prior Same Venue	0.121*	0.023	0.017	0.050		

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: IBKR Lite						
Dep var: the trade is routed to	Citadel	Virtu	G1X	Jane Street	Two Sigma	UBS
Venue Excess E/Q (t-1)	-0.822**	-0.724**		-0.523**		
Venue % (t-1)	1.039**	2.224**		1.490**		
Log(Price)	-0.047	-0.294**		0.170**		
Log(Volume)	0.110**	0.078**		-0.148**		
Return	-0.138	-0.063		0.155		
Abs(Return)	-0.142	-0.062		0.155		
Spread	-0.388*	-0.284		-0.002		
Buy(1/0)	-0.130**	0.504**		-0.092**		
SP500	0.192*	0.132		-0.185*		
Prior Same Venue	-0.131*	-0.109		-0.130**		
Panel D: Robinhood						
Dep var: the trade is routed to	Citadel	Virtu	G1X	Jane Street	Two Sigma	UBS
Venue Excess E/Q (t-1)	-0.410**	-0.341**	-0.755**	-0.260**	-0.271**	
Venue % (t-1)	2.423**	1.680**	3.638**	1.853**	2.355**	
Log(Price)	-0.002	0.026*	0.070**	-0.070**	0.017	
Log(Volume)	0.031**	-0.054**	0.047**	-0.009	-0.041**	
Return	-0.063	0.220**	0.001	-0.275**	0.187*	
Abs(Return)	-0.062	0.221**	0.004	-0.279**	0.189*	
Spread	-0.099*	-0.065	-0.012	0.180**	-0.116	
Buy(1/0)	-0.038**	-0.029*	0.017	0.013	0.014	
SP500	-0.105*	0.070	0.147*	-0.093	-0.228**	
Prior Same Venue	0.072*	0.054*	0.029	0.085*	0.141**	
Panel E: Schwab						
Dep var: the trade is routed to	Citadel	Virtu	G1X	Jane Street	Two Sigma	UBS
Venue Excess E/Q (t-1)	0.050	0.117	0.036	-0.041	-0.024	-0.241
Venue % (t-1)	-0.318	0.023	0.075	-0.281	1.131	-0.474
Log(Price)	-0.015	0.053*	-0.017	0.027*	-0.017	-0.064
Log(Volume)	0.012	-0.012	0.028	-0.019	-0.010	-0.047
Return	0.127	-0.065	0.068	-0.094	0.595	0.199
Abs(Return)	0.130	-0.064	0.063	-0.093	-0.751	0.049
Spread	0.007	-0.244*	0.105	0.113	-0.412	-0.320
Buy(1/0)	0.007	0.005	0.020	-0.044**	-0.024	-0.067
SP500	-0.086	-0.014	-0.045	0.012	0.065	0.522
Prior Same Venue	0.108	0.115	-0.005	0.089	0.763**	1.336**

	(1)	(2)	(3)	(4)	(5)	(6)
Panel F: TD Ameritrade						
Dep var: the trade is routed to	Citadel	Virtu	G1X	Jane Street	Two Sigma	UBS
Venue Excess E/Q (t-1)	-0.009	0.117*	0.004	0.041		
Venue % (t-1)	-0.040	0.182	0.054	0.845**		
Log(Price)	-0.005	0.007	0.002	-0.018		
Log(Volume)	-0.008	0.013*	0.030**	0.023**		
Return	-0.047	-0.058	0.067	-0.027		
Abs(Return)	-0.047	-0.060	0.067	-0.027		
Spread	0.011	0.018	0.031	0.100*		
Buy(1/0)	0.008	0.006	-0.019	-0.007		
SP500	0.079	-0.039	-0.097*	-0.102		
Prior Same Venue	-0.012	-0.096*	-0.127**	-0.284**		

Panel G: IBKR Pro

Dep var: the trade is routed to	IBKR ATS		Exchange		Wholesaler	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Venue Excess E/Q (t-1)	-0.485**		-0.088		-0.800**	
Venue % (t-1)	2.245**		0.889**		1.510**	
Log(Price)	0.218**	0.385**	-0.292**	-0.327**	-0.094*	-0.182**
Log(Volume)	0.014	-0.027	-0.023	-0.011	-0.038	0.030
Return	-0.024	-0.152	0.202	0.241	0.118	-0.038
Abs(Return)	-0.024	-0.173	0.194	0.249	0.128	-0.024
Spread	1.118**	1.683**	-1.402	-1.659**	-1.016*	-1.562**
Buy(1/0)	0.023	0.000	-0.123*	-0.067	0.058	0.052
SP500	-0.112	-0.535**	-0.020	0.145	0.202	0.475**
Prior Same Venue	-0.249**	-0.141*	0.384**	0.370**	-0.322**	-0.235**

Table 3: Average Excess Price Improvement by Wholesaler

This table examines wholesaler performance within each broker. Each month, we compute the excess price improvement for each wholesaler within each broker. Excess price improvement is the difference between the wholesaler average effective over quoted spread at that broker and the overall effective over quoted spread of that broker. We then compute the average across our sample period using Fama and MacBeth (1973) while standard errors are computed using Newey and West (1987) with one lag. We also report the broker's average effective over quoted spread for reference purposes. t-values are in parentheses. **,* represents significance at the 1%, 5% levels respectively.

	Average E/Q	Citadel	Virtu	Jane Street	G1X	Sigma	UBS
E*Trade	0.322	0.093**	-0.131**	-0.037**	0.048**	0.068*	-0.023
		(6.1)	(-17.1)	(-3.0)	(3.9)	(2.4)	(-0.5)
Fidelity	0.142	0.100**	-0.114**	-0.028	-0.059**	0.089	0.010
		(6.3)	(-9.0)	(-1.4)	(-4.4)	(1.6)	(0.4)
IBKR Lite	0.527	0.008	0.247**	-0.060**			
		(0.4)	(9.6)	(-4.7)			
Robinhood	0.421	-0.015	-0.046**	-0.045	0.129**	0.130**	
		(-1.0)	(-5.5)	(-1.7)	(6.6)	(7.0)	
Schwab	0.229	0.123**	-0.114**	-0.049**	0.005	-0.034	-0.043
		(11.9)	(-5.7)	(-3.0)	(0.9)	(-0.7)	(-1.5)
TD Ameritrade	0.093	0.041**	0.020	-0.064**	-0.066**	0.284**	0.170*
		(4.1)	(1.7)	(-3.5)	(-9.4)	(3.4)	(2.5)

Table 4: Persistence of Wholesaler Price Improvement

This table presents results examining the persistence of overall price improvement (Panels A and B) or stock-level price improvement (Panels C and D) by wholesaler. Each period, we compute the broker-adjusted overall (stock-level) price improvement of each wholesaler by subtracting the broker overall (stock-level) average effective over quoted spread (E/Q) from the wholesaler overall (stock-level) average for that broker. We then regress the broker-adjusted price improvements on prior period values, measured over the last one- and three-month averages. t-values are in parentheses (based on standard errors clustered by month.) **,* represents significance at the 1%, 5% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Proportional Brokers					Selective Brokers		
	Brokers	All	E*Trade	Fidelity	Schwab	TD	All	IBKR Lite	Robinhood
Panel A: Wholesaler Overall Price Improvement (Prior Month)									
Dep var:	Broker-adjusted E/Q (t)								
Broker-adjusted E/Q ($t-1$)	0.735**	0.746**	0.488**	0.627*	0.505**	0.857**	0.687**	0.916**	0.599**
	(12.31)	(13.35)	(3.75)	(3.04)	(6.00)	(13.08)	(5.83)	(11.09)	(4.19)
R-sq	0.569	0.590	0.245	0.344	0.373	0.765	0.489	0.811	0.384
Panel B: Wholesaler Overall Price Improvement (Prior 3-month Average)									
Dep var:	Broker-adjusted E/Q (t)								
Broker-adjusted E/Q ($t-1$, $t-3$)	0.834**	0.832**	0.654**	0.924**	0.826**	0.868**	0.819**	0.980**	0.741**
	(13.04)	(12.60)	(3.85)	(5.36)	(16.48)	(11.52)	(7.21)	(10.21)	(4.65)
R-sq	0.550	0.550	0.272	0.336	0.614	0.667	0.520	0.866	0.400
Panel C: Wholesaler Stock-level Price Improvement (Prior Month)									
Dep var:	Broker-adjusted E/Q (t)								
Broker-adjusted E/Q ($t-1$)	0.210**	0.196**	0.187**	0.169**	0.188**	0.219**	0.246**	0.507**	0.190**
	(11.00)	(11.07)	(6.98)	(5.62)	(7.08)	(6.95)	(7.33)	(7.95)	(5.01)
R-sq	0.043	0.037	0.037	0.024	0.033	0.048	0.058	0.246	0.035
Panel D: Wholesaler Stock-level Price Improvement (Prior 3-month Average)									
Dep var:	Broker-adjusted E/Q (t)								
Broker-adjusted E/Q ($t-1$, $t-3$)	0.478**	0.480**	0.464**	0.426**	0.495**	0.508**	0.467**	0.712**	0.407**
	(20.73)	(21.15)	(15.27)	(7.62)	(7.73)	(13.61)	(6.18)	(7.33)	(4.30)
R-sq	0.080	0.084	0.093	0.051	0.082	0.095	0.068	0.237	0.047

Table 5: Changes in Routing in Response to Price Improvement

This table examines how brokers alter their routing to wholesalers based on their prior overall (Panels A and B) or stock-level (Panels C and D) price improvement. Each period, we compute the broker-adjusted overall (stock-level) price improvement, measured as E/Q, of each wholesaler for each broker by subtracting the broker overall (stock-level) average from the wholesaler overall (stock-level) average for that broker. We then regress the percent change in orders routed next period to that wholesaler against the wholesalers' excess price improvement based on the prior one- and three-month periods, respectively. t-values are in parentheses (based on standard errors clustered by month.) **,* represents significance at the 1%, 5% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Proportional Brokers					Selective Brokers		
	Brokers	All	E*Trade	Fidelity	Schwab	TD	All	IBKR Lite	Robinhood
Panel A: Wholesaler Overall Price Improvement (Prior Month)									
Dep var:	Percent Change in Routed Orders (t)								
Broker-adjusted E/Q ($t-1$)	-0.029*	-0.018	-0.025	-0.043	-0.064	-0.005	-0.083*	-0.067	-0.104*
	(-2.30)	(-1.74)	(-0.67)	(-0.84)	(-0.90)	(-1.23)	(-2.13)	(-0.87)	(-2.36)
R-sq	0.013	0.008	0.009	0.022	0.042	0.002	0.041	0.022	0.076
Panel B: Wholesaler Overall Price Improvement (Prior 3-month Average)									
Dep var:	Percent Change in Routed Orders (t)								
Broker-adjusted E/Q ($t-1$, $t-3$)	-0.015	-0.014	-0.024	-0.046	0.007	-0.011	-0.026	-0.092	0.017
	(-0.84)	(-0.89)	(-0.34)	(-0.49)	(0.25)	(-1.98)	(-0.54)	(-1.11)	(0.29)
R-sq	0.003	0.004	0.005	0.015	0.001	0.005	0.004	0.037	0.002
Panel C: Wholesaler Stock-level Price Improvement (Prior Month)									
Dep var:	Percent Change in Routed Orders (t)								
Broker-adjusted E/Q ($t-1$)	-0.007	0.007	-0.003	0.014	0.015	0.007	-0.046**	-0.071	-0.039**
	(-1.24)	(1.45)	(-0.44)	(0.76)	(1.33)	(0.75)	(-3.51)	(-1.30)	(-3.45)
R-sq	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.003	0.002
Panel D: Wholesaler Stock-level Price Improvement (Prior 3-month Average)									
Dep var:	Percent Change in Routed Orders (t)								
Broker-adjusted E/Q ($t-1$, $t-3$)	-0.011	0.003	-0.016	-0.009	0.039	0.010	-0.049	-0.047	-0.049
	(-0.91)	(0.24)	(-0.74)	(-0.18)	(2.95)	(0.45)	(-1.93)	(-0.67)	(-1.73)
R-sq	0.000	0.000	0.000	0.000	0.002	0.000	0.001	0.001	0.001

Table 6: Levels of Venue Routing based on Prior Price Execution

This table examines how wholesalers' market shares are related to their prior price improvement. Each month, we compute the price improvement, measured as the effective over quoted spread (E/Q), of all our trades for each wholesaler by broker. We also compute the percentage of our orders routed to each wholesaler. We then regress the percent of orders routed to the wholesaler this month against the price improvement the prior month. Panel A examines the relation using all wholesalers. The second model only examines the "Top 4" wholesalers (Citadel, Virtu, Jane Street, and G1X), which filled 96% of our trades. Regressions are run with broker dummy variables where appropriate. t-values are in parentheses (based on standard errors clustered by month.) **,* represents significance at the 1%, 5% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Proportional Brokers					Selective Brokers		
	Brokers	All	E*Trade	Fidelity	Schwab	TD	All	IBKR Lite	Robinhood
Panel A: All Wholesalers									
Dep var:	Percentage of Routed Orders (t)								
Broker-adjusted E/Q ($t-1$)	-0.254**	-0.153**	-0.044	0.056	0.250	-0.293**	-0.765**	-1.064**	-0.670**
	(-8.46)	(-4.52)	(-0.40)	(0.60)	(2.17)	(-6.81)	(-6.33)	(-10.47)	(-4.16)
R-sq	0.071	0.035	0.002	0.002	0.085	0.184	0.331	0.474	0.513
Panel B: "Big 4" Wholesalers									
Dep var:	Percentage of Routed Orders (t)								
Broker-adjusted E/Q ($t-1$)	-0.144**	0.306**	0.095	0.463**	0.137	0.661**	-0.721**	-1.064**	-0.653**
	(-3.14)	(6.14)	(1.50)	(3.27)	(1.91)	(6.82)	(-5.43)	(-10.47)	(-3.00)
R-sq	0.017	0.121	0.014	0.241	0.204	0.270	0.281	0.474	0.426

Table 7: Hypothetical Price Improvement from Rerouting
This table presents results on hypothetical price improvement if our trades were rerouted based on prior execution. For each broker, we compute the average price improvement, measured as the effective over quoted spread, received on each stock from each wholesaler. In Panel A, we compute the overall price improvement we received from each wholesaler across all stocks in the prior month. We then reroute all of this month's trades to the best wholesaler for the prior month. In Panel B, we compute the average price improvement we received for each stock from each wholesaler the prior month. We then route all of this month's trades for that stock to the wholesaler that had the best price improvement the prior month. In each panel, we report the average original price improvement, the hypothetical price improvement, as well as the difference and the change relative to the original price improvement, across all the months in our sample. t-statistics are computed using Fama and MacBeth (1973). **,* represents significance at the 1%, 5% levels respectively.

Panel A: PI from Rerouting using Overall Execution

Broker	Original	Updated	Change	t-value	PI Change %
Proportional:					
E*Trade	0.352	0.223	-0.129	-12.61**	-36.6%
Fidelity	0.192	0.093	-0.099	-4.87**	-51.6%
Schwab	0.240	0.160	-0.079	-4.80**	-33.3%
TD Ameritrade	0.118	0.047	-0.071	-8.15**	-60.2%
Selective:					
IBKR Free	0.575	0.530	-0.046	-3.77**	-7.8%
Robinhood	0.402	0.346	-0.056	-5.23**	-13.9%
Average	0.313	0.233	-0.080		-33.9%

Panel B: PI from Rerouting using Stock Level Execution

Broker	Original	Updated	Change	t-value	PI Change %
Proportional:					
E*Trade	0.349	0.311	-0.038	-3.41**	-10.9%
Fidelity	0.197	0.149	-0.047	-3.08**	-24.4%
Schwab	0.232	0.190	-0.042	-3.09**	-18.1%
TD Ameritrade	0.108	0.021	-0.086	-7.64**	-80.6%
Selective:					
IBKR Free	0.571	0.590	0.020	1.37	3.3%
Robinhood	0.397	0.454	0.057	3.77**	14.4%
Average	0.309	0.286	-0.023		-19.4%

Table 8: Changes for Robinhood Wholesalers after Jane Street Addition
This table shows changes in Robinhood's wholesaler market after Jane Street became an additional venue. Panel A reports the percentage of our trades routed to each wholesaler before and after. Panel B reports the execution cost measured as the effective over quoted spread (E/Q) again before and after. In both panels, t values use standard errors clustered by stock. The prior period covers the six weeks before to February 24, 2022. The posterior period runs from February 24 to April 15 2022. In both cases, we average across all trades each day and then average across days, computing t-values using Fama and MacBeth (1973)). **, * represents significance at the 1%, 5% levels respectively.

Panel A: Wholesaler Shares

	Pre-Jane Street	Post-Jane Street	Difference	t-value	% Change
Virtu	39.0%	28.6%	-10.4%	-7.58**	-26.7%
Citadel	26.6%	21.5%	-5.1%	-4.13**	-19.2%
Two-Sigma	18.1%	18.7%	0.6%	0.57	3.2%
G1X	13.0%	8.1%	-4.9%	-4.43**	-37.7%
Jane Street	2.7%	22.5%	19.8%	19.57**	733.3%

Panel B: Execution Cost (E/Q)

	Pre-Jane Street	Post-Jane Street	Difference	t-value	% Change
Overall	0.548	0.470	-0.078	-5.66**	-14.3%
Virtu	0.483	0.448	-0.035	-1.15	-7.2%
Citadel	0.536	0.398	-0.138	-5.91**	-25.7%
Two-Sigma	0.612	0.597	-0.015	-0.42	-2.4%
G1X	0.703	0.643	-0.061	-2.53*	-8.6%
Jane Street	0.238	0.391	0.154	2.00	64.7%

Table 9: Drivers of Changes in Stock Allocation after Jane Street Addition
This table analyzes the drivers behind Robinhood's routing of stocks after Jane Street's addition to its routing venues. We separate the sample into the six weeks prior to February 24, 2022, and a post period from February 24 to April 15, 2022. For each stock-wholesaler observation, we compute the execution cost, measured as the effective over quoted spread, on that stock relative to the overall venue average (Excess E/Q) over the prior period. We then regress the change in the wholesaler's share in that stock from the pre- to post- period against Excess E/Q. We also include stock-level controls, i.e., the average spread, log of the stock price, log of the stock volume, and the average daily return. t-values are in parentheses. **,* represents significance at the 1%, 5% levels respectively.

	Citadel	Virtu	G1X	Two Sigma
Excess E/Q	0.092	0.027	-0.009	-0.064
	(1.12)	(0.24)	(-0.10)	(-0.99)
Avg. Spread	-0.023	-0.054	0.026	0.027
	(-0.65)	(1.27)	(0.74)	(0.79)
Log(Price)	0.007	0.036**	-0.024*	-0.016
	(0.73)	(3.08)	(-2.37)	(-1.78)
Log(Volume)	-0.012	-0.022*	-0.012	0.020**
	(-1.58)	(-2.56)	(-1.59)	(2.74)
Avg. Daily Return	-0.015	-0.003	0.038**	-0.035**
	(-1.19)	(-0.16)	(2.99)	(-2.97)

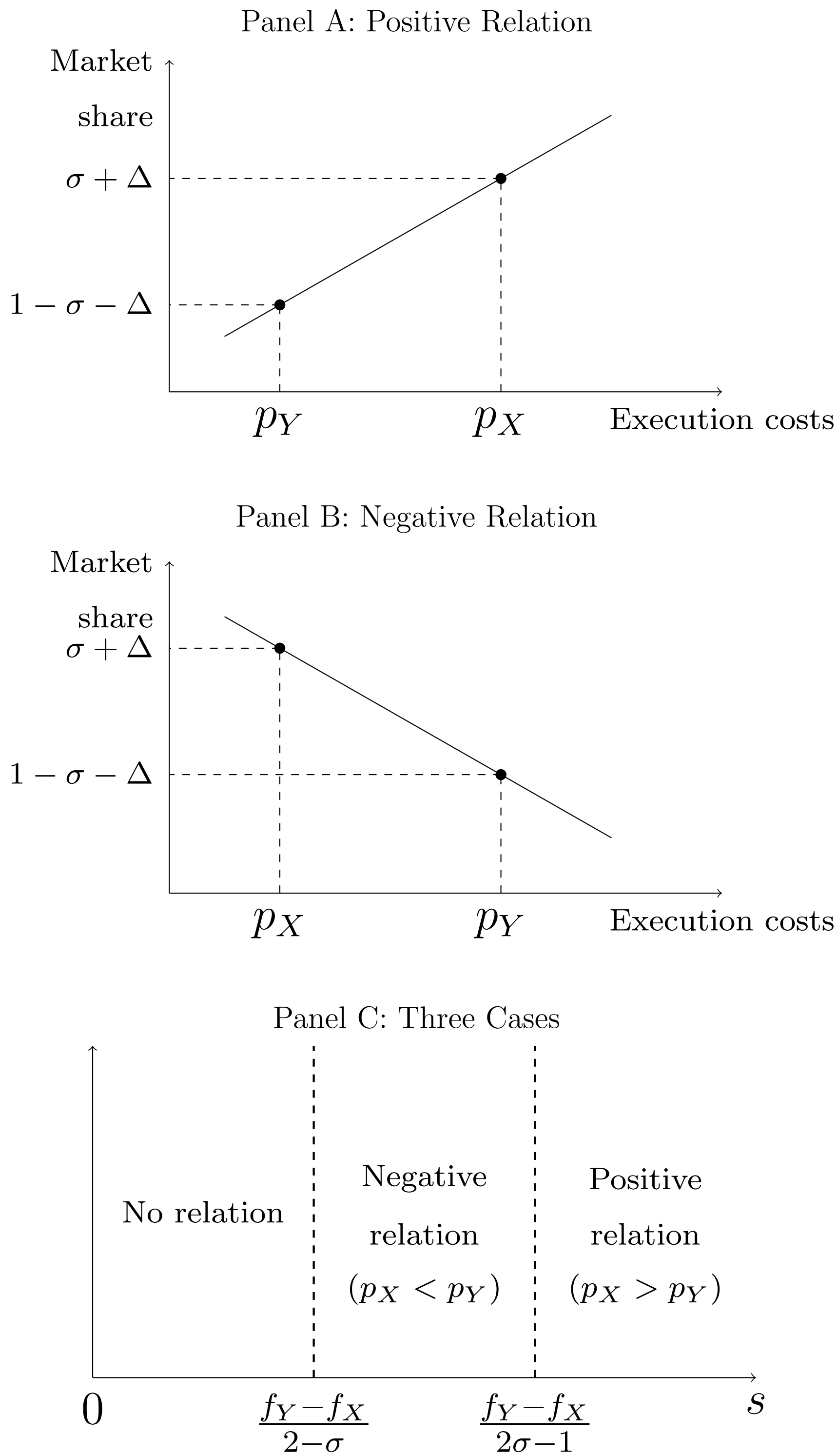


Figure 7: Model
Panel A plots the positive relation between execution and share, which arises when the wholesalers have the same marginal cost or when switching costs are high. Panel B plots the negative relation, which arises when switching costs are medium. Panel C shows how the size of switching costs affects the sign of the relation.

Appendix

A. Proofs

Proof of Proposition 1.

First, suppose that the broker incurs switching costs ($s > 0$). The wholesalers' marginal costs may or may not be the same ($f_X \leq f_Y$). The broker optimally chooses Δ that solves:

$$\min_{\Delta \in [-\sigma, 1-\sigma]} (\sigma + \Delta)p_X + (1 - \sigma - \Delta)p_Y + \frac{s}{2}\Delta^2. \tag{10}$$

The F.O.C. implies:

$$\Delta = \begin{cases} \frac{p_Y - p_X}{s} & \text{if } p_Y - p_X \in [-s\sigma, s(1-\sigma)], \\ 1 - \sigma & \text{if } p_Y - p_X > s(1-\sigma). \\ -\sigma & \text{otherwise.} \end{cases} \tag{11}$$

Each wholesaler optimally chooses prices to maximize profits. Wholesaler X solves

$$\max_{p_X} (p_X - f_X)(\sigma + \Delta) \tag{12}$$

Using Equation (11), the F.O.C. implies

$$p_X = \begin{cases} \frac{s\sigma + p_Y + f_X}{2} & \text{if } p_Y \in (f_X - s\sigma, f_X + s(2-\sigma)), \\ f_X & \text{if } p_Y \le f_X - s\sigma, \\ p_Y - s(1-\sigma) & \text{otherwise.} \end{cases} \tag{13}$$

Similarly, wholesaler Y's F.O.C. implies

$$p_Y = \begin{cases} \frac{s(1-\sigma) + p_X + f_Y}{2} & \text{if } p_X \in (f_Y - s(1-\sigma), f_Y + s(1+\sigma)), \\ f_Y & \text{if } p_X \le f_Y - s(1-\sigma), \\ p_X - s\sigma & \text{otherwise.} \end{cases} \tag{14}$$

Theoretically, there is a total of nine cases. However, given that $f_X \le f_Y$, p_Y cannot be less than f_X. It is also not optimal for wholesaler X to charge $p_X > f_Y + s(1+\sigma)$ such that wholesaler Y receives the entire order flow. Thus, a total of four cases remains.

Case 1: $p_X \in (f_Y - s(1-\sigma), f_Y + s(1+\sigma))$ **and** $p_Y \in (f_X - s\sigma, f_X + s(2-\sigma))$**.** From Equations (13) and (14), we have

$$p_X = \frac{2f_X + f_Y}{3} + \frac{s(1+\sigma)}{3} \qquad \text{and} \qquad p_Y = \frac{f_X + 2f_Y}{3} + \frac{s(2-\sigma)}{3}. \tag{15}$$

Ensuring that these solutions satisfy the conditions for the prices' ranges, we have

$$s > \frac{f_Y - f_X}{2 - \sigma}. \tag{16}$$

Case 2: $p_X \in (f_Y - s(1-\sigma), f_Y + s(1+\sigma))$ and $p_Y \geq f_X + s(2-\sigma)$. Again from Equations (13) and (14), we have

$$p_X = f_Y - s(1-\sigma) \qquad \text{and} \qquad p_Y = f_Y. \tag{17}$$

Ensuring that these solutions satisfy the conditions, we have

$$s \leq \frac{f_Y - f_X}{2-\sigma}. \tag{18}$$

Case 3: $p_X \leq f_Y - s(1-\sigma)$ and $p_Y \in (f_X - s\sigma, f_X + s(2-\sigma))$. From Equations (13) and (14), we have

$$p_X = \frac{f_X + f_Y + s\sigma}{2} \qquad \text{and} \qquad p_Y = f_Y. \tag{19}$$

Substituting these solutions to the conditions yields contradictions. $p_Y = f_Y \in (f_X - s\sigma, f_X + s(2-\sigma))$ implies:

$$f_Y - f_X \in (f_X - s\sigma, f_X + s(2-\sigma)), \tag{20}$$

while $p_X = \frac{f_X + f_Y + s\sigma}{2} \leq f_Y - s(1-\sigma)$ implies:

$$f_Y - f_X \geq s(2-\sigma). \tag{21}$$

Both conditions cannot be satisfied simultaneously.

Case 4: $p_X \leq f_Y - s(1-\sigma)$ and $p_Y \geq f_X + s(2-\sigma)$. In this case, $p_Y = f_Y$ and wholesaler X has no incentive to reduce prices strictly below $f_Y - s(1-\sigma)$ since it already receives the entire order flow. Thus, the result is identical to Case 2.

Finally, if the broker does not incur switching costs (i.e., $s = 0$), the broker's optimal strategy is

$$\Delta = \begin{cases} 1 - \sigma & \text{if } p_X \leq p_Y \\ \\ -\sigma & \text{otherwise.} \end{cases} \tag{22}$$

Given this, wholesalers X and Y's optimal strategies are $p_X = p_Y = f_Y$. Wholesaler Y has no incentive to raise or reduce prices, since any other prices imply zero or negative profits. Wholesaler X also has no incentive to raise or reduce prices. Raising prices imply zero market share. Reducing prices only lower profits since it is already receiving the entire order flow. ■