Many Facets of Best Execution: Order Routing and Competition in Retail Trading

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Abstract

Using a controlled trading experiment spanning 150,000 trades, we study how retail brokers route orders and respond to execution quality. Within each broker, execution quality varies substantially and persistently across wholesalers. Yet broker responses to these dispersions are strikingly heterogeneous: while some route more orders to lower-cost wholesalers, others consistently send more to higher-cost ones. We develop a switching cost model that rationalizes these contrasting behaviors. A natural experiment involving wholesaler entry demonstrates that competition improves execution quality even for the most responsive broker. This heterogeneity in how brokers implement best execution requirements shapes the competitive pressure on wholesalers.

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1. Introduction

The U.S. equity market for retail investors has undergone fundamental structural changes over the past two decades, sharply lowering trading costs. A key change is that retail brokers increasingly route orders to over-the-counter market makers known as "wholesalers," who provide payment for order flow (PFOF) to brokers that enabled the industry's shift to zero commissions. Because brokers typically receive uniform PFOF rates across venues to avoid conflicts of interest, wholesalers compete primarily on execution quality for investors rather than payment rates.[1] While investors bear all execution costs, brokers still have a legal duty of best execution and must route orders to venues offering the most beneficial terms for their investors (FINRA (2014)). This system has evolved into a market where four firms handle over 90% of retail order flow.[2] Such concentration raises questions about whether wholesalers face sufficient competitive pressure from broker routing decisions to benefit retail investors.

This paper examines competition in the retail broker-wholesaler market using a controlled trading experiment spanning over 150,000 trades across six major retail brokers. We document large and persistent dispersions in execution quality across wholesalers within the same broker, with the gap between best and worst wholesaler ranging from 42% to 151% of that broker's average cost. Broker responses to these wide dispersions are strikingly heterogeneous: while some brokers route more orders to lower-cost wholesalers, others consistently route more flow to higher-cost ones. We develop a model with switching costs that explains this heterogeneity. A natural experiment involving wholesaler entry demonstrates that additional competition improves execution quality even for the most responsive broker in our sample. These findings have direct implications for regulatory debates about market

[1] Bartlett et al. (2023), Ernst et al. (2024), and Schwarz et al. (2023) show that PFOF is economically small and does not explain cross-sectional variation in execution quality for U.S. equities.

[2] The four wholesalers (Citadel, Virtu, G1X, and Jane Street) handle 94% of orders across commission-free accounts in our sample (Table 1). This concentration has drawn regulatory scrutiny, with the SEC proposing sweeping reforms in 2022; see also Hu and Murphy (2022) and SEC (2024).

concentration and disclosure requirements in retail execution markets.

Our experimental approach addresses key limitations of existing public data. Current SEC disclosures aggregate execution statistics across all brokers (Rule 605 reports) or provide routing shares without execution quality (Rule 606 reports), making it impossible to assess wholesaler performance for individual brokers or identify the broker heterogeneity we document.[3] We execute over 150,000 market orders totaling $22.4 million in notional value across identical timestamps, stocks, and order sizes, creating randomized parallel trades. We obtain detailed routing information through SEC Rule 606(b)(1) disclosures, allowing us to trace each order's path from broker to specific wholesaler. This granular approach enables clean *within-broker* comparisons of wholesaler performance, avoiding potential confounding from the substantial *cross-broker* execution cost differences.[4]

Most of our trades are odd lots. While our findings may not generalize to larger round-lot orders, odd lots are economically significant. In the TAQ data, odd lot trades for our sample represent 65% of trades, 15% of share volume, and 32% of dollar-weighted quoted spreads, consistent with SEC market-wide data showing 14-22% of share volume.[5] Further, our observed routing patterns closely match brokers' 606(a) filings, which include all order sizes (Figure 1, Panel B). The focus on odd lots is also policy-relevant: one of the stated goals of the SEC's Enhanced Disclosure of Order Execution information is to include odd-lot trades.[6]

We have three main findings. First, measuring execution costs as the effective-over-quoted spread (E/Q), we document large and persistent dispersions in execution quality

[3]Rule 606 reports routing shares across all venues, including exchanges, alternative trading systems (ATS), and wholesalers. Since our analysis focuses exclusively on wholesaler execution, we use "wholesaler" and "venue" interchangeably throughout the paper.

[4]See Battalio et al. (2001) and Schwarz et al. (2023).

[5]https://www.sec.gov/marketstructure/datavis/ma_overview.html

[6]https://www.sec.gov/newsroom/press-releases/2024-32

across wholesalers within each broker.[7] Within each broker, the gap between the highest- and lowest-cost wholesalers as a fraction of that broker's average execution cost (or, the "normalized dispersion") ranges from 42% to 151%, representing economically meaningful differences in trading costs that customers experience based solely on their broker's routing choices. These dispersions persist over time at both aggregate and stock levels, allowing brokers to predict wholesaler performance using historical data.

Second, we examine broker responses to these dispersions along three dimensions: whether brokers adjust routing shares in response to past execution quality, whether current routing allocations reflect historical performance patterns, and the potential costs of current routing practices through counterfactual analysis.

The results reveal striking heterogeneity across brokers. Only one broker shows statistically significant routing adjustments to past performance—the broker with the smallest normalized dispersion. Moreover, only two brokers (those with the smallest normalized dispersions) route more orders to lower-cost wholesalers, showing the expected negative relationship between routing shares and execution costs. The other four brokers exhibit the opposite pattern, systematically routing more flow to higher-cost wholesalers. Our counterfactual analysis suggests that routing all orders to the best-performing wholesaler from the prior month would reduce average execution costs by 34%. The potential gains vary substantially across brokers, with larger improvements for those currently exhibiting positive relationships between routing shares and costs.

Third, we examine how the entry of a new wholesaler impacts competition in a natural experiment. Entry occurred during our sample period for the most responsive broker with the smallest normalized dispersion. Immediately after entry, incumbent wholesalers reduced their execution costs by an average of 14%, with reductions ranging from 2% to 26%. These

[7] E/Q is defined as the effective spreads relative to the National Best Bid and Offer (NBBO), which captures how much of the quoted spread investors actually pay.

sharp competitive responses demonstrate that additional competition meaningfully improves execution quality even for brokers that already adjust their routing actively, consistent with sizable entry barriers in this market (Goolsbee and Syverson (2008)).

To explain the striking heterogeneity in broker routing behavior, we develop a simple theoretical framework where brokers face switching costs when reallocating order flow between wholesalers. We analyze equilibrium outcomes across three cases depending on the magnitude of these costs. When switching costs are low, the lower-cost wholesaler captures the entire market, as in standard Bertrand competition. As costs increase to moderate levels, the equilibrium features the expected negative relationship between routing share and execution costs, matching our findings for the two most responsive brokers. However, when switching costs are high, the relationship turns positive, consistent with our empirical findings for the other four brokers. The key insight is that brokers do not route more orders because wholesalers charge more; rather, dominant wholesalers can charge more because switching costs make brokers reluctant to reallocate away from them. We then explore how differences in broker priorities and order flow characteristics explain the heterogeneity in switching costs.

Finally, we discuss additional results and policy implications. The heterogeneity in broker routing we document has direct implications for interpreting aggregate regulatory disclosures and debates about disclosure requirements. We find that more responsive brokers with smaller dispersions also have higher average execution costs, suggesting they handle order flows that are inherently more expensive to execute.[8] This composition effect creates a classic example of Simpson's paradox: wholesalers providing superior execution quality to individual brokers may appear indistinguishable or worse in aggregate data, just as skilled doctors may show lower survival rates because they treat sicker patients. This highlights a

[8]This, in fact, may incentivize them to adjust routing more actively due to an increased chance of violating the NBBO execution requirements. We explore this mechanism in Section 4.3.

key limitation of current aggregate disclosure requirements.[9] Detailed, disaggregated data at the broker-wholesaler level is essential for accurately assessing wholesaler performance and the effectiveness of competition. Implementing such granular public disclosures would strengthen market discipline and ultimately benefit retail investors.

Our analysis reveals two distinct routing approaches: selective routing that adjusts allocations stock-by-stock, adopted by the two most responsive brokers, and proportional routing with fixed percentages across all stocks, adopted by the other four brokers. Among the four less responsive proportional brokers, two brokers exhibit greater variability of routing shares month to month, potentially reflecting that these brokers may still respond to execution quality of other order segments. The other two proportional brokers, on the other hand, maintain nearly static routing shares, consistent with the limited responsiveness to execution quality we document for these brokers.

Related Literature. Prior execution quality research focused primarily on exchange-based trading in the pre-2019 commission era, a market structure that differs fundamentally from today's zero-commission retail environment. For example, Battalio et al. (2016) and Battalio (2018) examine limit order rebates on exchanges using 2012-2016 data. Recent studies have examined the modern wholesale market. Bartlett et al. (2023) compare wholesaler execution quality to that on exchanges and show that wholesaler execution is consistently superior. Our paper is most closely related to Dyhrberg et al. (2023) and Ernst et al. (2023), who study competition and routing practices in the retail broker-wholesaler market.

Dyhrberg et al. (2023) use public disclosures aggregated at the wholesaler level. They find that routing share and execution costs are negatively related, suggesting larger wholesalers offer better execution, and that Jane Street's entry had no pricing response from competitors.

[9]Under the recently adopted disclosure requirements (SEC (2024)), the 605 forms will now also be required for retail brokers, not just wholesalers, and extended to odd lots. However, the proposal still does not require disclosing execution costs for each broker-wholesaler pair (SEC (2005)).

Our broker-level analysis reveals substantial heterogeneity that aggregate data obscures. While we replicate their negative relationship in pooled data, disaggregating by broker shows this pattern holds for only two of six brokers, but reverses for four others. Moreover, isolating entry for a specific broker, we find significant reductions in execution costs, highlighting how aggregation can mask competitive effects. Their analysis also does not cover odd lots, which Form 605 disclosures excluded during their sample period, so our focus on small orders provides complementary evidence for this economically significant segment.

Ernst et al. (2023) present a model of optimal routing under asymmetric information and examine broker responsiveness using proprietary data from three anonymous brokers. Consistent with our natural experiment findings, they document that wholesaler entry improved execution quality. They also find that wholesalers adjust execution costs across order segments when broker priorities shift. This pattern is consistent with our theoretical framework where broker priorities can raise switching costs for non-prioritized segments like odd lots that we study (Section 4.3.2). Finally, they find that routing shares and execution costs are negatively related for their three brokers, which aligns with our results for our two most responsive brokers but contrasts with those for the other four brokers. Given the stark heterogeneity we document, this difference may simply reflect sample composition. While their brokers are anonymous, more responsive brokers might be more willing to voluntarily provide the data, potentially creating a selection bias tilting their sample toward more responsive brokers.

Overall, our results highlight a more nuanced view of competition compared to findings from Dyhrberg et al. (2023) and Ernst et al. (2023), which seem to suggest a uniformly competitive market. Using granular data from the six largest retail brokers, we document substantial heterogeneity in routing behavior across brokers. Different brokers implement best execution requirements in markedly different ways, and this heterogeneity translates directly into varying competitive pressure on wholesalers.

Our paper is also related to Ernst et al. (2024), who compare the current broker-routing system to the SEC's proposed Order Competition Rule based on order-by-order auctions (SEC (2022)). They assume that competition is ensured in the status-quo, but our findings suggest this may not hold in practice.

More generally, our paper is related to the industrial organization literature. Numerous studies show how market outcomes reflect the exercise of market power in specific industries.[10] Here, we focus on the broker-wholesaler market. We use switching costs, a concept traditionally applied to consumer behavior (Klemperer, 1987; Farrell and Klemperer, 2007), as a modeling device to represent brokers' limited adjustments and connect them to wholesaler market power. We also highlight the role of regulations in providing heterogeneous and insufficient incentives for brokers to reduce switching costs, limiting competition. This connects to earlier studies like Daughety (1984), which show how uniform regulatory requirements across heterogeneous firms can lead to inefficiencies.

The remainder of the paper is organized as follows. Section 2 describes our trading experiment and data. Section 3 presents the empirical analysis of retail execution competitiveness. Section 4 develops a theoretical framework that rationalizes the empirical findings. Section 5 discusses additional results and policy implications. Section 6 concludes.

2. Data and Institutional Background

This section explains the institutional background of the retail broker-wholesaler market, provides an overview of our trading experiment that generates granular execution data, and presents summary statistics.

[10] See for example Porter (1983), Bresnahan (1987), and Nevo (2001). Einav and Levin (2010) provide a comprehensive survey of the empirical industrial organization literature, including studies on market power.

2.1. Institutional Background

The broker-wholesaler relationship operates through flexible, private arrangements. Brokers select a pool of wholesalers and typically receive identical PFOF rates across them to avoid routing conflicts. Wholesalers, in turn, decide whether to accept incoming order flow. There are no other contractual obligations: brokers may route to any venue, and wholesalers are not required to provide specific levels of price improvement. Brokers do not receive pre-trade quotes from wholesalers, making routing decisions inherently based on historical performance rather than real-time pricing.

Both brokers and wholesalers are subject to FINRA's best execution rules, which require regular, rigorous reviews of execution quality and corresponding adjustments to routing practices when material differences are identified; see FINRA Rule 5310 and related guidance in FINRA (2014, 2015). In practice, best execution is broadly defined, allowing routing decisions to reflect diverse broker priorities, client characteristics, and trade types.[11] Brokers typically provide wholesalers with anonymized scorecards comparing execution quality across size buckets and can shift routing or request improvements when performance lags. However, practical constraints may slow routing adjustments: brokers must preserve competition among wholesalers, manage operational risk, ensure adequate technical capacity, and maintain stable order flow for meaningful performance comparisons.

2.2. Data from Trading Experiment

Our primary data come from a controlled trading experiment based on the simultaneous placement of identical orders (same stock, size, and timestamp) across six major retail brokers: E*Trade, Fidelity, Interactive Brokers (IBKR, both Pro and Lite versions), Robinhood, Schwab, and TD Ameritrade. All accounts charge zero commissions except IBKR Pro.

[11] Industry participants indicated that while other execution quality dimensions (speed, reliability) are baseline requirements, price improvement remains the primary determinant of routing decisions.

We place round-trip market orders during regular trading hours for 128 stocks, randomly selected from bins sorted along four dimensions: market capitalization, daily volatility, share turnover, and stock price. Our trades span December 21, 2021–May 31, 2023. We use randomized submission times to ensure representativeness and unwind all positions within 30 minutes. We use market orders, the most common order type among retail investors.[12] Each order targets $100 in notional value, subject to a minimum of one share, resulting in most trades being odd lots. Our focus on odd lots, which now represent a significant share of equity trading activity, is consistent with the growing retail investor base that typically executes smaller position sizes. For our stratified sample, odd lot trades represent 65.1% of all trades, 14.6% of share volume, and 31.5% of dollar-weighted quoted spreads based on the authors' calculations using TAQ data.[13] Further details on the experimental setup appear in Schwarz et al. (2023) and Barber et al. (2023), which use an earlier version of this dataset.

In total, we place over 150,000 trades, representing $22.4 million in notional value. We supplement our trading data with the TAQ database, which provides a complete record of all U.S. equity trades. Each of our trades is identified in TAQ, and the corresponding National Best Bid and Offer (NBBO) is retrieved via WRDS.[14]

To evaluate routing decisions and wholesaler execution, it is essential to identify the actual wholesalers to which our trades are routed. While TAQ provides a broad classification of trade locations, most of our trades are executed off-exchange and coded simply as "D," which is insufficient for our purposes. To obtain detailed routing information, we rely on SEC Rule 606(b)(1), which requires brokers to disclose the exact venue for each client trade

[12] Schwab (2022), p. 10, reports that approximately 75% of its equity trades are market orders.

[13] This is consistent with the SEC Market Structure data showing that odd lots account for roughly 14-22% of share volume in U.S. equities during our 2021-2023 sample period (see https://www.sec.gov/marketstructure/datavis/ma_overview.html). See also O'hara et al. (2014) and Bartlett et al. (2023), who emphasize the growing role of odd lot trades in price discovery and market microstructure.

[14] Our main analysis uses NBBO at execution time. For the three brokers where we used application programming interfaces (APIs), we could capture NBBO quotes immediately before trade submission as an additional robustness check. Results are consistent with our main findings and available upon request.

upon request, covering the prior six months.

By independently collecting granular execution data across leading retail brokers, we observe the complete routing and execution path for every trade, detail unavailable in the monthly aggregates reported under SEC Rules 605 and 606.[15] Because the trades are generated through a randomized experiment, they are orthogonal to unobserved factors such as investor information, evolving stock characteristics, or market conditions that typically confound archival studies. These features enable clean comparisons of execution quality and provide a detailed window into broker-wholesaler behavior in today's retail execution market.

2.3. Summary Statistics

Table 1 summarizes our order routing data. Row totals report the number of trades executed through each brokerage account; column totals report the number of trades routed to each wholesaler across all accounts. Panel A presents raw trade counts by broker and wholesaler, while Panel B converts these counts to broker-level percentages, also shown in Figure 1 Panel A.

[**Insert Table 1 about here**]

Routing in the IBKR Pro account, which charges commissions, looks markedly different from the other accounts, with most trades executed in their own alternative trading system (ATS) or on lit exchanges.[16] We exclude IBKR Pro from our analysis.

Across our commission-free accounts, 94% of orders are routed to four wholesalers—Citadel, Virtu, Jane Street, and G1X. The residual flow goes mostly to Two Sigma (largely from Robinhood) and to UBS, whose share declined over our sample period. Given this concentration, we focus our analysis on these four dominant wholesalers, with robustness checks

[15] Rule 605 provides wholesalers' execution statistics aggregated across all clients, whereas Rule 606 discloses brokers' routing shares without information on execution quality.

[16] An alternative trading system (ATS)—including electronic communication networks (ECNs)—is an off-exchange venue that matches buyers and sellers; a "dark pool" is an ATS without displayed quotes.

using the full sample in Appendix IA.3.

[Insert Figure 1 about here]

Figure 1 Panel B compares our data with public data from 606(a) reports. Routing shares appear remarkably identical across all brokers except for Robinhood. The difference appears to stem from differences in routing styles across brokers, which we discuss in detail in Section 5.2.

We measure execution cost with the effective-over-quoted spread (E/Q). For a buy order, the effective spread equals twice the difference between the execution price and the NBBO midpoint, divided by the NBBO quoted spread, yielding a unitless ratio. Price improvement (PI) for a buy order is the NBBO ask minus the execution price, scaled by the same spread, and satisfies $E/Q = 1 - 2 \cdot \text{PI}$. Thus, a lower E/Q (i.e., higher PI) indicates lower execution cost.

Our data show considerable time-series and cross-sectional variation in both order routing and execution costs. Figure 2 illustrates this variation using Robinhood and Fidelity as examples. Panels A and C plot the share of our trades routed to each wholesaler over the 18-month sample, whereas Panels B and D report the corresponding average effective-over-quoted spread (E/Q) for each wholesaler.

[Insert Figure 2 about here]

3. Competitiveness of Retail Trade Execution

This section examines competition within the wholesaler marketplace where our retail trades are directed. After documenting persistent execution quality dispersion across wholesalers within brokers in Section 3.1, we examine broker responses in Section 3.2 by (1) testing whether brokers change routing based on past execution; (2) examining whether routing share levels reflect past execution; (3) quantifying hypothetical execution improvements through counterfactual analysis. Section 3.3 studies how new wholesaler entry affects incumbents in a natural experiment.

3.1. Persistent Dispersion of Execution Quality

We begin by examining execution cost dispersion across wholesalers within brokers. Table 2 presents average effective-over-quoted spreads (E/Q) for each broker in Column (1) and broker-adjusted E/Q in Columns (2)-(5), representing each wholesaler's deviation from the broker average. We average deviations across trades within each month, then across all sample months. Standard errors use the Fama and MacBeth (1973) approach with Newey and West (1987) one-lag correction for autocorrelation. Column (6) shows the normalized dispersion: the difference between maximum and minimum deviations divided by the broker average E/Q.

[Insert Table 2 about here]

All brokers exhibit statistically and economically large execution cost dispersion across wholesalers. The normalized dispersion ranges from 42% to 151%, demonstrating substantial heterogeneity across brokers. Robinhood and IBKR Lite show the smallest dispersion (42% and 58%), while TD Ameritrade and Fidelity exhibit the largest (115% and 151%). This dispersion represents meaningful economic differences in execution quality that customers experience based on their broker's routing practices. Interestingly, the brokers with the smallest normalized dispersion also exhibit the highest average execution costs, while those with the largest dispersion show lower average costs. We explore a potential explanation for this pattern in Section 4.3 based on differences in order flow characteristics and further discuss policy implications in Section 5.1.

Since brokers observe execution costs only after orders are executed as discussed in Section 2.1, they cannot route based on current execution quality. However, if execution cost differences across wholesalers are persistent, brokers could use historical performance to inform routing decisions and potentially reduce customer execution costs.

To test whether such persistence exists, we regress monthly average broker-adjusted E/Q against one-month and three-month lagged values, estimating regressions across all brokers and for each broker individually. Standard errors are clustered by month. Table 3 presents the results.

[Insert Table 3 about here]

Panels A and B show that wholesaler broker-adjusted performance is highly persistent at the aggregate level. Across all brokers, the one-month (three-month) lag coefficient is 0.72 (0.83), both economically large and statistically significant, with R-squared exceeding 50%. The coefficients near one indicate performance gaps between wholesalers remain highly stable over time. This persistence appears across all individual brokers, with slope coefficients ranging from 0.59 to 0.92. Figure 3 illustrates this relationship.

[Insert Figure 3 about here]

We perform the same analysis at the individual stock level. Monthly broker-adjusted E/Q is calculated as each wholesaler's deviation from the broker-level average E/Q for that specific stock. Panels C and D of Table 3 show the results are consistent with the aggregate level: execution costs remain persistent across all brokers and within each broker. The slope coefficients for one-month and three-month lags are statistically significant across all brokers, although the coefficients and R-squared values are systematically lower than at the aggregate level, likely reflecting noisier execution costs at the stock level.

3.2. Broker Routing Responses to Execution Quality

Having established persistent execution quality differences across wholesalers, we examine how brokers respond to past execution. From an economic perspective, since wholesalers' execution quality is predictable, brokers can use prior data to adjust their routing practices to reduce execution costs for their customers. From a regulatory standpoint, under best execution obligations, brokers are required to evaluate the execution quality of wholesalers over time and act upon this evaluation. Brokers reportedly comply with these obligations "by establishing routing allocations based on this historical performance" (Schwab, 2023, p. 14).

We empirically examine broker responsiveness along three dimensions. First, we test whether brokers change routing based on past execution quality, increasing allocations to better-performing wholesalers and reducing them for worse performers. Second, we examine whether current routing shares reflect historical execution quality, asking whether wholesalers with larger routing shares have systematically better or worse past performance. Third, we quantify the hypothetical execution cost improvements if brokers routed all orders to the historically best-performing wholesaler each month.

3.2.1. Changes in Routing Allocation

We first examine whether brokers change routing in response to past execution quality, expecting brokers to reduce routing shares to wholesalers with higher execution costs. We measure routing adjustments as monthly changes in the percentage of orders routed to each wholesaler, then regress these changes against the wholesaler's prior broker-adjusted E/Q over one-month and three-month periods. We estimate regressions across all brokers and for each broker individually, conducting the analysis at both aggregate and individual stock levels, including broker dummies when appropriate and clustering standard errors by month.

[Insert Table 4 about here]

Table 4 Panels A and B report results at the aggregate level.[17] Across all brokers, we find limited evidence that brokers change routing toward wholesalers with lower prior-month execution costs. The one-month lag coefficient is negative and significant for only one broker, Robinhood, which has the smallest normalized dispersion (42% of the broker average E/Q). The effects are not significant for the other five brokers, and no broker shows significant effects at the 3-month lag. Figure 4 illustrates these patterns by plotting changes in routing share against prior month excess E/Q.

[Insert Figure 4 about here]

We also examine changes in stock-by-stock routing allocation as a function of prior stock-specific execution quality, with results in Panels C and D of Table 4. Consistent with our findings at the aggregate level, only Robinhood shows a statistically significant response to lagged execution costs.

3.2.2. Levels of Routing Allocation

Our analysis of routing changes revealed a surprising finding: except for Robinhood, brokers show little response to past execution quality when adjusting their routing. One explanation for this apparent inertia is that brokers may have already reached a steady state. If so, their current routing allocation should reflect past performance, with better-executing wholesalers receiving larger routing shares. To test this idea, we examine the relationship between routing shares and past execution quality.

Each month, we regress the percentage of our trades routed to each wholesaler against its prior month's excess E/Q for each broker. We present results in Table 5.

[Insert Table 5 about here]

[17] Untabulated results examining weekly changes and two-month lags yield similar findings.

The results reveal striking heterogeneity across brokers. Robinhood and IBKR Lite, the brokers with the smallest normalized dispersions in execution costs, exhibit significant negative relationships between routing shares and execution costs, as expected. In contrast, TD Ameritrade and Fidelity, brokers with the largest normalized dispersions, show a surprising positive relationship. E*Trade and Schwab also display positive relationships, though the coefficients are insignificant for E*Trade. Figure 5 illustrates this heterogeneity across brokers.

[**Insert Figure 5 about here**]

Consider Fidelity as an example. Panel D of Figure 2 shows that Citadel consistently provides the poorest execution among the four wholesalers, while Virtu offers the best execution. Yet Panel C reveals that Citadel receives approximately 40% of Fidelity's order flow, the largest share among all wholesalers, and maintains this dominance throughout our sample period.

Our findings provide a more nuanced view than previous studies examining this market. Dyhrberg et al. (2023), using aggregate 605 form data, find a negative relationship between routing shares and execution costs, suggesting that larger wholesalers offer better execution. While we replicate their finding using pooled data across all brokers, our granular analysis reveals substantial heterogeneity: the negative relationship holds for some brokers, but reverses for others. The aggregate relationship masks important variation in broker behavior with significant implications for retail investor execution quality. This phenomenon, analogous to the well-known Simpson's paradox, underscores the importance of disaggregated analysis in understanding market structure, further discussed in Section 5.1.

Similarly, Ernst et al. (2023), using proprietary data from three anonymous brokers, find evidence of broker responsiveness to execution quality. Our results are consistent with their findings for some brokers in our sample, but reveal that responsiveness varies dramatically across the industry. The stark differences between our most responsive brokers (such as Robinhood) and least responsive brokers (such as Fidelity) suggest that studies focusing on brokers that voluntarily provide the data may not capture the full range of routing practices in the retail market.

3.2.3. Counterfactual Analysis

The heterogeneous responsiveness documented above raises a natural question: what are the economic costs? To provide a rough estimate of this cost, we simulate counterfactual routing strategies that allocate orders based on past execution quality.

Each month for each broker, we reroute all orders to the wholesaler with the best prior-month execution quality, then assign these trades that wholesaler's actual current-month execution costs. We consider both aggregate-level routing (using overall wholesaler performance) and stock-level routing (using stock-specific performance), reported in Panels A and B of Table 6, respectively.

[Insert Table 6 about here]

Hypothetical aggregate-level routing (Panel A) reduces average execution costs from 0.313 to 0.233, a substantial 34% improvement across brokers. The gains vary sharply: brokers with greater normalized dispersion achieve larger reductions, while those with smaller dispersion benefit less. This pattern is consistent with the heterogeneous relationships between routing shares and execution costs documented above. For example, TD Ameritrade's execution costs fall by 60%, while Robinhood's decrease by only 14%. Hypothetical stock-level routing (Panel B) also lowers costs, but the improvements are more modest, reflecting both the lower persistence of stock-specific execution quality and less pronounced reallocation across wholesalers.

3.3. Impact of a New Wholesaler on Execution Quality

We examine how the entry of a new wholesaler impacts competition using a natural experiment. Jane Street entered the retail wholesaler market in 2020, gaining significant market share progressively across brokers.[18] Most of these entrances predate our trading experiment, which starts in early 2022. However, Jane Street did not become a wholesaler for Robinhood until the first quarter of 2022, providing a unique opportunity to study competitive effects of entry within our sample period. Notably, Robinhood exhibits the smallest normalized dispersion in execution quality and its routing appears the most responsive among the six brokers in our earlier analysis. Our natural experiment therefore provides a particularly strong test of whether entry can further improve execution quality for a broker that already adjusts routing actively.

When we began trading, none of our orders were routed to Jane Street. By February 24, 2022, Jane Street received almost a quarter of our trades, as shown in Panel A of Figure 2. Initially, it provided exceptionally low trading costs—even negative E/Q ratios (Panel B). Once Robinhood began allocating substantial flow to Jane Street, its execution costs converged to levels comparable with the best other wholesalers.

To examine the impact of Jane Street's entry, we analyze changes in routing share and execution costs for Robinhood's wholesalers before and after February 24, 2022. If entry increased competition, we expect incumbents to lose market share to the new entrant and reduce execution costs to retain business. Table 7 documents both effects.

[Insert Table 7 about here]

Jane Street's entry substantially disrupted the wholesaler market for Robinhood. Robinhood's allocation to Jane Street jumps from 3% to 23%, causing large drops in shares for

[18] Based on Form 606 filings, 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.

Virtu, Citadel, and G1X. As anticipated if entry increased competition, execution costs decreased for all incumbent wholesalers, with Citadel showing the sharpest reduction from 0.54 to 0.40. For Robinhood overall, average execution costs decreased from 0.55 to 0.47, an economically significant 14% improvement.

Our findings align with Ernst et al. (2023), who also find that entry improved execution quality using different data. In contrast, Dyhrberg et al. (2023) find that Jane Street's entry did not impact execution between the second and fourth quarters of 2021. One key difference is that we focus on Jane Street's actual entry date for one specific broker, while they use SEC Rule 605 reports which provide averages across all brokers with different entry timing.

4. Theoretical Framework

This section provides a theoretical framework that explains the brokers' heterogeneous responsiveness and the heterogeneous relationships between routing shares and execution costs documented in Section 3, using a simple model where brokers face switching costs when reallocating order flow. After describing the model setup in Section 4.1 and analyzing equilibrium in Section 4.2, Section 4.3 extends the baseline setup to explore potential sources of these switching cost differences.

4.1. Model Setup

Consider a broker that can route orders from its retail customers to two wholesalers, indexed by $j \in \{X, Y\}$. The broker and both wholesalers are risk neutral. Order size is normalized to one. Initially, a share $\sigma \in [0, 1]$ of orders is routed to wholesaler X, with the remaining $1 - \sigma$ routed to wholesaler Y. Wholesaler j incurs a constant marginal cost f_j to execute an order, with $\delta_f := f_Y - f_X \geq 0$. Let p_j denote the equilibrium execution cost (i.e., E/Q) charged by wholesaler j to the broker's customers.[19]

We assume that brokers face frictions when adjusting routing shares across wholesalers. Specifically, reallocating an additional share $\Delta \in [-\sigma, 1-\sigma]$ to wholesaler X incurs a "switching" cost of $\frac{s}{2}\Delta^2$, where $s > 0$. These switching costs may reflect several practical frictions brokers face when reallocating order flow. First, monitoring wholesaler performance typically requires significant time and expense. Second, technological constraints and operational considerations can create inertia when implementing changes to routing schemes. Third, brokers may need to maintain sufficient volume with each wholesaler to generate statistically meaningful performance comparisons. In Section 4.3, we discuss two potential channels that give rise to heterogeneous switching costs based on differences in broker priorities and variation in incentives based on order characteristics.

We study a pure-strategy Nash equilibrium in which: (i) the broker chooses the routing share adjustment Δ to minimize total costs, including both execution and switching costs; and (ii) each wholesaler j selects its execution cost p_j to maximize profit.

4.2. Equilibrium Analysis

We now turn to the main implications of the equilibrium; the full characterization is provided in Proposition 1 in the Appendix IA.1. We analyze equilibrium outcomes in three cases that depend on the magnitude of switching costs s (Figure 6).

[Insert Figure 6 about here]

First, when switching costs are low ($s \leq \delta_f/(2-\sigma)$), there is no relationship between routing share and execution costs. The lower-cost wholesaler drives the other to zero profits

[19]In practice, brokers do not observe execution costs at the time of routing. For simplicity, we assume that execution costs and routing decisions are determined simultaneously in equilibrium. As we show in Section 3, execution costs are highly persistent, allowing brokers to use past execution quality to inform routing decisions. See also Ernst et al. (2023), where optimal routing under asymmetric information is implemented as an allocation function based on past execution.

and captures the entire market, as in standard Bertrand competition. Interestingly, switching costs actually reduce the prices paid by the broker, since the low-cost wholesaler must offset the broker's switching costs to attract the full order flow.

Second, when switching costs are moderate ($s \in (\delta_f/(2-\sigma), \delta_f/(2\sigma-1))$), the relationship between routing share and execution costs is negative, provided that the lower-cost wholesaler (X) initially holds a larger routing share (i.e., $\sigma > 1/2$). Wholesaler X charges lower execution costs to retain its dominant share. The larger wholesaler faces competing incentives: charge more to extract rents from its dominant position, or charge less to capitalize on its cost advantage. When switching costs are not too high, the incentive to undercut dominates, and the larger wholesaler sets a lower execution cost than its rival in equilibrium. This results in a negative relationship between routing share and execution costs.

Finally, when switching costs are high ($s \geq \delta_f/(2\sigma-1)$), or when they are moderate but the lower-cost wholesaler initially holds a smaller routing share, the relationship between routing share and execution costs is positive. The larger wholesaler optimally exercises market power by charging higher execution costs, while keeping the price gap narrow enough to retain its dominant share. Although this result may seem counterintuitive, the model provides a clear economic intuition: brokers do not route more orders because wholesalers charge more. Rather, wholesalers are able to charge more because brokers route more orders to them.

These results are consistent with our empirical findings in Section 3: brokers that are more responsive to execution quality and exhibit lower normalized dispersion (consistent with lower switching costs) show a negative relationship between routing share and execution costs, while less responsive brokers with higher dispersion (consistent with higher switching costs) show a positive relationship.

4.3. What Explains Heterogeneous Broker Switching Costs?

We now explore two potential channels that may explain why switching costs vary across brokers.

4.3.1. Heterogeneous Broker Order Flow Characteristics

Our empirical analysis reveals substantial heterogeneity in broker routing behavior, which we interpret as reflecting differences in switching costs. Interestingly, brokers that engage in more active routing (suggestive of lower switching frictions) tend to have higher average execution costs (Table 2). At first glance, this pattern is surprising: all else equal, more active routing to lower-cost wholesalers should lead to lower, not higher, execution costs.

It, however, becomes intuitive when considering that brokers whose order flows are inherently more expensive to execute are more likely to violate regulatory NBBO thresholds, creating stronger incentives to monitor execution quality and invest in more active routing strategies. For example, Robinhood invested substantially in routing technology following its $65 million settlement with the SEC in 2020, where the firm was required to pay particular attention to the execution quality of customer orders.[20] If the benefits of lower switching costs do not fully offset the inherently higher execution costs of their order flows, these brokers may still incur higher overall execution costs in equilibrium. The key insight is that lower switching costs do not cause higher execution costs. Rather, higher execution costs create stronger incentives to reduce switching frictions. In Appendix IA.2, we formalize this mechanism and endogenously derive a negative relationship between switching costs and execution costs.

Order flow "toxicity", typically defined as persistent directionality in trades, is one characteristic that can make certain order flows inherently more expensive to execute. Directional

[20] See https://www.sec.gov/litigation/admin/2020/33-10906.pdf.

patterns can push prices up or down systematically, prompting wholesalers to widen effective spreads and degrade execution quality. Such directionality can arise either when informed traders split large orders into consecutive trades to mitigate market impact (Easley et al. (1996)), or when retail investors coordinate on online platforms and herd on the same market sentiment (Baldauf et al. (2024)). Although toxicity is difficult to measure, evidence suggests systematic differences across brokers. Eaton et al. (2022) exploit brokerage outages and find that spreads narrow when Robinhood is offline, but widen during outages at other brokers, suggesting systematic differences in toxicity. Schwarz et al. (2023) show that order imbalances can generate spread variation consistent with the magnitude of observed execution differences across brokers.

4.3.2. Broker Priorities and Switching Costs

We consider an extension where a broker handles two segments of order flow but routes both segments using identical routing shares across wholesalers, a pattern we document for several brokers in Section 5.2. We show that when the broker prioritizes one segment over another, this effectively raises switching costs for the non-prioritized segment.

Suppose segment 1 accounts for a fraction w of total dollar flow, and segment 2 for $1-w$. The broker prioritizes segment 2 in its internal scorecard, assigning segment 1 a reduced effective weight $w' < w$. For simplicity, assume that the two wholesalers have the same marginal costs, which are equal to zero.

Intuitively, a wholesaler can lower execution costs for segment 2 and raise them for segment 1 while keeping the total markup unchanged. Because the broker prioritizes segment 2, this pricing structure makes the wholesaler more attractive. In equilibrium, both wholesalers optimally set execution costs for segment 2 to zero. Then the broker's routing problem becomes

$$\min_{\Delta \in [-\sigma, 1-\sigma]} (\sigma + \Delta)(w' p_{1X}) + (1 - \sigma - \Delta)(w' p_{1Y}) + \frac{s}{2}\Delta^2. \tag{1}$$

This problem is equivalent to the baseline case without segmentation but with a rescaled switching cost parameter, $s' := s/w'$, which exceeds the true switching cost s. Thus, segmentation effectively increases the broker's switching costs for the non-prioritized segment.

This extension accommodates the possibility that brokers that appear unresponsive to execution quality in our data based on odd-lot orders, may in fact respond more actively in other segments, such as round-lot trades. This form of cross-subsidization is consistent with Ernst et al. (2023), who find that wholesalers raise execution costs for non-prioritized segments when broker priorities shift.

5. Discussion and Policy Implications

This section connects theoretical insights from Section 4 to broader empirical patterns and policy implications through two related discussions. Section 5.1 examines how broker heterogeneity complicates the interpretation of aggregate 605 data and considers the implications for disclosure policy. Section 5.2 documents that several brokers maintain the same routing shares across different segments and discusses how the variability in routing shares and priorities across segments affect the generalizability of our findings from odd-lot trades to other segments.

5.1. Simpson's Paradox: Implications for 605 Reports

We discuss the implications of broker heterogeneity for interpreting aggregate execution quality data in 605 reports and for ongoing regulatory debates about disclosure requirements. In Table 2, brokers with smaller normalized dispersions in execution quality who also appear more responsive to execution quality have higher average execution costs. As discussed in

Section 4.3, this pattern is consistent with brokers facing more "toxic" order flows, which are inherently more expensive to execute and thus more likely to violate regulatory NBBO thresholds, having stronger incentives to reduce switching frictions and adjust routing more actively.

This creates a composition effect where wholesalers providing superior execution quality attract disproportionately more order flow from brokers handling toxic trades. When measured at the aggregate level across all their clients, these high-performing wholesalers may appear indistinguishable from, or even worse than, other wholesalers despite providing superior service to each individual broker. This phenomenon represents a classic case of Simpson's paradox, a well-known statistical phenomenon in which a trend appears in several groups of data but disappears or reverses when the groups are combined.

This composition bias significantly limits the utility of current SEC Rule 605 disclosures, which report execution statistics aggregated across all clients. Just as highly skilled doctors may show lower survival rates because they treat sicker patients, a wholesaler can simultaneously offer the best execution for each individual broker while appearing to provide poor or indistinguishable execution quality in aggregate 605 reports. This compositional effect may help explain why Dyhrberg et al. (2023), using aggregate 605 forms, find a negative relationship between routing shares and execution costs, while our broker-level analysis reveals substantial heterogeneity in this relationship.

Meaningful assessment of wholesaler performance thus requires disaggregated reporting at the broker-wholesaler level to control for differences in order flow characteristics. Without this granular data, regulators, academics, and market participants cannot accurately evaluate competitive dynamics or identify best practices in retail execution. Our within-broker analysis demonstrates both the limitations of current aggregate 605 reporting and the critical need for broker-wholesaler level disclosures.

5.2. *Heterogeneous Broker Routing Styles and Generalizability*

We now describe heterogeneous routing styles and explore the generalizability of our findings from odd-lot trades to other segments.

Heterogeneous Broker Routing Styles. Our analysis of the routing data reveals two distinct approaches brokers use for order routing. The first is "proportional" routing, where brokers simply route a fixed percentage of their entire order flow to each wholesaler. With proportional routing, each wholesaler receives the same fraction of the broker's order flow across all stocks, maintaining consistent order flow composition. The second approach is "selective" routing, where brokers route orders on a stock-by-stock basis. With selective routing, different wholesalers receive varying order flow compositions across stocks, as brokers can adjust routing based on individual stock performance or other criteria.

We examine how brokers vary in their stock-level routing by computing the percentage of our orders routed to Citadel (as an example) for each stock for each broker, requiring at least 100 trades per stock, and sorting these percentages from lowest to highest. If a broker uses proportional routing, the percentage should be roughly constant across all stocks. Conversely, selective routing would produce large variation across stocks.

Figure 7 compares two brokers: Fidelity, which employs proportional routing, and Robinhood, which exhibits selective routing. Each stock is represented on the horizontal axis, with vertical lines summarizing the distribution of Citadel routing percentages over time for that stock. The circle shows the historical average, with whiskers indicating 95% confidence intervals. Red lines indicate stocks where the average routing percentage differs significantly from the broker's overall average.

[Insert Figure 7 about here]

We show that E*Trade, Schwab, and TD Ameritrade follow proportional routing like

Fidelity, while IBKR Lite exhibits selective routing like Robinhood (these four brokers are presented in Appendix Figure IA.1). Both selective brokers actively advertise their "smart" routing capabilities.[21] Notably, these two brokers are the same ones that demonstrated greater responsiveness to execution quality and exhibited negative relationships between routing shares and execution costs in our earlier analysis, while the proportional brokers showed limited responsiveness and positive relationships. Appendix Table IA.4 presents broker-wholesaler-level logistic regressions of routing decisions, confirming that proportional brokers exhibit mostly insignificant coefficients on potential routing determinants, while selective brokers show significant coefficients for many variables.

These routing styles are also evident in publicly reported 606(a) market share data. As shown in Panel B of Figure 1, proportional brokers exhibit nearly identical market shares across S&P 500 and non-S&P 500 stocks, closely matching our observed routing patterns. This suggests that proportional brokers send the fixed routing share to each wholesaler not only across all stocks but also across order segments. In contrast, Robinhood displays clear differences in market share between these stock categories, explaining the divergence between public disclosures and our sample (IBKR is excluded since they combine Lite and Pro accounts in 606(a) reports.)

Variability of Routing Shares and Generalizability. To explore the generalizability of our findings from odd-lot trades to other segments, we next complement our trading experiment by analyzing 606(a) disclosures from 2020Q1 to 2024Q4.[22] In Section 4.3.2, we

[21] 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." 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." See https://robinhood.com/us/en/support/articles/how-robinhood-makes-money/ and https://www.interactivebrokers.com/lib/cstools/faq/#/content/38448530/

[22] We use public 606(a) reports to analyze a longer sample period. Using our data or public data over our sample period (December 2021 through May 2023) reveals a similar pattern.

show that for brokers with "proportional" routing, prioritizing one segment over another effectively increases switching costs for the non-prioritized segment. Thus, high switching costs observed in a particular segment could arise from two sources: either the broker faces high overall switching costs across all segments, or the segment receives lower priority relative to other segments. To shed light on the overall switching costs and routing responsiveness, we examine the variability of routing shares.

Figure 8 shows monthly changes in routing market share by broker. Consistent with our finding that selective brokers are more responsive to execution quality, Robinhood exhibits the largest variability in routing composition over time.[23]

[Insert Figure 8 about here]

Interestingly, there is significant heterogeneity in routing variability among proportional brokers. TD Ameritrade and Fidelity show greater variation in their monthly routing shares, suggesting they adjust routing more actively over time. This indicates that the muted responsiveness we observe for odd-lot orders may not extend to other order segments for these brokers. As discussed in Section 4.3.2, different treatment across order segments may result from brokers prioritizing certain segments over others, effectively inflating switching costs for lower-priority segments through cross-subsidization.

In contrast, E*Trade exhibits nearly zero month-to-month changes in routing shares, suggesting a highly static policy. Schwab shows similarly low variability in its routing composition over time. This static behavior suggests that the limited responsiveness to execution quality we document for these brokers may be generalized to other order segments as well.

[23] IBKR is excluded since they combine Lite and Pro accounts in 606(a) reports.

6. Conclusions

With the shift to zero-commission trading, execution quality has become a primary determinant of retail investor trading costs in the U.S. equity market. Using data from a controlled trading experiment spanning over 150,000 trades across six retail brokers, we study the competitiveness of retail trade execution. We document substantial and persistent differences in execution costs within brokers across wholesalers, yet find striking heterogeneity in brokers' routing behavior. Many brokers consistently route more flow to higher-cost venues while others adjust routing more actively.

A theoretical framework explains these patterns through switching costs. When brokers face high costs of adjusting routing shares, dominant wholesalers exercise market power, creating the counterintuitive result where larger routing shares coincide with higher execution costs in equilibrium. Our natural experiment based on the entry of a new wholesaler demonstrates that competition can improve execution quality even for brokers who actively adjust their routing. Overall, different brokers implement best execution requirements in markedly different ways, and this heterogeneity generates varying competitive pressure on wholesalers.

These findings have important policy implications. Current disclosure rules aggregate statistics across brokers, masking the heterogeneity we document and making it difficult to assess competitive dynamics. Enhanced transparency at the broker-wholesaler level could improve market discipline, benefiting retail investors who rely on this market infrastructure.

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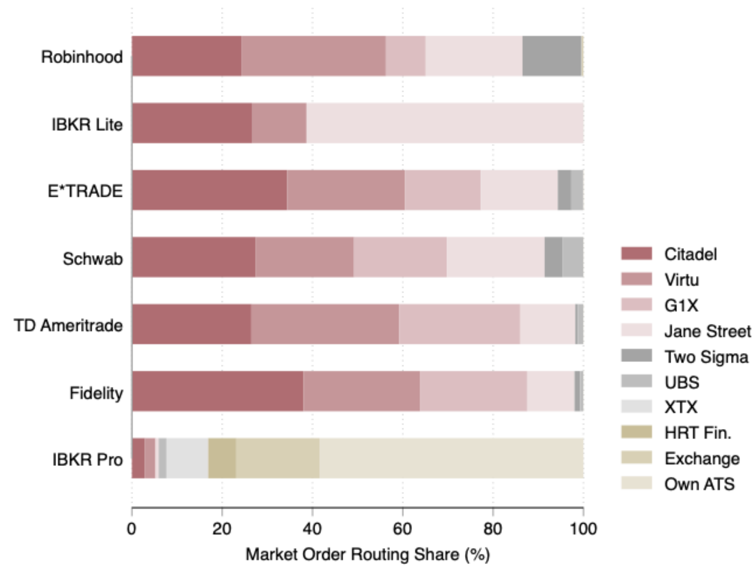
Panel A: Our Sample

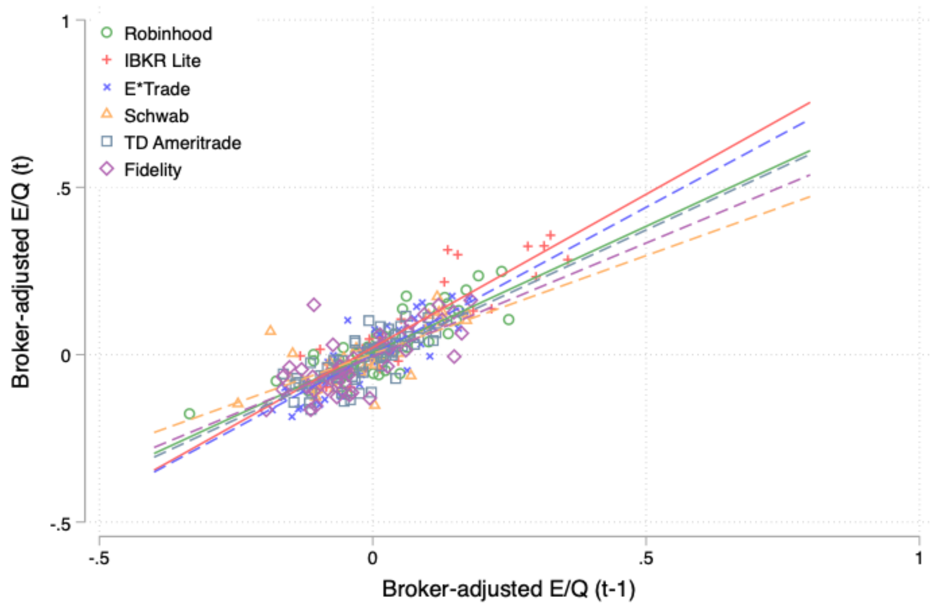


Panel B: Our Sample excluding IBKR vs. Broker 606(a) Routing Report (April 2023)

Figure 1: Market Order Routing Share by Broker
This figure presents the routing of market orders across major wholesalers based on our sample and broker-reported routing disclosures. Panel A presents the distribution of market order routing across wholesalers based on our sample during the whole sample period. The raw statistics are also presented in Panel B of Table 1. Panel B compares our sample's routing distribution with the routing shares reported in brokers' SEC Rule 606(a) disclosures in a specific month (April 2023). Each broker has three bars: routing share based on our sample of executed market orders, and routing share in 606(a) reports for S&P 500 and non-S&P 500 stocks. We exclude IBKR in Panel B because they combine Lite and Pro in 606(a) reports.

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

Panel A: Scatter Plot



Panel B: Regression Coefficient

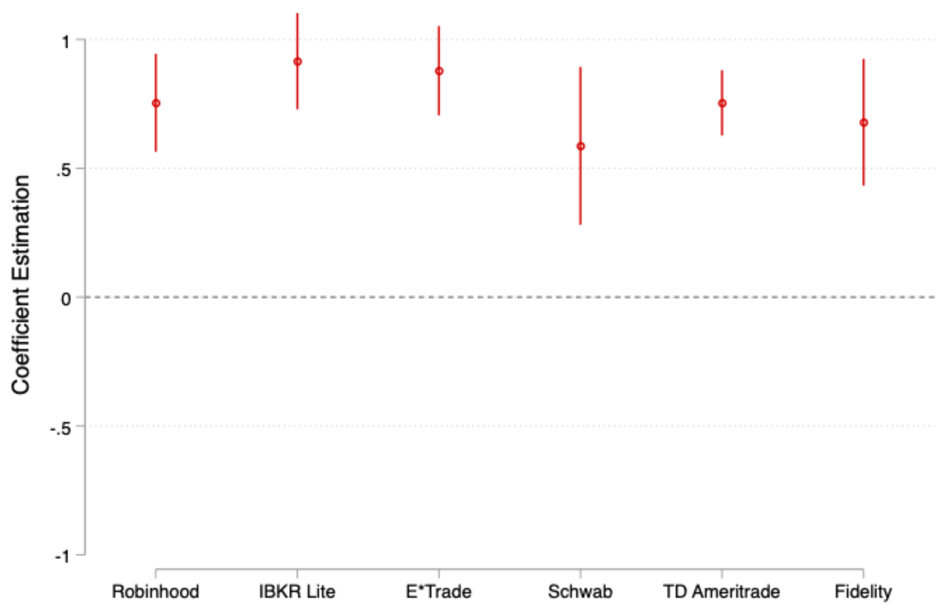
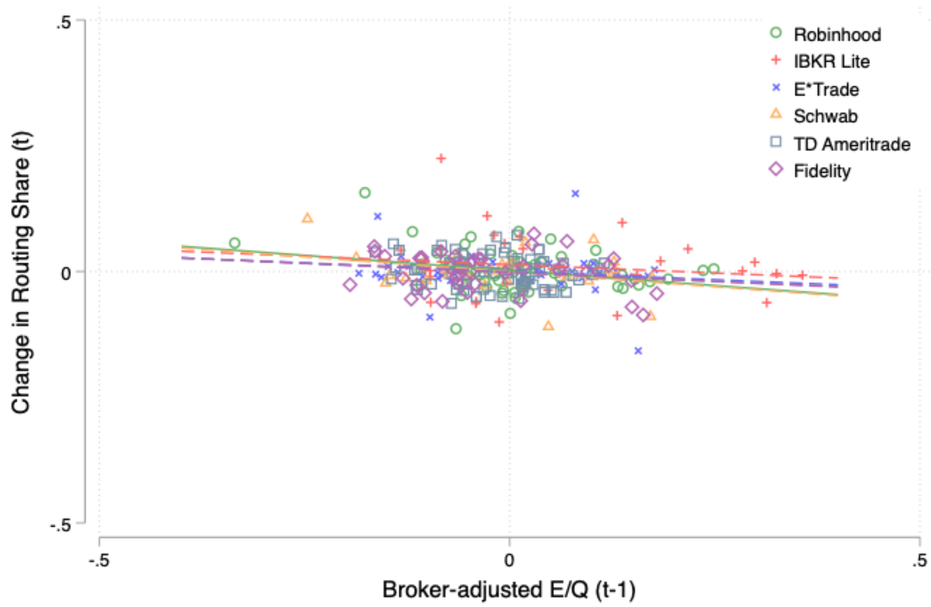


Figure 3: Persistence of Wholesaler Price Improvement
Panel A presents scatter plots of the broker-adjusted effective over quoted trade spread (E/Q) against the prior month's broker-adjusted E/Q for each broker-wholesaler pair. Broker-adjusted E/Q is computed as each wholesaler's average E/Q at a given broker minus the broker's overall average across all wholesalers. Panel B reports the regression coefficients from Panel A in Table 3, where the dependent variable is monthly broker-adjusted E/Q and the independent variable is the prior month broker-adjusted E/Q.

Panel A: Scatter Plot



Panel B: Regression Coefficient

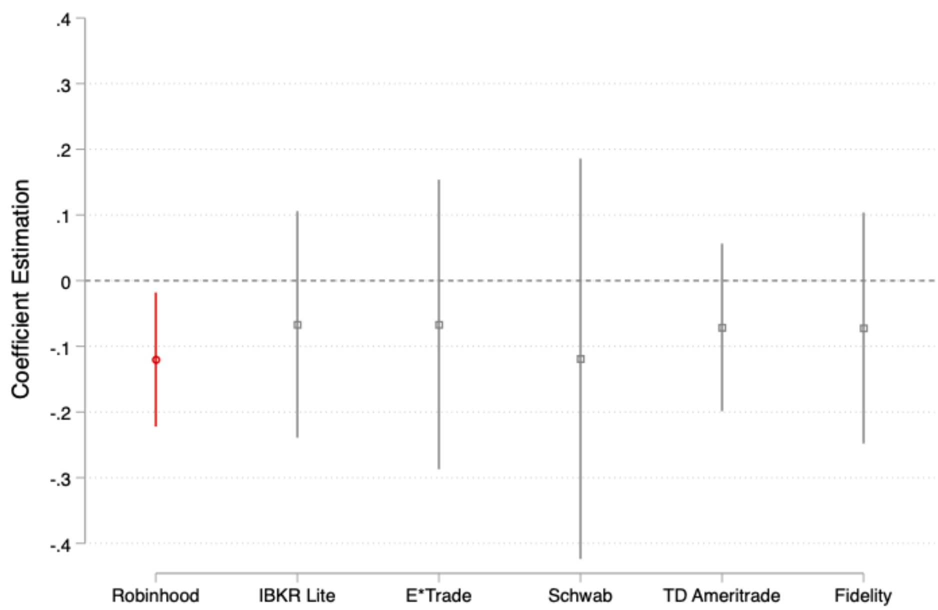
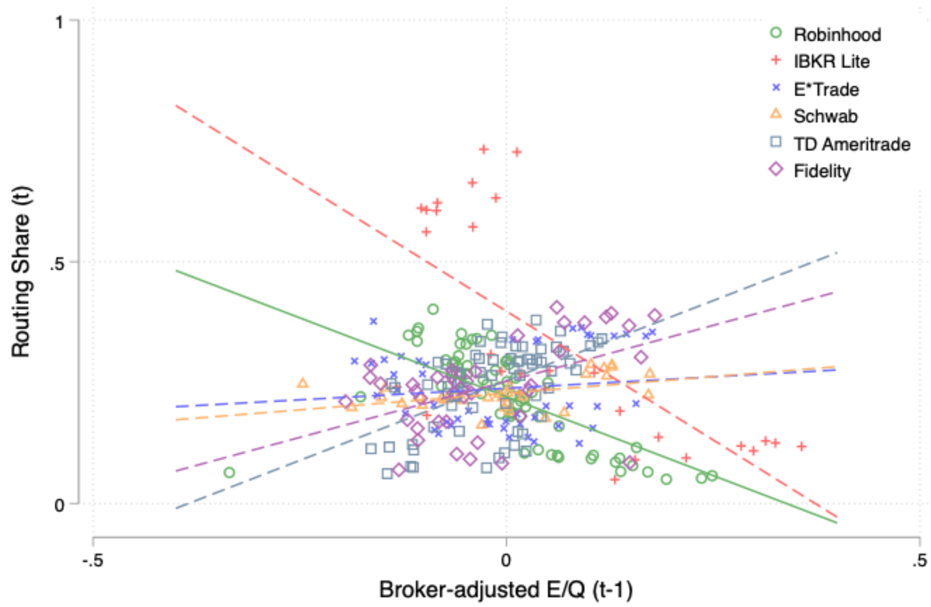


Figure 4: Changes in Routing Shares in Response to Prior Execution Cost
Panel A presents scatter plots of the change in monthly routing shares to wholesalers against the prior month's broker-adjusted effective over quoted trade spread (E/Q) for each broker-wholesaler pair. Broker-adjusted E/Q is computed as each wholesaler's average E/Q at a given broker minus the broker's overall average across all wholesalers. Panel B reports the regression coefficients from Panel A in Table 4, where the dependent variable is the change in routing shares and the independent variable is the prior month broker-adjusted E/Q.

Panel A: Scatter Plot



Panel B: Regression Coefficient

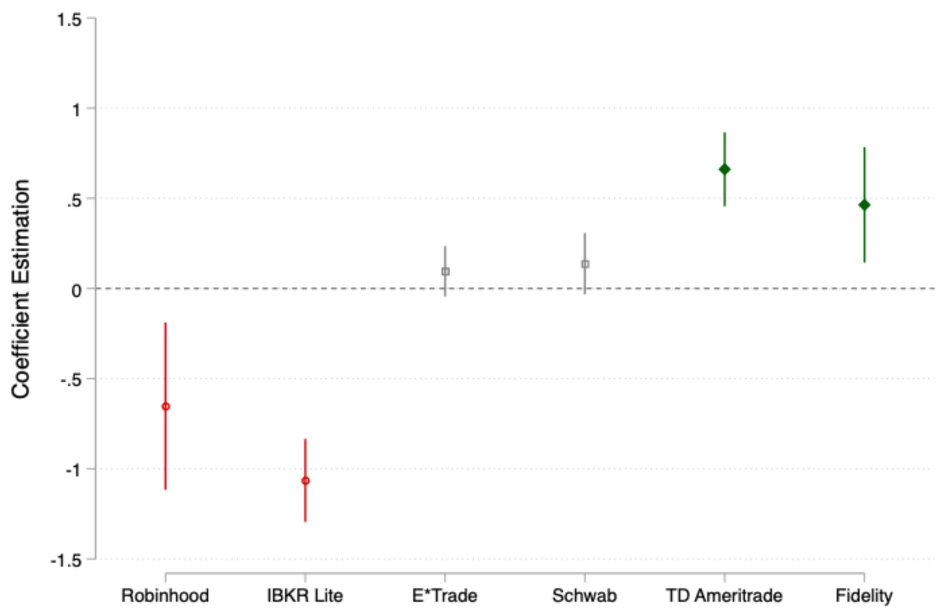


Figure 5: Levels of Routing Shares and Prior Execution Cost
Panel A presents scatter plots of the levels of monthly routing shares to wholesalers against the prior month's broker-adjusted effective over quoted trade spread (E/Q) for each broker-wholesaler pair. Broker-adjusted E/Q is computed as each wholesaler's average E/Q at a given broker minus the broker's overall average across all wholesalers. Panel B reports the regression coefficients from Panel A in Table 5, where the dependent variable is the levels of routing shares and the independent variable is the prior month broker-adjusted E/Q.

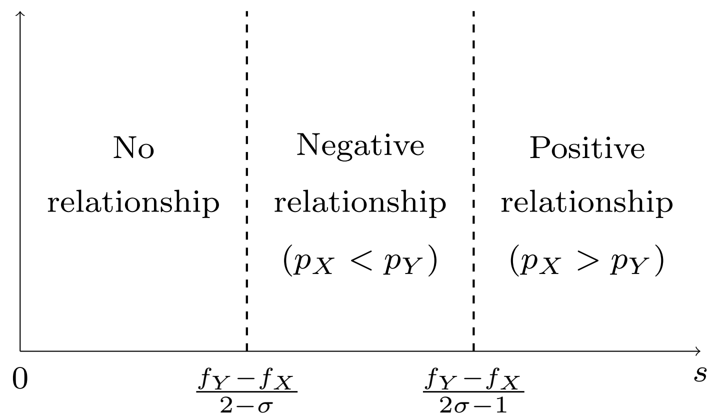
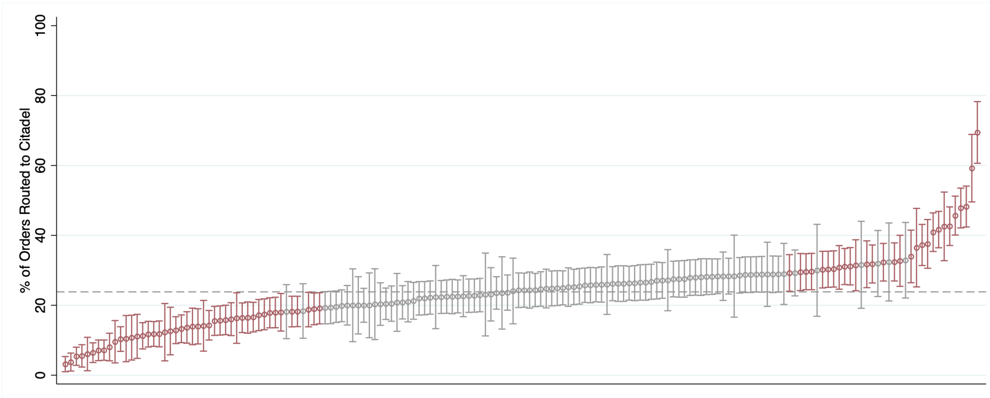


Figure 6: Model

This figure shows the three equilibrium cases characterized in Proposition 1, where switching cost magnitude determines whether the relationship between routing share and execution costs is positive, negative, or nonexistent.

Panel A: Robinhood to Citadel



Panel B: Fidelity to Citadel

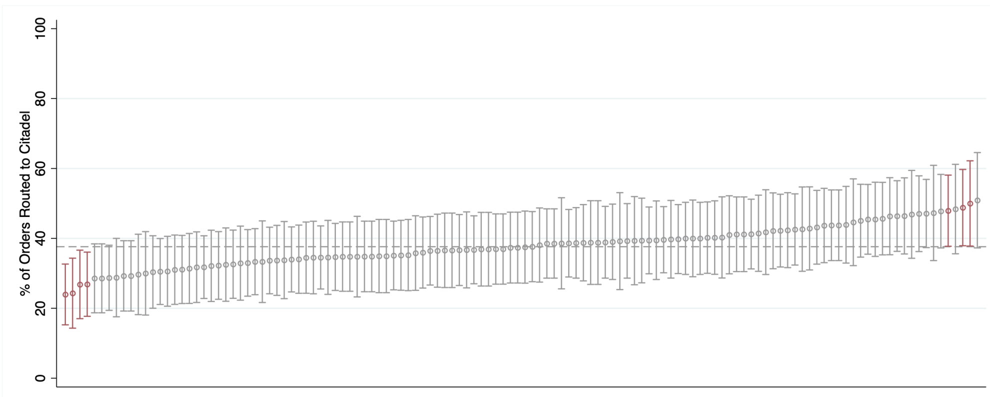


Figure 7: Order Routing Patterns across Individual Stocks for Robinhood and Fidelity

This figure shows the percentage of our orders for each stock that are routed to a specific venue for Robinhood and Fidelity. 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 gray.

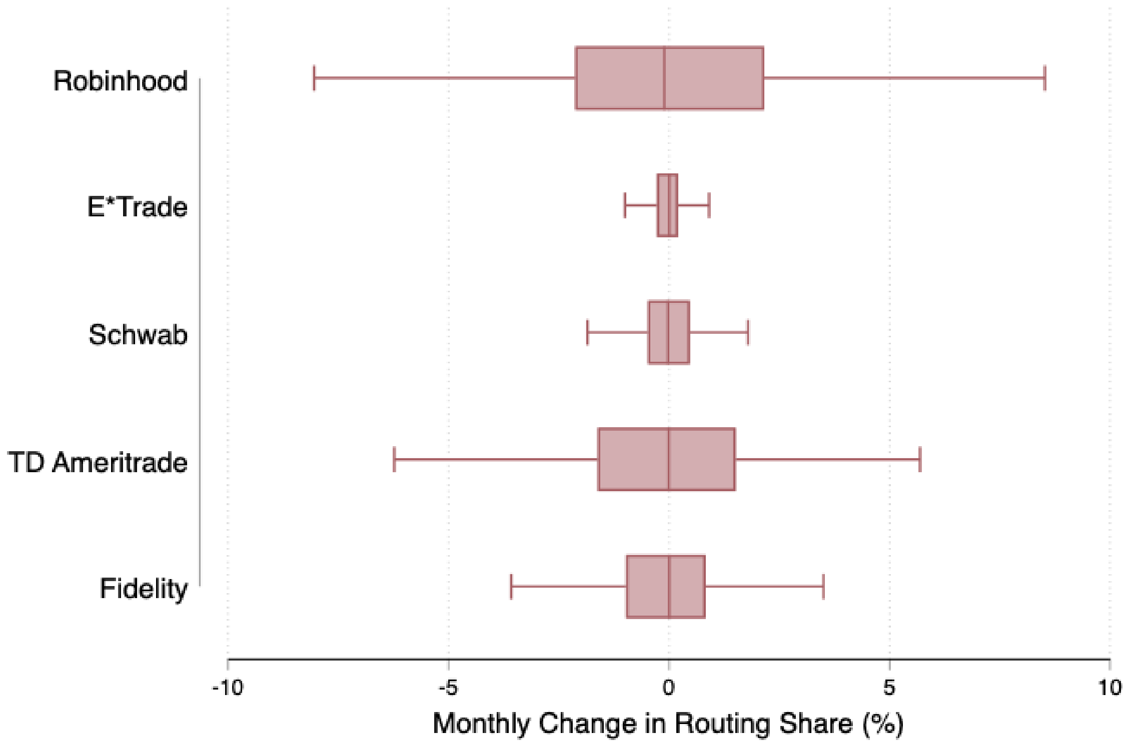


Figure 8: Monthly Change in Routing Share: Broker 606(a) Routing Report
This figure presents box plots of the monthly change in the share of market orders routed to different wholesalers for five retail brokers in our sample. The underlying data are constructed from each broker's SEC Rule 606(a) order routing reports, which disclose the allocation of retail market orders across wholesale market makers. Each box plot summarizes the distribution of these monthly changes across all wholesalers that received routed orders from the broker. The center line in each box represents the median monthly change; the upper and lower hinges of the box indicate the 75th and 25th percentiles, respectively. The whiskers extend to the most extreme values within 1.5 times the inter-quartile range from the box. Observations outside this range, if any, are not displayed in this figure.

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 from the brokers 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.

Panel A: Broker-Wholesaler Routing Count

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Citadel	Virtu	Jane Street	G1X	Two Sigma	UBS	Exchange	Other	Own ATS	Total
E*Trade	10,699	8,206	5,327	5,267	938	818	10	-	-	31,265
Fidelity	4,561	3,103	1,262	2,847	148	83	1	228	-	12,233
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	-	1	-	11,085
TD Ameritrade	11,088	13,660	5,161	11,160	224	497	-	520	-	42,310
Total	41,898	41,433	29,261	25,060	6,958	1,910	161	841	42	147,564
IBKR Pro	126	96	31	-	-	71	776	688	2,477	4,265

Panel 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%	-	-	100%
Fidelity	37%	25%	10%	23%	1%	1%	0%	2%	-	100%
IBKR Lite	26%	12%	61%	-	-	-	-	-	0%	100%
Robinhood	24%	32%	21%	9%	13%	-	0%	0%	-	100%
Schwab	27%	22%	22%	21%	4%	5%	-	0%	-	100%
TD Ameritrade	26%	32%	12%	26%	1%	1%	-	1%	-	100%
Average	29%	25%	24%	16%	4%	2%	0%	1%	0%	100%
IBKR Pro	3%	2%	1%			2%	18%	16%	58%	100%

Table 2: Average Excess Execution Cost by Wholesaler

This table examines wholesaler execution cost within each broker, using the effective over quoted spread (E/Q). Each month, we compute the execution cost for each wholesaler within each 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-level average E/Q for reference purposes in the first column. t-values are in parentheses. **,* represents significance at the 1%, 5% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Broker-level	Broker-adjusted E/Q (Deviation from broker-level E/Q)				Dispersion (Max-Min) Normalized by
	E/Q	Citadel	Virtu	Jane Street	G1X	Broker-level E/Q
Robinhood	0.421	-0.015	-0.046**	-0.045	0.129**	41.57%
		(-1.0)	(-5.5)	(-1.7)	(6.6)	
IBKR Lite	0.527	0.008	0.247**	-0.060**		58.25%
		(0.4)	(9.6)	(-4.7)		
E*Trade	0.322	0.093**	-0.131**	-0.037**	0.048**	69.57%
		(6.1)	(-17.1)	(-3.0)	(3.9)	
Schwab	0.229	0.123**	-0.114**	-0.049**	0.005	103.49%
		(11.9)	(-5.7)	(-3.0)	(0.9)	
TD Ameritrade	0.093	0.041**	0.020	-0.064**	-0.066**	115.05%
		(4.1)	(1.7)	(-3.5)	(-9.4)	
Fidelity	0.142	0.100**	-0.114**	-0.028	-0.059**	150.70%
		(6.3)	(-9.0)	(-1.4)	(-4.4)	

Table 3: Persistence of Wholesaler Execution Cost

This table examines the persistence of price improvement by wholesaler, measured as E/Q in excess of the broker averages, at the overall level (Panels A and B) or stock-level level (Panels C and D). We regress the broker-adjusted price improvements against 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)
	All	Robinhood	IBKR Lite	E*Trade	Schwab	TD	Fidelity
Panel A: Wholesaler-level Persistence (1-month Lag))							
Dep Var:				Broker-adjusted E/Q (t)			
Broker-adjusted E/Q (t-1)	0.803**	0.754**	0.916**	0.879**	0.587**	0.754**	0.679**
	(16.00)	(8.46)	(11.09)	(11.16)	(4.53)	(12.61)	(6.24)
R-squared	0.686	0.705	0.811	0.754	0.510	0.551	0.528
Panel B: Wholesaler-level Persistence (3-month Lag)							
Dep Var:				Broker-adjusted E/Q (t)			
Broker-adjusted E/Q (t-1)	0.888**	0.717**	0.980**	0.917**	0.923**	0.803**	0.833**
	(18.03)	(6.21)	(10.21)	(10.92)	(8.64)	(8.12)	(5.95)
R-squared	0.694	0.536	0.866	0.776	0.842	0.441	0.525
Panel C: Wholesaler-stock-level Persistence (1-month Lag)							
Dep Var:				Broker-adjusted E/Q (t)			
Broker-adjusted E/Q (t-1)	0.210**	0.190**	0.507**	0.187**	0.188**	0.219**	0.169**
	(11.00)	(5.01)	(7.95)	(6.98)	(7.08)	(6.95)	(5.62)
R-squared	0.043	0.035	0.246	0.037	0.033	0.048	0.024
Panel D: Wholesaler-level Persistence (3-month Lag)							
Dep Var:				Broker-adjusted E/Q (t)			
Broker-adjusted E/Q (t-1, t-3)	0.478**	0.407**	0.712**	0.464**	0.495**	0.508**	0.426**
	(20.73)	(4.30)	(7.33)	(15.27)	(7.73)	(13.61)	(7.62)
R-squared	0.080	0.047	0.237	0.093	0.082	0.095	0.051

Table 4: Changes in Routing Shares in Response to Prior Execution Cost

This table examines how brokers adjust their routing to wholesalers based on their prior aggregate (Panels A and B) and stock-level (Panels C and D) execution cost. Each month, for each broker, we compute the wholesaler broker-adjusted execution cost (E/Q) as the deviation of the wholesaler's execution cost from the broker-level average. This measure is calculated at both the aggregate level and the individual stock level. We then regress the percentage point change in orders routed to a given wholesaler against the wholesalers' lagged execution cost, 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)
	All	Robinhood	IBKR Lite	E*Trade	Schwab	TD	Fidelity
Panel A: Wholesaler-level Routing Responses (1-month Lag)							
Dep Var:			Change in Routing Share (t)				
Broker-adjusted E/Q (t-1)	-0.0747*	-0.120*	-0.0667	-0.0667	-0.119	-0.0711	-0.0722
	(-2.12)	(-2.51)	(-0.87)	(-0.67)	(-0.92)	(-1.18)	(-0.93)
R-squared	0.033	0.080	0.022	0.027	0.110	0.020	0.036
Panel B: Wholesaler-level Routing Responses (3-month Lag)							
Dep Var:			Change in Routing Share (t)				
Broker-adjusted E/Q (t-1)	-0.0328	0.0280	-0.0924	-0.0306	0.00787	-0.145	-0.0597
	(-0.78)	(0.50)	(-1.11)	(-0.26)	(0.25)	(-2.02)	(-0.57)
R-squared	0.006	0.005	0.037	0.005	0.001	0.064	0.021
Panel C: Wholesaler-stock-level Routing Responses (1-month Lag)							
Dep Var:			Change in Routing Share (t)				
Broker-adjusted E/Q (t-1)	-0.00913	-0.0479**	-0.0715	-0.00573	0.0196	0.0120	0.0150
	(-1.43)	(-3.61)	(-1.30)	(-0.66)	(1.33)	(1.01)	(0.75)
R-squared	0.000	0.003	0.003	0.000	0.001	0.000	0.000
Panel D: Wholesaler-stock-level Routing Responses (3-month Lag)							
Dep Var:			Change in Routing Share (t)				
Broker-adjusted E/Q ($t$$-1)	-0.00775	-0.0402	-0.0467	-0.0172	0.0365	0.0103	-0.00861
	(-0.66)	(-1.82)	(-0.67)	(-0.80)	(2.66)	(0.44)	(-0.18)
R-squared	0.000	0.001	0.001	0.000	0.001	0.000	0.000

Table 5: Levels of Routing Shares and Prior Execution Cost

This table examines how brokers' routing shares to wholesalers are related to their prior aggregate (Panels A and B) and stock-level (Panels C and D) execution cost. Each month, for each broker, we compute the wholesaler broker-adjusted execution cost (E/Q) as the deviation of the wholesaler's execution cost from the broker-level average. This measure is calculated at both the aggregate level and the individual stock level. We then regress the levels of routing shares of our orders to a given wholesaler on the wholesaler's lagged execution cost, 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)
	All	Robinhood	IBKR Lite	E*Trade	Schwab	TD	Fidelity
Panel A: Wholesaler-level Routing Share (1-month Lag)							
Dep Var:				Routing Share (t)			
Broker-adjusted E/Q (t-1)	-0.144**	-0.653**	-1.064**	0.0951	0.137	0.661**	0.463**
	(-3.14)	(-3.00)	(-10.47)	(1.50)	(1.91)	(6.82)	(3.27)
R-squared	0.017	0.426	0.474	0.014	0.204	0.270	0.241
Panel B: Wholesaler-level Routing Share (3-month Lag)							
Dep Var:				Routing Share (t)			
Broker-adjusted E/Q (t-1, t-3)	-0.229**	-0.960**	-1.164**	0.0612	0.265**	0.752**	0.493**
	(-4.84)	(-10.34)	(-12.50)	(0.84)	(9.26)	(7.84)	(4.04)
R-squared	0.038	0.734	0.603	0.005	0.581	0.265	0.195
Panel C: Wholesaler-stock-level Routing Share (1-month Lag)							
Dep Var:				Routing Share (t)			
Broker-adjusted E/Q (t-1, t-3)	-0.0387**	-0.190**	-0.484**	0.0000155	0.0352*	0.0308*	0.0690**
	(-5.24)	(-11.25)	(-8.47)	(0.00)	(2.49)	(2.45)	(3.78)
R-squared	0.003	0.061	0.129	0.000	0.005	0.003	0.014
Panel D: Wholesaler-stock-level Routing Share (3-month Lag)							
Dep Var:				Routing Share (t)			
Broker-adjusted E/Q (t-1, t-3)	-0.0809**	-0.438**	-0.803**	-0.00581	0.0797*	0.0352	0.106**
	(-3.56)	(-12.37)	(-11.84)	(-0.20)	(4.53)	(1.43)	(4.46)
R-squared	0.005	0.091	0.153	0.000	0.011	0.001	0.015

Table 6: 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 execution cost, measured as the effective over quoted spread, received on each stock from each wholesaler. In Panel A, we compute the overall cost 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 cost 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 cost the prior month. In each panel, we report the average original cost, the hypothetical cost, as well as the difference and the change relative to the original execution cost, 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: Execution Cost from Rerouting using Overall Execution

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

Panel B: Execution Cost from Rerouting using Stock Level Execution

Broker	Original	Hypothetical	Change	t-value	%Change
Robinhood	0.397	0.454	0.057	3.77**	14.4%
IBKR Lite	0.571	0.590	0.020	1.37	3.3%
E*Trade	0.349	0.311	-0.038	-3.41**	-10.9%
Schwab	0.232	0.190	-0.042	-3.09**	-18.1%
TD Ameritrade	0.108	0.021	-0.086	-7.64**	-80.6%
Fidelity	0.197	0.149	-0.047	-3.08**	-24.4%
Average	0.309	0.286	-0.023		-7.4%

Table 7: Changes for Robinhood Wholesalers after Jane Street Addition

This table shows changes in Robinhood's wholesaler market after Jane Street became an additional venue for that broker. Panel A reports the percentage of our trades routed to each wholesaler before and after the start date of February 24, 2022. Panel B reports the (E/Q) execution cost again before and after. In both panels, t values use standard errors clustered by stock. The prior period covers the six weeks before the start date. The posterior period runs from February 24 to April 15, 2022. In both cases, we take the 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%

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

Xing Huang, Philippe Jorion, Jeongmin Lee, and Christopher Schwarz

In this Internet Appendix, we provide XX

Sections

Figures

Tables

IA.1. Proofs of Main Model

Proposition 1 *There are two cases. If either the wholesalers have the same marginal cost (i.e., $f_X = f_Y$), or the switching costs are sufficiently high (i.e., $s > \frac{f_Y - f_X}{2-\sigma}$, where $f_Y > f_X$), then in equilibrium the wholesalers charge*

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

and the broker adjusts its market share by

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

Otherwise, meaning that the wholesalers have different marginal costs and the switching costs are not sufficiently high (i.e., $0 < s \leq (f_Y - f_X)/(2-\sigma)$), in equilibrium

$$p_X = f_Y - s(1-\sigma), \qquad p_Y = f_Y, \qquad \text{and} \qquad \Delta = 1 - \sigma, \tag{4}$$

assuming that when the broker is indifferent to routing, it sends all orders to wholesaler X.

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:

$$\min_{\Delta \in [-\sigma, 1-\sigma]} (\sigma + \Delta)p_X + (1 - \sigma - \Delta)p_Y + \frac{s}{2}\Delta^2. \tag{5}$$

The F.O.C. implies:

$$\Delta = \begin{cases} \frac{p_Y - p_X}{s} & \text{if } p_Y - p_X \in [-s\sigma, s(1-\sigma)], \\ 1 - \sigma & \text{if } p_Y - p_X > s(1-\sigma). \\ -\sigma & \text{otherwise.} \end{cases} \tag{6}$$

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

$$\max_{p_X} (p_X - f_X)(\sigma + \Delta) \tag{7}$$

Using Equation (6), the F.O.C. implies

$$p_X = \begin{cases} \frac{s\sigma + p_Y + f_X}{2} & \text{if } p_Y \in (f_X - s\sigma, f_X + s(2-\sigma)), \\ f_X & \text{if } p_Y \leq f_X - s\sigma, \\ p_Y - s(1-\sigma) & \text{otherwise.} \end{cases} \tag{8}$$

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

$$p_Y = \begin{cases} \frac{s(1-\sigma) + p_X + f_Y}{2} & \text{if } p_X \in (f_Y - s(1-\sigma), f_Y + s(1+\sigma)), \\ f_Y & \text{if } p_X \leq f_Y - s(1-\sigma), \\ p_X - s\sigma & \text{otherwise.} \end{cases} \tag{9}$$

Theoretically, there is a total of nine cases. However, given that $f_X \leq f_Y$, 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 (8) and (9), we have

$$p_X = \frac{2f_X + f_Y}{3} + \frac{s(1+\sigma)}{3} \qquad \text{and} \qquad p_Y = \frac{f_X + 2f_Y}{3} + \frac{s(2-\sigma)}{3}. \tag{10}$$

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

$$s > \frac{f_Y - f_X}{2-\sigma}. \tag{11}$$

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 (8) and (9), we have

$$p_X = f_Y - s(1-\sigma) \qquad \text{and} \qquad p_Y = f_Y. \tag{12}$$

Ensuring that these solutions satisfy the conditions, we have

$$s \leq \frac{f_Y - f_X}{2-\sigma}. \tag{13}$$

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 (8) and (9), we have

$$p_X = \frac{f_X + f_Y + s\sigma}{2} \qquad \text{and} \qquad p_Y = f_Y. \tag{14}$$

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

$$f_Y - f_X \in (f_X - s\sigma, f_X + s(2-\sigma)), \tag{15}$$

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

$$f_Y - f_X \geq s(2-\sigma). \tag{16}$$

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

$$\Delta = \begin{cases} 1-\sigma & \text{if } p_X \leq p_Y \\ -\sigma & \text{otherwise.} \end{cases} \tag{17}$$

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. ■

Proposition 2 *Holding the difference in marginal costs ($f_Y - f_X$) constant, optimal switching costs decrease in marginal costs, while equilibrium execution costs increase in marginal costs.*

Proof of Proposition 2. The overall execution costs $\bar{p}$ is defined by

$$\bar{p} := (\sigma + \Delta)p_X + (1 - \sigma - \Delta)p_Y. \tag{18}$$

Substituting Δ, p_X and p_Y in Proposition 1 into above yields

$$\bar{p} = f_X + \left(\frac{5 - 2\sigma + 2\sigma^2}{9}\right) s - (f_Y - f_X)\left(\frac{f_Y - f_X}{9s} + \frac{4+\sigma}{9}\right). \tag{19}$$

Notice, $\bar{p}$ is always strictly increasing in switching costs s, and also increasing in the marginal cost f_X, holding $\Delta_F := f_Y - f_X$ constant.

Thus, the optimal switching costs are given by

$$s = \min\{s_{\max}, s^*\}, \tag{20}$$

where s^* is a unique solution to

$$0 = G(f_X, s) := f_X + \left(\frac{5 - 2\sigma + 2\sigma^2}{9}\right) s - \Delta_F \left(\frac{\Delta_F}{9s} + \frac{4+\sigma}{9}\right) - p_{\max}. \tag{21}$$

Since $G(\cdot)$ is increasing in f_X and s, we have

$$\frac{ds^*}{df_X} < 0 \qquad \text{and} \qquad \frac{ds}{df_X} \leq 0. \tag{22}$$

Then the equilibrium execution costs are given by

$$\bar{p} = p_{\max} + \min\{0, G(f_X, s_{\max})\}. \tag{23}$$

Since $G(\cdot)$ is increasing in f_X, we have

$$\frac{d\bar{p}}{df_X} \geq 0 \qquad \text{and} \qquad \frac{d\bar{p}}{df_X} > 0 \text{ if } s = s_{\max}. \tag{24}$$

Since Δ_F is held constant, the derivatives with respect to f_Y remain the same. ∎

IA.2. Endogenous Switching Costs

We endogenize brokers' switching costs based on heterogeneous order flow characteristics.

Timeline. There are three points in time: $t = 0, 1, 2$. At $t = 0$, brokers choose optimal switching costs. At $t = 1$, brokers route order flows to wholesalers X and Y with given switching costs (as in Section 4.1). At $t = 2$, investors pay execution costs. We solve by backward induction.

Broker's Decision. At $t = 0$, each broker chooses its switching cost by solving:

$$\min_{s \in [0, s^{\max}]} g(s^{\max} - s) \qquad \text{subject to} \qquad \bar{p} \le p_{\max}. \tag{25}$$

Here, $g(\cdot)$ is the investment required to reduce switching costs from the maximum $s^{\max}$, $\bar{p}$ is the overall execution cost paid by customers, and $p_{\max}$ is the regulatory ceiling (set at one for E/Q under NBBO requirements).[24] Brokers minimize investment since customers bear all execution costs and order flow size is largely insensitive to execution quality.

Full Equilibrium. Assuming uniform marginal costs across wholesalers, the overall execution cost is:

$$\bar{p} := (\sigma + \Delta) p_X + (1 - \sigma - \Delta) p_Y. \tag{26}$$

Substituting equilibrium values from Proposition 1 yields:

$$\bar{p} = f + \left(\frac{5 - 2\sigma + 2\sigma^2}{9} \right) s. \tag{27}$$

Solving the broker's optimization problem (25) gives optimal switching costs:

$$s = \begin{cases} \frac{9}{5 - 2\sigma + 2\sigma^2} \left(p^{\max} - f \right), & \text{if } f > \bar{f} \\ s^{\max}, & \text{otherwise,} \end{cases} \tag{28}$$

where $\bar{f} := p^{\max} - \left(\frac{5-2\sigma+2\sigma^2}{9} \right) s^{\max}$.

Optimal switching costs decrease in marginal costs when marginal costs are sufficiently high, but reach the maximum $s^{\max}$ when marginal costs are low. Brokers with inherently more expensive order flows face greater regulatory pressure under uniform NBBO standards, creating incentives to reduce switching costs. However, this reduction may not fully offset higher marginal costs, explaining why execution costs still increase with marginal costs.

[24] In practice, brokers maintain execution costs below NBBO spreads to avoid regulatory violations.

IA.3. Full Wholesaler Sample and Additional Results

This section provides robustness checks and additional empirical results. We first examine whether our main findings hold when including all wholesalers rather than focusing on the four dominant ones. While our primary analysis focuses on the four dominant wholesalers that handle 94% of order flow (Citadel, Virtu, Jane Street, and G1X), we verify that our key results remain robust when we include all wholesalers in our sample. Main findings are qualitatively similar, though including smaller wholesalers masks the important heterogeneity we document across brokers because regressions give equal weight to small wholesalers with minimal market shares and dominant players alike. The section concludes with supplementary results.

Table IA.1: Persistence of Wholesaler Price Improvement: All Wholesalers

This table examines the persistence of price improvement by wholesaler, measured as E/Q in excess of the broker averages, at the overall level (Panels A and B) or stock-level level (Panels C and D). The sample covers the full sample of all wholesalers. We regress the broker-adjusted price improvements against 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)
	All	Robinhood	IBKR Lite	E*Trade	Schwab	TD	Fidelity
Panel A: Wholesaler-level Persistence (1-month Lag))							
Dep Var:				Broker-adjusted E/Q (t)			
Broker-adjusted E/Q (t-1)	0.729**	0.599**	0.916**	0.488**	0.505**	0.857**	0.627*
	(12.57)	(4.19)	(11.09)	(3.75)	(6.00)	(13.08)	(3.04)
R-squared	0.558	0.384	0.811	0.245	0.373	0.765	0.344
Panel B: Wholesaler-level Persistence (3-month Lag)							
Dep Var:				Broker-adjusted E/Q (t)			
Broker-adjusted E/Q (t-1, t-3)	0.834**	0.741**	0.980**	0.654**	0.826**	0.868**	0.924**
	(13.04)	(4.65)	(10.21)	(3.85)	(16.48)	(11.52)	(5.36)
R-squared	0.550	0.400	0.866	0.272	0.614	0.667	0.336
Panel C: Wholesaler-stock-level Persistence (1-month Lag)							
Dep Var:				Broker-adjusted E/Q (t)			
Broker-adjusted E/Q (t-1)	0.210**	0.190**	0.507**	0.187**	0.188**	0.219**	0.169**
	(11.00)	(5.01)	(7.95)	(6.98)	(7.08)	(6.95)	(5.62)
R-squared	0.043	0.035	0.246	0.037	0.033	0.048	0.024
Panel D: Wholesaler-level Persistence (3-month Lag)							
Dep Var:				Broker-adjusted E/Q (t)			
Broker-adjusted E/Q (t-1, t-3)	0.478**	0.407**	0.712**	0.464**	0.495**	0.508**	0.426**
	(20.73)	(4.30)	(7.33)	(15.27)	(7.73)	(13.61)	(7.62)
R-squared	0.080	0.047	0.237	0.093	0.082	0.095	0.051

Table IA.2: Changes in Routing Shares in Response to Prior Execution Cost: All Wholesalers
This table examines how brokers adjust their routing to wholesalers based on their prior aggregate (Panels A and B) and stock-level (Panels C and D) execution cost. The sample covers the full sample of all wholesalers. Each month, for each broker, we compute the wholesaler broker-adjusted execution cost (E/Q) as the deviation of the wholesaler's execution cost from the broker-level average. This measure is calculated at both the aggregate level and the individual stock level. We then regress the percentage point change in orders routed to a given wholesaler against the wholesalers' lagged execution cost, 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.

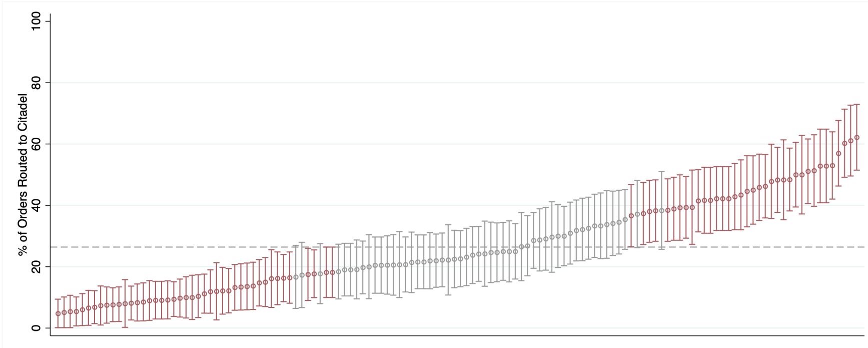
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Robinhood	IBKR Lite	E*Trade	Schwab	TD	Fidelity
Panel A: Wholesaler-level Routing Responses (1-month Lag)							
Dep Var:	Change in Routing Share (t)						
Broker-adjusted E/Q (t-1)	-0.0293*	-0.104*	-0.0667	-0.0254	-0.0644	-0.00550	-0.0432
	(-2.25)	(-2.36)	(-0.87)	(-0.67)	(-0.90)	(-1.23)	(-0.84)
R-squared	0.013	0.076	0.022	0.009	0.042	0.002	0.022
Panel B: Wholesaler-level Routing Responses (3-month Lag)							
Dep Var:	Change in Routing Share (t)						
Broker-adjusted E/Q (t-1, t-3)	-0.0151	0.0167	-0.0924	-0.0238	0.00701	-0.0107	-0.0464
	(-0.84)	(0.29)	(-1.11)	(-0.34)	(0.25)	(-1.98)	(-0.49)
R-squared	0.003	0.002	0.037	0.005	0.001	0.005	0.015
Panel C: Wholesaler-stock-level Routing Responses (1-month Lag)							
Dep Var:	Change in Routing Share (t)						
Broker-adjusted E/Q (\$t\$-1)	-0.00655	-0.0374**	-0.0715	-0.00325	0.0145	0.00727	0.0143
	(-1.24)	(-3.53)	(-1.30)	(-0.44)	(1.33)	(0.75)	(0.76)
R-sq	0.000	0.002	0.003	0.000	0.000	0.000	0.000
Panel D: Wholesaler-stock-level Routing Responses (3-month Lag)							
Dep Var:	Change in Routing Share (t)						
Broker-adjusted E/Q (t-1, t-3)	-0.0113	-0.0493	-0.0467	-0.0160	0.0392	0.0101	-0.00861
	(-0.91)	(-1.73)	(-0.67)	(-0.74)	(2.95)	(0.45)	(-0.18)
R-squared	0.000	0.001	0.001	0.000	0.002	0.000	0.000

Table IA.3: Levels of Routing Shares and Prior Execution Cost: All Wholesalers

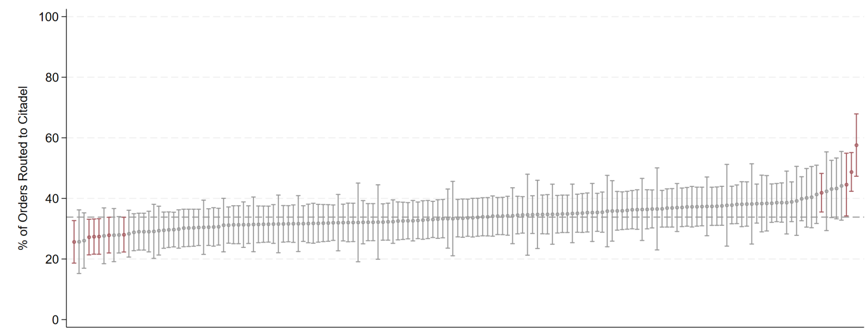
This table examines how brokers' routing shares to wholesalers are related to their prior aggregate (Panels A and B) and stock-level (Panels C and D) execution cost. The sample covers the full sample of all wholesalers. Each month, for each broker, we compute the wholesaler broker-adjusted execution cost (E/Q) as the deviation of the wholesaler's execution cost from the broker-level average. This measure is calculated at both the aggregate level and the individual stock level. We then regress the levels of routing shares of our orders to a given wholesaler on the wholesaler's lagged execution cost, 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)
	All	Robinhood	IBKR Lite	E*Trade	Schwab	TD	Fidelity
Panel A: Wholesaler-level Routing Share (1-month Lag)							
Dep Var:				Routing Share (t)			
Broker-adjusted E/Q (t-1)	-0.254**	-0.670**	-1.064**	-0.0436	0.250	-0.293**	0.0556
	(-8.46)	(-4.16)	(-10.47)	(-0.40)	(2.17)	(-6.81)	(0.60)
R-squared	0.071	0.513	0.474	0.002	0.085	0.184	0.002
Panel B: Wholesaler-level Routing Share (3-month Lag)							
Dep Var:				Routing Share (t)			
Broker-adjusted E/Q (t-1)	-0.350**	-0.917**	-1.164**	-0.0855	0.488**	-0.349**	0.0645
	(-8.00)	(-9.97)	(-12.50)	(-0.75)	(5.01)	(-10.61)	(0.55)
R-squared	0.111	0.754	0.603	0.005	0.164	0.219	0.002
Panel C: Wholesaler-stock-level Routing Share (1-month Lag)							
Dep Var:				Routing Share (t)			
Broker-adjusted E/Q (t-1)	-0.0479**	-0.189**	-0.484**	-0.00233	0.0324*	-0.0111	0.0586**
	(-6.02)	(-10.44)	(-8.47)	(-0.23)	(2.56)	(-0.74)	(3.70)
R-squared	0.005	0.063	0.129	0.000	0.004	0.000	0.010
Panel D: Wholesaler-stock-level Routing Share (3-month Lag)							
Dep Var:				Routing Share (t)			
Broker-adjusted E/Q (t-1)	-0.107**	-0.492**	-0.803**	-0.0103	0.0997*	0.0226	0.106**
	(-3.40)	(-11.86)	(-11.84)	(-0.36)	(5.01)	(0.84)	(4.46)
R-squared	0.009	0.120	0.153	0.000	0.016	0.001	0.015

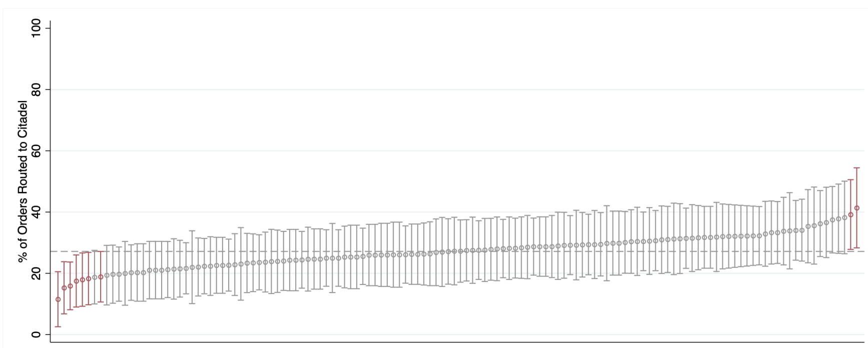
Panel A: IBKR Lite to Citadel



Panel B: E*Trade to Citadel



Panel C: Schwab to Citadel



Panel D: TD Ameritrade to Citadel

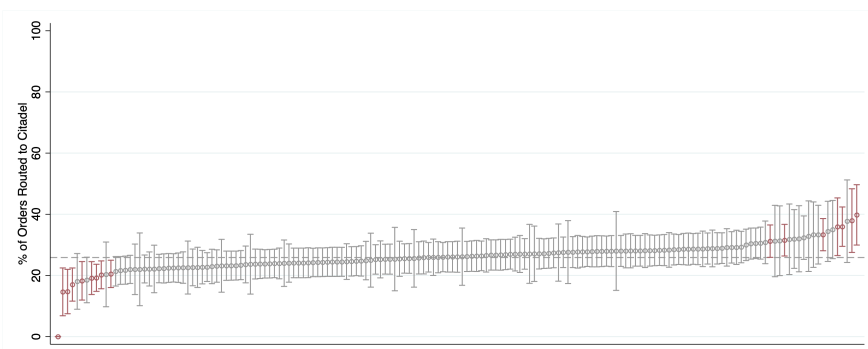


Figure IA.1: Order Routing Patterns across Individual Stocks
This figure shows the percentage of our orders for each stock that are routed to Citadel. Each vertical bar represents one stock, with whiskers showing 95% confidence intervals. A stock requires at least 100 trades to be included. If a stock percentage is significantly different from the average at the 5% level, lines are shown in red; otherwise, lines are in gray.

Table IA.4: 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
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**	-0.292**	-0.094*
Log(Volume)	0.014	-0.023	-0.038
Return	-0.024	0.202	0.118
Abs(Return)	-0.024	0.194	0.128
Spread	1.118**	-1.402	-1.016*
Buy (1/0)	0.023	-0.123*	0.058
SP500	-0.112	-0.020	0.202
Prior Same Venue	-0.249**	0.384**	-0.322**