# Clearing the Murky Waters: How the First Analyst Recommendation Affects Retail Trading Costs

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**Abstract**

As retail trading has expanded over the past few decades, concerns have grown that noisy social-media signals dominate the information environment, leaving it unclear whether analyst recommendations still matter or can improve it. I examine the effect of a stock's first analyst recommendation on transaction costs using Rule 605 data across wholesalers and exchanges. After the first coverage, effective spreads decline on both venues, with the largest reductions at the leading wholesalers. The leading wholesalers also cede market share, particularly for larger orders, as they do not provide a greater reduction in effective spread compared to others, and rivals catch up on price improvement. Thus, credible information production strengthens venue competition and delivers measurably better retail execution.

**JEL codes**: G20, G23, G24

**Keywords**: Market Microstructure, Retail Trading, Wholesalers, Execution Quality

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# I Introduction

In the United States, retail investors now account for nearly 20% to 30% of trading volume in the equity market,[1] a notable increase from just 2% in the early 2000s.[2] Despite their growing market presence, retail investors face an information environment that is limited and often fragmented. For stocks with high retail trading interest, social media platforms have become a dominant source of information,[3] but the content is often noisy.[4] One formalized and reliable alternative is the stock analyst recommendation report. However, small-cap stocks, those favored by retail investors, are often under-covered by analysts, partly due to the strict regulation, as well as the rise of AI tools.[5]

Motivated by the boom in retail trading and the murky information environment surrounding stocks with high retail trading interest, I examine the influence of an official information source, analyst recommendations, on retail investors' trading costs. This paper seeks to answer a central question: Do analyst recommendations improve the information environment for retail investors and lower their trading costs? My analysis focuses on the first analyst recommendation, as the first recommendation represents a structural change in a stock's information environment.

Although analyst recommendations are known to help improve the information environment and lower transaction costs (Irvine, 2003), it is uncertain whether they still play the

[1] "Retail Trading Just Hit All Time High," by Derek Saul, *Forbes*, February 3, 2023. Available at: `https://www.forbes.com/sites/dereksaul/2023/02/03/retail-trading-just-hit-an-all-time-high-heres-what-stocks-are-the-most-popular/`

See also: "Tonight we're going to stonk-punt like it's 2021," *Financial Times*. Available at: `https://www.ft.com/content/14135d5e-6b50-4767-a9dd-781c268e8366`

[2] Alicia J. Davis, "A Requiem for the Retail Investor?" Available at: `https://repository.law.umich.edu/articles/118/`

[3] Avila et al. (2024) documents that analyst coverage on small stocks is low.

[4] Dim (2020) argues only 13% of the Seeking Alpha authors are generating substantial positive returns.

[5] See: U.S. Securities and Exchange Commission, "Selective Disclosure and Insider Trading," available at: `https://www.sec.gov/news/extra/seldsfct.htm`; Stephen Morris and Nicholas Megaw, "Give retail investors fair access to stock research," *Financial Times*, April 4, 2023. Available at: `https://www.ft.com/content/0f5af15b-2c5c-4d64-8488-1b6f730806bc`; and "Research on Stocks Has Lost Its Allure—And the Salaries," *Moomoo*, March 26, 2024. Available at: `https://www.moomoo.com/news/post/47903930/research-on-stocks-has-lost-its-allure-and-the-salaries`

same role today given the substantial changes in the information environment. With the rise of the social media, investors now have access to the vast amount of information, making it unclear whether analyst recommendations still matter to investors.

In addition to changes in the information environment, the structure of equity markets has also changed significantly over the past few decades. Modern equity markets are highly segmented, with retail orders largely separated from institutional flows and primarily executed off-exchange through wholesalers (Dyhrberg et al., 2025). On the one hand, retail orders are expected to receive a lower trading cost because of the segmentation. On the other hand, it raises concerns about the lack of competition in the wholesalers market, where most retail orders are executed.

Wholesalers, the market makers in the retail market, know the source of the orders. Although retail orders can be informed or 'toxic' to some extent, they are likely less informed than institutional orders. As a result, both academic and regulatory perspectives argue that retail investors should bear lower trading costs if their orders are segregated from institutional flow.

Wholesalers do provide a better order execution quality, according to the prior literature (Battalio and Jennings, 2023; Dyhrberg et al., 2025). However, the U.S. Securities and Exchange Commission (SEC) has expressed concerns about the lack of competition in the wholesalers' market, where a few dominant players execute a large share of order flow. When some wholesalers possess significant market power, they can charge retail investors 'unfair' prices, potentially offsetting the benefit of lower information asymmetry.[6]

The SEC made a lot of effort to enhance the competition and enhance pricing for retail investors, such as proposing order-by-order auctions,[7] and reforming trading fees and tick

[6] In the proposed Rule 615, the SEC argues that the level of price improvement offered by wholesalers does not fully reflect the much lower cost. The amount of this "competitive shortfall" is estimated to be 1.08 basis points per dollar traded by wholesalers, with an estimated total annual amount of $1.5 billion. For details, see `https://www.federalregister.gov/documents/2023/01/03/2022-27617/order-competition-rule`

[7] U.S. Securities and Exchange Commission Press Release, "SEC Proposes Rule to Enhance Competition for Individual Investor Order Execution," December 2022. Available at: `https://www.sec.gov/newsroom/press-releases/2022-225`

sizes.[8] My paper tries to explore, besides those structural changes, whether an improvement in the stocks' information environment can reduce retail investors' trading costs.

Before the first analyst recommendation, the information sources that retail investors rely on are social media discussions and news articles. These sources, however, are often noisy (Avila et al., 2024). Analyst recommendations, by contrast, provide more consolidated information. Following the release of the first analyst recommendation, the information environment should therefore become less murky. Even though retail investors may continue to monitor and participate in social media discussions, these discussions are likely to improve in quality as they begin to incorporate and reflect the newly available, authoritative information from analyst reports.

I use the effective spread in cents, as reported in Rule 605 reports,[9] as my primary measure of trading costs. Under Rule 605, all market centers that handle customer orders are required to publicly disclose standardized monthly execution quality metrics. The 605 reports from wholesalers are widely regarded as the most representative public data for retail trading activity (Battlio et al., 2024). Therefore, I rely on 605 data as my main source for capturing retail trading costs. I gather reports from the eight largest wholesalers and fourteen exchanges.[10]

Retail orders in the U.S. equity market are predominantly executed by wholesalers, while orders executed on exchanges are more likely to originate from institutional investors (Dyhrberg et al., 2025). However, not all orders handled by wholesalers are retail, and not all exchange orders are institutional orders. Especially, 605 reports include large orders (e.g., 2,000 shares or more), which are less likely to be submitted by retail investors. To avoid over-interpretation, I refer to orders by their routing destination—"wholesaler orders" and "exchange orders".

[8]U.S. Securities and Exchange Commission Press Release, "SEC Adopts Rules to Amend Minimum Pricing Increments and Access Fee Caps and to Enhance the Transparency of Better Priced Orders." Available at: https://www.sec.gov/newsroom/press-releases/2024-37

[9]605 reports record the effective spread in dollars. I convert them to cents in my paper.

[10]See Table A4 for details about these exchanges and wholesalers.

I start my analysis by investigating the influence of the first analyst recommendation on exchange orders and wholesaler orders. Wholesaler orders are less 'toxic' (measured by price impact), and correspondingly, they have a lower effective spread. This result indicates the benefit to retail investors of segregating different orders. Following the first-time analyst recommendations, the effective spread declines for orders routed to wholesalers and orders routed to exchanges with a similar magnitude (9.16% on exchanges versus 7.79% in the wholesalers market). Moreover, the reduction in effective spread is not purely driven by the declines in quoted spread. I scale the effective spread by the corresponding quoted spread and find that the effective-over-quoted spread also declines for wholesaler orders. These results highlight two important points: traditional analyst recommendations still play a significant role in today's market, and they significantly reduce the trading cost for wholesaler orders, which mainly come from retail investors.

To have a better understanding of the influence of the first analyst recommendation on wholesaler orders, I take a closer look at the structure of the wholesaler market. In my sample, two wholesalers, Citadel and Virtu, together execute approximately 70% of all flows. This high market concentration persists both across the full universe of stocks and for stocks experiencing their first analyst recommendations. Given this market concentration, it is not surprising that the SEC is concerned with the lack of competition in the wholesalers market.

Within the wholesalers market, Citadel and Virtu charge a 1.27 cents higher effective spread than the rest of the wholesalers, and they also give a worse effective-over-quoted spread. The effective-over-quoted spread is a standard measure of price improvement, with lower values indicating better price improvement (i.e., investors receive executions better than the prevailing public quote). Notably, Citadel and Virtu provide a 2.67% higher effective-over-quoted spread than their competitors, indicating less favorable price improvement for investors.

Though the two leading wholesalers charge a higher effective spread than other wholesalers, the reduction in their effective spread following the first analyst recommendations is also significantly more pronounced than others (9.71% versus 3.75%). This result is consistent with the improved competition after analyst recommendations. If the playing field is leveled following the disclosure of public information, we would expect to see a general reduction in spreads across the market, with a more pronounced decrease for the dominant players who previously held market power.

To explore the dynamics of competition, I examine the market share changes of two leading wholesalers before and after the first analyst recommendation. I find that these leading wholesalers lose market share to the overall market (exchanges and wholesalers) and also lose market shares to other wholesalers after the first analyst recommendation. Although most of the retail orders are routed to wholesalers, brokers always retain the option to send orders to exchanges, making exchanges effective competitors. Thus, decline in market share of the two leading wholesalers in the overall market and wholesalers market suggests that the dominant wholesalers lose some of their execution advantage after the information environment improves.

Since the main competition occurs among wholesalers, I investigate the wholesalers market more. Among the eight wholesalers in my sample, I find that the reduction in effective spreads charged by the top two wholesalers is most pronounced in the smallest order size bucket. However, I do not find statistically significant evidence showing that they offer greater reductions in effective spreads than other wholesalers in the largest order size bucket. Correspondingly, the decline in the top two wholesalers' market share is concentrated in the largest order size bucket. These results indicate that the top two wholesalers lose market share specifically on orders where they do not provide a greater reduction in effective spread than other wholesalers.

To see a more complete picture of competition among wholesalers, I examine the price improvement across order size buckets. I find that the two leading wholesalers provide superior price improvement on large orders. However, they provide worse price improvement on small orders. After the first analyst recommendation, other wholesalers catch up in providing price improvement on large orders. As a result, the gap in price improvement between the two leading wholesalers and their competitors narrows.

In sum, my results suggest that analyst recommendations continue to play a significant role in today's market, particularly in lowering trading costs for retail investors. Analyst coverage improves the information environment for previously uncovered stocks and promotes greater competition among wholesalers. My results have important policy implications: besides restructuring the market, encouraging analysts to cover stocks also helps in enhancing the pricing for retail investors.

The remainder of the paper is organized as follows: Section II discusses the related literature and contribution; Section III outlines the data; Section IV reports the summary statistics; Section V goes through the hypotheses. Section VI presents regression results, and Section VII concludes.

# II Related Literature and Contribution

My paper contributes to the growing literature on retail trading costs. One focus of this strand of literature is the competitiveness of the wholesaler market. The evidence is mixed on this issue. For example, Huang et al. (2023)'s findings are inconsistent with a competitive market, while others, such as Ernst et al. (2023) and Dyhrberg et al. (2025), document vigorous competition among wholesalers for order flow. My paper is closely related to Dyhrberg et al. (2025). Their work examines wholesaler competition across the broad universe of stocks. In contrast, I focus on stocks which have a murky information environment—specifically, those that receive their first analyst recommendations. My paper complements and extends their work by showing that, although wholesalers generally compete for order flow in the average stock, competition is weaker for stocks with limited information flow. I provide evidence that the first analyst recommendations promote greater competition among wholesalers and improve pricing for these previously uncovered stocks.

My paper is also related to the literature examining the relation between the first analyst recommendations and stock market liquidity. Irvine (2003) established the link between the first analyst recommendations and the increased liquidity in the equity market. However, the landscape of financial information dissemination has changed significantly over the past two decades. Social media has surged and become an increasingly important news source.[11] It is now an integral part of the financial information environment (Cookson et al., 2024). In this new environment, it is not certain whether the traditional analyst reports still play a role in producing information for market participants. My paper demonstrates that analyst recommendations continue to play a meaningful role by providing valuable information to under-informed wholesalers, and hence improve the pricing for retail investors whose orders are executed by wholesalers.

In addition, the current market is highly segmented, with retail orders predominantly executed by wholesalers and institutional orders executed on exchanges. Battalio and Jennings (2023) analyzes the performance of wholesalers and market segmentation, showing that wholesalers consistently provide better price improvement than exchanges. My paper investigates the interaction between the first analyst recommendation and order execution across exchanges and wholesalers. The influence of the analyst recommendations on orders executed by wholesalers can be different from that for orders executed on exchanges, since the client base is different. I find that although wholesalers provide better effective spreads than exchanges, the reduction in effective spread following analyst recommendations is similar for the two groups (9.16% for exchanges vs. 7.79% for wholesalers). My findings provide suggestive evidence that analyst recommendations are significant for retail orders' trading costs.

[11] Pew Research Center. "Social Media and News Fact Sheet." September 17, 2024. https://www.pewresearch.org/journalism/fact-sheet/social-media-and-news-fact-sheet/; see also Our World in Data, "The Rise of Social Media," https://ourworldindata.org/rise-of-social-media.

# III Data and Sample

A. 605 Reports

On January 30, 2001, the SEC adopted Rule 605 to improve public disclosure of order execution quality. All market centers, including wholesalers that trade National Market System (NMS) securities, are required to submit monthly reports containing standardized statistics on execution quality.[12] According to industry consensus, Rule 605 reports submitted by wholesalers primarily reflect retail order flow—wholesalers purchase from retail sellers and aim to resell to retail buyers. These reports cover all order types and include comprehensive execution quality metrics. To date, they remain the most representative and publicly available data source on retail order execution (Battlio et al., 2024).

I collect reports from the eight biggest wholesalers and fourteen exchanges. Given that retail orders are predominantly captured by wholesalers' 605 reports, the orders reported by exchanges are likely mostly institutional orders. My sample's time horizon is from January 2019 through December 2022. I merge the 605 reports with stock-level data from the Center for Research in Security Prices (CRSP), using the security identifier in the 605 data and TSYMBOL in CRSP. I restrict the sample to Class A shares.

I focus exclusively on liquidity-demanding orders (market orders and marketable limit orders) because liquidity-providing orders (non-marketable limit orders) are handled differently by wholesalers. Such orders are typically either routed directly to exchanges (Dyhrberg et al., 2025) or managed internally by wholesalers under the no-knowledge exemption (FINRA Rule 5320.02) or the riskless principal exemption (FINRA Rule 5320.03).

I further narrow my sample to stocks receiving their first analyst recommendations. To isolate the impact of these recommendations, I exclude recommendations issued around firms' initial public offering (IPO) periods and earnings announcement dates, thereby reducing potential confounding effects from these recommendations. My final sample includes

[12] For more details, see: `https://www.sec.gov/rules-regulations/2001/03/disclosure-order-execution-routing-practices`

1,324 unique PERMNOs,[13] which I refer to as 'stocks'. When working with metrics, I winsorize the effective spread, realized spread, quoted spread,[14] effective-over-quoted spread and control variables[15] at 1st and 99th percentile to mitigate the influence of extreme values. I winsorize exchange orders and wholesaler orders separately to preserve the distinct distributional characteristics of each market segment. Although exchange orders are included in the analysis, the primary focus of this paper is on wholesaler orders, as these predominantly represent retail orders.

Wholesalers may vary in their expertise across different stocks, leading to heterogeneous market shares. To examine this, I compare the market share of the eight wholesalers in executing the universe of stocks over my four-year horizon versus the subset of stocks with first analyst coverage. Panel A of Table 1 shows that Citadel and Virtu dominate retail order execution, jointly accounting for 70.30% of all retail trading volume from 2019 to 2022. The third-largest wholesaler, G1, executes 9.88% of volume, while the smallest, Merrill Lynch and Morgan Stanley, each hold less than 2%.

The market shares for the first-covered stocks closely mirror those for the full sample. Citadel and Virtu remain dominant, with a combined share of 70.77%. The only notable difference is in the ranking between Two Sigma and UBS: UBS executes more volume in the full sample (5.39%) than Two Sigma (3.71%), but the ranking reverses in the first-covered stock subsample, where Two Sigma (4.44%) slightly surpasses UBS (4.13%).

I refer Citadel and Virtu as the top two wholesalers in the rest of my paper, since they two together execute most of the orders in the wholesalers market.

[13]PERMNOs are company identifiers used in CRSP.
[14]The quoted spreads are not required by Rule 605, and I derive the quoted spreads are discussed in Appendix.
[15]The control variables winsorized are log price, Volatility, log volume, and log market capitalization.

Table 1: Wholesaler Market Share

This table reports the market share of each wholesaler based on the number of shares executed (SHS) as a percentage of the total shares executed over the full sample period (2019–2022). Panel A presents market shares for all stocks executed by wholesalers. Panel B focuses on the subset of stocks that received first analyst recommendations during the sample period. Market shares are computed using cumulative executed share volume across all relevant months.

**Panel A: The Universe of Stocks**

| Wholesalers | Shares Executed, bil | Market Shares, %. |
|---|---|---|
| Citadel | 661.50 | 41.17 |
| Virtu | 468.01 | 29.13 |
| G1 | 158.74 | 9.88 |
| Jane Street | 124.02 | 7.72 |
| UBS | 86.53 | 5.38 |
| Two Sigma | 59.66 | 3.71 |
| Merrill Lynch | 31.35 | 1.95 |
| Morgan Stanley | 16.65 | 1.06 |

**Panel B: First Covered Stocks**

| Wholesalers | Shares Executed, bil | Market Shares, %. |
|---|---|---|
| Citadel | 122.87 | 40.41 |
| Virtu | 92.32 | 30.36 |
| G1 | 33.21 | 10.92 |
| Jane Street | 22.75 | 7.48 |
| Two Sigma | 13.49 | 4.44 |
| UBS | 12.53 | 4.12 |
| Merrill Lynch | 5.38 | 1.77 |
| Morgan Stanley | 1.53 | 0.50 |

## B. Measures of Order Execution Quality

The main outcome variable in this study is effective spread reported in 605 reports, which captures the actual trading cost borne by liquidity demanders. Another commonly used metric is the quoted spread, which reflects the cost advertised by liquidity providers.

Understanding the difference between these two measures is helpful. The quoted spread is defined as the difference between the national best offer and the national best bid across all exchanges. The effective spread is calculated as twice the deviation between the transaction price and the prevailing midpoint of the best bid and ask. For buyer-initiated trades, it is double the amount of the transaction price minus the midquote of consolidated best bid and offer at the time of order receipt; for seller-initiated trades, it is double the amount of the midquote of consolidated best bid and ask minus the transaction price. Thus, the effective spread captures the price concession necessary to execute the trade and reflects the true cost incurred by liquidity-demanding traders. Because the central goal of this paper is to examine how the first analyst recommendation affects the actual transaction costs for retail investors, the effective spread is the most appropriate measure.

In the market microstructure literature, the effective spread is often decomposed into two components: realized spread and price impact. In the Rule 605 data, the realized spread is calculated as twice the difference between the trade price and the midpoint of the consolidated best bid and offer measured five minutes after execution. The 605 reports do not include the price impact. I derive the price impact by subtracting the realized spread from the effective spread. The price impact captures the adverse selection cost associated with a trade, i.e., the information-driven price movement that occurs after execution. By contrast, the realized spread reflects the non-informational component of execution cost. It can represent market-making costs related to inventory management, fixed costs, and it could also be the profit earned by market makers.

Besides these measures, the prior literature uses the effective-over-quoted spread as a measure of price improvement. As the quoted spread is the trading cost that liquidity providers advertise, and the effective spread is the trading cost that investors are actually incurring; the lower ratio indicates a better price improvement.

In my regression analysis, I use effective spread in cents as the primary outcome variable. I also include price impact, realized spread, and effective-over quoted spread in my tables to aid in the interpretation of the main findings based on effective spread.

### C. I/B/E/S Recommendations

I refer to Irvine (2003) and Irvine et al. (2007) to define the first recommendations. Analyst recommendation data is collected from the I/B/E/S detail recommendation file. I define a recommendation as the first recommendation if it is the first instance of a given recommendation for a stock, following similar filtering criteria as in Irvine (2003) and Irvine et al. (2007).

Specifically, I exclude recommendations from brokerage firms that have not appeared in the I/B/E/S recommendation detail file for at least six months. Occasionally, I/B/E/S expands its coverage universe, typically reflecting a broadening of its dataset rather than the emergence of new brokerage firms. Additionally, I exclude recommendations issued within six months of a firm's IPO period and those made within five trading days after an earnings release. This step is to disentangle between the effect of other events and the recommendations. After applying these filters, I define the first recommendation as the first instance of a recommendation associated with a stock.

# IV Summary Statistics

Table 2 presents the summary statistics for the four outcome variables: effective spread, price impact, realized spread, and effective-over-quoted spread (ES/QS) based on the 605 data. The 605 data contains the share-weighted order execution quality for a security in a certain order size and order type bucket.

Panel A compares orders executed on exchanges with those executed by wholesalers. On average, the effective spread for wholesaler orders (5.85 cents) is narrower than for exchange orders (6.62 cents), indicating lower trading costs for orders executed in the wholesalers market. In terms of price impact, which typically reflects the "toxicity" of an order, or the extent to which it is informed, exchange orders exhibit a higher average price impact than wholesaler orders (7.02 cents vs. 3.99 cents).

The realized spread captures the toxicity-adjusted trading cost for investors, since it is the residual of effective spread minus price impact. This cost for investors is typically related to market makers' market-making costs, such as inventory management, fixed costs. However, it could also capture the market makers' profit. Based on panel A, the wholesaler orders have a larger realized spread than exchange orders (1.95 cents vs. -0.29 cents), suggesting that the higher effective spread on exchanges can be largely explained by toxicity.

Exchange orders also exhibit a higher effective-over-quoted spread (ES/QS) than wholesaler orders (0.98 vs. 0.74). Since the ES/QS ratio reflects the proportion of the quoted spread paid by investors, a lower ratio indicates greater cost savings. Overall, these comparisons suggest that wholesaler orders achieve better execution quality across multiple dimensions than exchange orders.

Table 2: Summary Statistics of Order Execution Quality Metrics

This table reports the summary statistics for the four outcome variables: effective spread, price impact, realized spread, and effective-over-quoted spread. Panel A compares the means and standard deviations of these variables between orders executed on exchanges and those executed by wholesalers. Panel B focuses on wholesaler orders, comparing the four outcome variables between the top two wholesalers (Citadel and Virtu) and all other wholesalers.

| Panel A: Exchanges vs. Wholesalers | | | | | |
|---|---|---|---|---|---|
| | Exchanges mean | Exchanges sd | Wholesalers mean | Wholesalers sd | Diff |
| Effective Spread (cents) | 6.6165 | 0.0942 | 5.8518 | 0.0937 | *** |
| Price Impact (cents) | 7.0237 | 0.1872 | 3.9931 | 0.1425 | *** |
| Realized Spread (cents) | -0.2894 | 0.1702 | 1.9517 | 0.1375 | *** |
| ES/QS | 0.9824 | 0.2541 | 0.7353 | 0.4248 | *** |
| Panel B: Top Two Wholesalers vs. Other Wholesalers | | | | | |
| | Top Two mean | Top Two sd | Others mean | Others sd | Diff |
| Effective Spread (cents) | 6.9070 | 0.1025 | 5.3654 | 0.0889 | *** |
| Price Impact (cents) | 4.8840 | 0.1337 | 3.5828 | 0.1462 | *** |
| Realized Spread (cents) | 2.0821 | 0.1249 | 1.8920 | 0.1423 | *** |
| ES/QS | 0.7704 | 0.3647 | 0.7191 | 0.4488 | *** |

Panel B of Table 2 reports the execution quality within the wholesalers market, comparing the top two wholesalers (Citadel and Virtu) to all other wholesalers. On average, the top two wholesalers charge an effective spread that is 1.5 cents higher than that of their peers. They also exhibit a higher price impact than others, indicating that the orders received by the top two wholesalers are likely more toxic than others. The top two wholesalers also have a slightly higher realized spread than others (2.08 cents vs. 1.90 cents), which reflects higher profits or greater market-making costs. Finally, they provide worse price improvement relative to other wholesalers - the effective-over-quoted spread is larger for them than for others.

Table 3 reports the descriptive statistics of stock characteristics. My sample contains stocks receiving their first recommendations. These stocks are predominantly small-cap and young firms. The mean market capitalization is approximately $2.00 billion, but the median is only $442.19 million, reflecting a right-skewed distribution. This skewness highlights the presence of a few large firms, but the typical firms in my sample are much smaller in size.

These firms also tend to be relatively young, with an average age since IPO of 2.24 years and a median of 1.50 years. These figures make sense since analysts often initiate coverage on firms relatively early in their public lifecycle. On average, in my sample, there are about 2.62 analysts covering each stock, and the median is just 1. This statistic indicates limited analyst coverage for many of these firms.

Table 3: Sample Description

This table reports the summary statistics for other characteristics of the stocks.

| Metric | Mean | Median | SD |
|---|---|---|---|
| Stock Price ($) | 17.9603 | 10.3000 | 22.6921 |
| Log Stock Price | 2.2551 | 2.3321 | 1.2153 |
| Market Capitalization, mil. | 1,997.10 | 442.19 | 4971.04 |
| Log Market Capitalization | 19.9318 | 19.9073 | 1.7883 |
| Number of Analysts | 2.6018 | 1.0000 | 3.6275 |
| Volatility | 0.2218 | 0.2020 | 0.1293 |
| Stock Return | -0.0171 | -0.0217 | 0.2123 |
| Age (Since IPO) | 2.2400 | 1.5003 | 3.9683 |

The average stock price is $18.00. The volatility of share prices in the table is 22.18%, which is calculated as the monthly high minus the monthly low and scaled by the monthly high. The average monthly stock return over the sampling window is slightly negative at -1.71%. One thing worth noting is that the stock price has a much higher standard deviation (22.69) than the spreads.[16] One reason I do not scale the spread by price in my main analysis is that the variation in the scaled metrics may be primarily driven by changes in stock prices rather than by changes in the spread itself. However, I conduct a robustness check using the price-scaled metrics and find that the results remain consistent.[17]

Table 4 presents the distribution of ratings for the first analyst recommendations in the sample. These recommendations are predominantly positive, with 20.24% classified as "Strong Buy" and 48.56% as "Buy". Brown et al. (2015) documents that sell-side analysts value their clients' perception of their credibility and would love to provide accurate recommendations. However, issuing stock recommendations that are well below the consensus can damage analysts' relationships with managers of the firms they follow. This finding interprets the heavily positive-skewed recommendations in my sample. While 27.19% are "Hold"

[16] Table 2 presents the standard deviation of the share prices and the trading costs.

[17] Table A1 presents the regression results of the effect of the first analyst recommendation on trading costs scaled by share price.

ratings, the combined share of “Underperform” and “Sell” recommendations is below 5%.

Table 4: Distribution of Recommendation Ratings

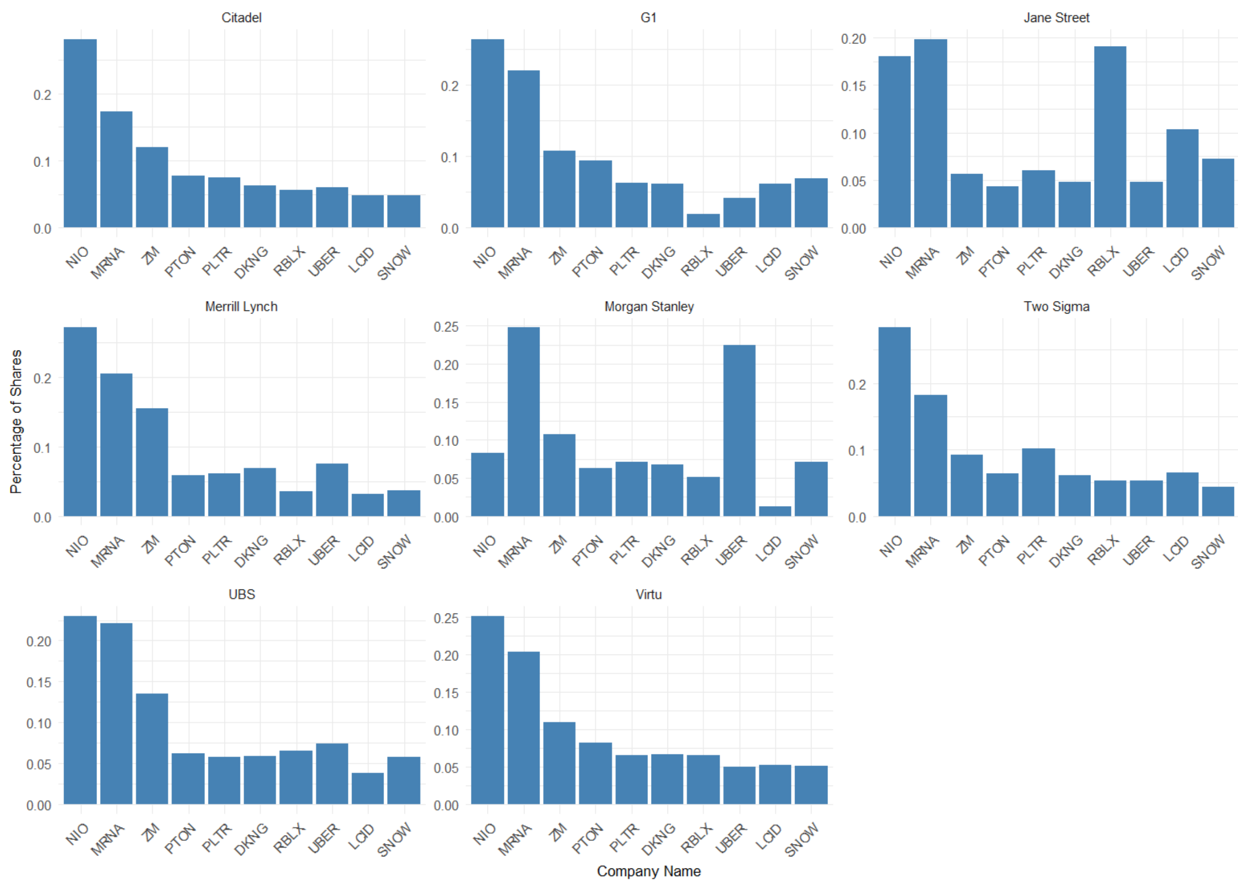
This table presents the distribution of the rating of the first recommendations.

| **Rating** | **Count** | **Percentage** |
|---|---|---|
| Buy | 643 | 48.56% |
| Hold | 360 | 27.19% |
| Strong Buy | 268 | 20.24% |
| Underperform | 51 | 3.85% |
| Sell | 2 | 0.15% |

Figure 1 displays the top 10 most traded stocks (dollar volume) among wholesalers. For each wholesaler, the figure shows the percentage of their total executed shares in the top 10 stocks (percentages for each wholesaler sum to 100%).

Since retail orders are predominantly executed by wholesalers, the top ten most traded stocks represent retail investors’ trading interest. The most traded stock in my sample is NIO, which is a Chinese maker of electric vehicles. Moderna, inc. (MRNA) and Zoom Communications (ZM) follow in second and third place, respectively. Since my sample covered the pandemic period, the high ranking of these two firms is likely driven by the lasting effects of the COVID-19 pandemic. Moderna’s presence highlights retail interest in the biotech sector, while Zoom remains a key player in remote communication. Another firm on the list, Roblox Corporation (RBLX), also experienced accelerated growth during the COVID-19 pandemic. The lockdowns led millions of children to use Roblox as a means of communication.[18]

[18] https://www.pcgamer.com/roblox-is-now-the-game-of-choice-for-over-half-of-all-us-kids/




This figure displays the distribution of executed shares among the top 10 most traded stocks for each wholesaler. For each wholesaler, the figure shows the percentage of their total executed shares in the top 10 stocks. Percentages for each wholesaler sum to 100%.

Figure 1: Wholesaler Execution in the Top 10 Most Traded Stocks

Peloton Interactive, inc. (PTON) is a fitness company that provides users with at-home workout classes. Palantir Technologies, Inc. (PLTR) engages in the business of building and deploying software platforms that serve as central operating systems for organizations. DraftKings Inc. (DKNG), an online sports betting and fantasy sports platform, gained traction as sports betting legalization expanded in several U.S. states. Uber Technologies Inc. (UBER) remained a popular retail trade due to its prominent role in ride-hailing and food delivery. Lucid Group Inc. (LCID) is an electric vehicle manufacturer. Finally, Snowflake Inc. (SNOW) is a cloud-based data warehousing company.

Among the top ten most traded stocks, wholesalers exhibit varying concentrations in the percentage of shares they execute for each stock. For example, Citadel, G1, Merrill

Lynch, Two Sigma, UBS, and Virtu execute the largest share of NIO trades. However, Morgan Stanley and Jane Street execute the highest share of MRNA trades. Jane Street also shows a notable concentration in RBLX executions, while Morgan Stanley has a similar concentration in UBER executions.

Wholesalers have different client bases (Dyhrberg et al., 2025). The observed difference in execution could come from the difference in the clientele's preferences. However, wholesalers may have different expertise in executing different stocks. Many wholesalers have multiple roles in the market. For example, Citadel Security and Virtu Financial are leading Designated Market Maker in NYSE stocks.[19] Citadel Security, Virtu, G1, Two Sigma, Jane Street, and UBS are High Frequency Traders.[20] Besides equity market, Citadel is a dominant market maker in the option market.[21] Morgan Stanley is know for investment banking and Merrill Lynch is recognized for its wealth management. These different roles could provide certain wholesalers with informational advantages in trading specific stocks. This information advantage can be a source of market power.

# V Hypotheses Development

This paper addresses two main questions. The first is whether first-time analyst recommendations have any impact on stock trading costs. In today's market, investors have access to a wide range of alternative information sources, such as X (formerly Twitter), Reddit, and Seeking Alpha (Cookson et al., 2024). Given these alternatives, it is unclear whether traditional analyst recommendations still influence market behavior. If they do, I expect a reduction in effective spreads following the recommendations, as they help mitigate information asymmetry between market makers and informed traders.

The second question I address in this paper considers the mechanism through which the

[19] https://www.citadelsecurities.com/what-we-do/equities/designated-market-maker-dmm/ and https://fintech.tv/virtu-financial-nyse-designated-market-maker-dmm/

[20] https://www.investopedia.com/articles/active-trading/092114/strategies-and-secrets-high-frequency-trading-hft-firms.asp

[21] https://www.bloomberg.com/news/newsletters/2025-07-10/citadel-securities-strengthens-position-with-morgan-stanley-deal

first analyst recommendations influence retail order trading costs. A growing strand of literature examines the competitiveness of the wholesaler market, with mixed evidence(Huang et al., 2023; Ernst et al., 2023; Dyhrberg et al., 2025). If some wholesalers have a competitive advantage over others, the playing field should be leveled when public information comes out. Consequently, if the first analyst recommendations enhance competition among wholesalers, I expect the reduction in trading costs to be more pronounced for wholesalers that possessed greater market power prior to the recommendations.

# VI Regression Results

## VI.1 First Recommendations and All Orders

To access the average effect of the first analyst recommendations on all orders from my sample (fourteen exchanges and eight wholesalers), I estimate the following regression:

$$\textit{Order Execution Quality}_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + Controls + \varepsilon_{ijt}, \tag{1}$$

where $\textit{Order Execution Quality}_{ijt}$ is effective spread, price impact, realized spread, or effective-over-quoted spread (EFQ) for stock i with certain order type and order size[22] in month t. As the focus of this paper is the actual trading cost incurred by retail investors, I chose the effective spread in cents as my main outcome variable.

$FR_{it}$ is a dummy variable equal to 1 beginning in the date a stock receives its first recommendation, and 0 otherwise. The control variables are $Log(PRC)_{it-1}$, $Volatility_{it-1}$, $Log(Volume)_{it-1}$, $Log(Mktcap)_{it-1}$, $Log(\#\text{ of Analysts})_{it-1}$, and $Ret_{it-1}$. $Log(PRC)_{it-1}$ is the natural log of the price at the end of each month. $Volatility_{it-1}$ is the difference between the highest daily price and the lowest daily price or the Bid/Ask average during the month. $Log(Volume)_{it-1}$ is the natural log of the market-wide trading volume in each

[22] The order type can be market order or marketable limit order, coded as '11' and '12' respectively in the 605 report. There are four order size buckets: 100-499 shares - '21'; 500-1999 shares - '22'; 2000-4999 shares - '23'; 5000 or more shares - '24'.

month. $Log(\#\text{ of Analysts})_{it-1}$ is the number of recommendations from unique analysts in each month. $Ret_{it-1}$ is the stock return in each month. I calculate all control variables by using the data from CRSP to capture the market-wide activity. All control variables are lagged for one month to avoid look-ahead bias.

The control variables I add are linked to my dependent variables and analysts' decisions to cover a stock. Share price appears to attract different types of investors who affect the liquidity (Baker and Gallagher, 1980; Dennis and Strickland, 2003), and analysts' recommendations are also related to their audience (Jiang et al., 2011; Brown et al., 2015; Hirshleifer et al., 2024). Greater price fluctuation often reflects increased information flow; as a result, it tends to reduce adverse selection costs and is generally associated with lower effective spread. However, if increased volatility occurs prior to the analyst recommendations, it indicate that other information is influencing spreads. To account for this, I control for lagged volatility, isolating the effect of the recommendation from pre-existing market conditions.

The market-wide trading volume is associated with narrower spreads, and analysts have motivations to cover the stocks that are in high demand among their clients (Brown et al., 2015). Larger stocks tend to be more liquid, and analysts are more likely to cover them. I control for the number of recommendations from unique analysts since the change in liquidity can be driven by the amount of information produced. Liquidity comoves with returns, and analyst recommendations may come up after a price run-up or drop. Thus, I control for the lagged return.

$\alpha_i$ denotes stock fixed effects, augmented with order size and order type fixed effects. This specification accounts for systematic differences in execution quality across stocks, order sizes, and order types. Large orders can require higher inventory capacity to execute, and thus incur a higher trading cost. Market orders and marketable limit orders can also have different execution quality (Harris and Hasbrouck, 1996). Thus, to account for these differences, I include fixed effects for order size and order type, thereby controlling for variation in execution quality across orders of different types and sizes. $\gamma_t$ is the year-month fixed effect.

The results for equation (1) are shown in Table 5. The coefficient of $FR_{it}$ in column (1) indicates that the first analyst recommendations are associated with a statistically significant reduction of 0.73 cents in the effective spread, at 1% significance level. Given that the average effective spread in the sample for all exchange orders and wholesaler orders is 8.65 cents before the first recommendation, the reduction in percentage is 8.44%. This sizable reduction highlights the economically significant role the first analyst recommendation plays in improving the market liquidity.

To estimate the differential effect of the first analyst recommendations on the orders executed on exchanges and orders executed by wholesalers, I introduce a dummy variable $WHOL_j$ in the regression and interact it with $FR_{it}$:

$$\textit{Order Execution Quality}_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 WHOL_j + \beta_3 FR_{it} \times WHOL_j + Controls + \varepsilon_{ijt}, \quad (2)$$

where $WHOL_j$ is a dummy variable equal to 1 if the order is executed by any of the eight wholesalers and 0 if the order is executed on any of the fourteen exchanges in my sample.

Column (2) shows the heterogeneous effect of the first recommendation on the effective spread of wholesaler orders and exchange orders. It is noteworthy that wholesalers provide a 0.58-cent better effective spread than exchanges before the first recommendation. The first recommendation is associated with a 0.86-cent reduction in effective spread for exchange orders and a 0.63-cent reduction (-0.8564 + 0.2244) for wholesaler orders. The average effective spreads are 8.09 cents and 9.39 cents for wholesaler orders and exchange orders, respectively, before the first recommendation. Thus, the corresponding reduction in percentage is 7.79% for wholesaler orders and 9.16% for exchange orders.

## Table 5: First Recommendations and Order Execution Quality

The table estimates the effect of First Analyst Recommendation on four measures of order execution quality - Effective Spread, Realized Spread, Price Impact, and EFQ (effective-over-quoted spread). Regression (1), (3), (5), (7) report coefficient estimates from regressions of the following form:

$$Order\ Execution\ Quality_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + Controls + \varepsilon_{ijt}$$

where $Order\ Execution\ Quality_{ijt}$ is the $Effective\ Spread_{ijt}$, $Price\ Impact_{ijt}$, $Realized\ Spread_{ijt}$, or $EFQ_{ijt}$ (effective-over-quoted spread) for stock i with a certain order type and order size executed by market center j in month t. $FR$ is a dummy variable equal to 1 starting from the month a stock is first covered by an analyst, and 0 otherwise. $log(PRC)$ is the natural log of the stock price. $Volatility$ is the difference between high and low prices scaled by the high price. $Log(Volume)$ is the natural log of trading volume. $Log(Mktcap)$ is the natural log of market capitalization. $Log(\#\ of\ Analysts)$ is the natural log of 1 plus the number of recommendations from unique analysts. I use CRSP value for $Volatility$ and $Log(Volume)$ to capture the market-wide activity. Regressions (2), (4), (6), and (8) report coefficient estimates from regressions of the following form:

$$Order\ Execution\ Quality_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 WHOL_j + \beta_3 FR_{it} \times WHOL_j + Controls + \varepsilon_{ijt}$$

$WHOL_j$ takes a value of 1 if the order is executed by a wholesaler and 0 if the order is executed by an exchange. All models are estimated with stock, order type, order size, and year-month fixed effects, and the standard errors are double-clustered across stocks and year-months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | Effective Spread | | Price Impact | | Realized Spread | | EFQ | |
|---|---|---|---|---|---|---|---|---|
| $FR_{it}$ | -0.7259*** | -0.8564*** | -0.5715*** | -1.391*** | -0.1772** | 0.4976*** | 0.0067*** | 0.0219*** |
| | (0.1768) | (0.1834) | (0.1616) | (0.2263) | (0.0732) | (0.1033) | (0.0022) | (0.0025) |
| $WHOL_j$ | | -0.5849*** | | -3.424*** | | 2.798*** | | -0.1679*** |
| | | (0.0989) | | (0.2219) | | (0.1839) | | (0.0042) |
| $FR_{it}$ x $WHOL_j$ | | 0.2244** | | 1.415*** | | -1.166*** | | -0.0330*** |
| | | (0.1074) | | (0.2018) | | (0.1435) | | (0.0026) |
| $Log(PRC)_{it-1}$ | 2.111*** | 2.139*** | 1.757*** | 1.925*** | 0.4224*** | 0.2849*** | 0.0114*** | 0.0176*** |
| | (0.2715) | (0.2706) | (0.2156) | (0.2168) | (0.1032) | (0.0988) | (0.0027) | (0.0027) |
| $Vol_{it-1}$ | 6.601*** | 6.538*** | 5.477*** | 5.108*** | 1.227*** | 1.528*** | 0.0662*** | 0.0495*** |
| | (0.6583) | (0.6551) | (0.5853) | (0.5680) | (0.2231) | (0.2234) | (0.0069) | (0.0060) |
| $Log(Mktcap)_{it-1}$ | 1.147*** | 1.113*** | 1.150*** | 0.9459*** | -0.0120 | 0.1549* | 0.0028 | -0.0064** |
| | (0.2014) | (0.1997) | (0.1877) | (0.1782) | (0.0785) | (0.0796) | (0.0027) | (0.0025) |
| $Log(Volume)_{it-1}$ | -1.448*** | -1.447*** | -1.160*** | -1.156*** | -0.3076*** | -0.3106*** | -0.0029*** | -0.0035*** |
| | (0.0943) | (0.0942) | (0.0806) | (0.0799) | (0.0366) | (0.0365) | (0.0008) | (0.0008) |
| $Log(\#\ of\ Analysts)_{it-1}$ | -1.145*** | -1.146*** | -1.271*** | -1.277*** | 0.1367 | 0.1416* | -0.0042** | -0.0045** |
| | (0.1691) | (0.1692) | (0.1509) | (0.1513) | (0.0815) | (0.0817) | (0.0020) | (0.0020) |
| $Ret_{it-1}$ | 1.240*** | 1.242*** | 1.213*** | 1.227*** | 0.0429 | 0.0314 | 0.0082*** | 0.0089*** |
| | (0.2523) | (0.2515) | (0.2416) | (0.2382) | (0.1003) | (0.1019) | (0.0024) | (0.0023) |
| Fixed-Effects: | | | | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Order Type | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Order Size | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,294,614 | 3,294,614 | 3,287,933 | 3,287,933 | 3,289,993 | 3,289,993 | 3,262,256 | 3,262,256 |
| Adjusted R2 | 0.50026 | 0.50069 | 0.13590 | 0.14042 | 0.01926 | 0.02272 | 0.18305 | 0.23543 |

To have a better understanding of the effective spread, I decompose it into price impact and realized spread.[23] Price impact typically captures the adverse selection costs generated by a trade. Based on column (4), the wholesaler orders have a significantly lower price impact than exchange orders. The retail orders are predominantly executed by wholesalers, and thus, the orders executed on exchanges are mostly institutional orders (Dyhrberg et al.,

[23]See Table A3 for more details about price impact and realized spread.

2025). It is therefore unsurprising that wholesaler orders incur lower adverse selection costs than exchange orders. This result also indicates the benefit of segregating different orders. The first analyst recommendation is associated with a 1.39 cents reduction in price impact for exchange orders. However, it barely has any sizable effect on wholesaler orders (1.415 - 1.391 = 0.024). It turns out that the first analyst recommendation mainly reduces the price impact for exchange orders which on average incur a higher adverse selection cost.

In terms of the realized spread, wholesaler orders have a higher realized spread than exchange orders. The realized spread is a composite metric that captures the cost of market making that is unrelated to adverse selection cost, and the profit made by market makers. Thus, the observed higher realized spread for wholesalers indicates a higher market-making cost, greater profit, or a combination of these two. The first analyst recommendation is associated with an increase in realized spread for exchange orders and a decrease in realized spread for wholesaler orders, both at the 1% significance level. Wholesalers have a lower effective-over-quoted spread (EFQ),[24] which means they provide a better price improvement than exchanges.

A natural question arises: why is the EFQ on exchanges below 1? The answer lies in hidden liquidity. The quoted spread used in this analysis is based on the National Best Bid and Offer (NBBO), which only reflects displayed (lit) liquidity, in round lots ($\geq$ 100 shares). However, there are also some odd-lot orders ($<$ 100 shares) on exchanges, which are likely access liquidity at better prices. These improvements are not captured in the NBBO, but are reflected in the effective spread. Because the EFQ is calculated as a share-weighted average, it can fall below 1 when such price improvements occur. Given this context, the result on EFQ is not trivial: wholesalers provide a better price improvement than exchanges even though exchanges benefit from hidden liquidity. The EFQ is further reduced for wholesaler orders after the first recommendations. However, it increases for exchange orders.

In sum, the first analyst recommendation is associated with reduced effective spread

[24] 605 reports do not incorporate quoted spread; I derive the quoted spread by using the data in 605 reports. For more details, see Table A3.

for both exchange orders and wholesaler orders. The reduction in price impact is more pronounced for exchange orders. Wholesalers provide superior price improvement, and the price improvement is further improved after the analyst recommendations for wholesaler orders. The next session explores the effect of analyst recommendations within the wholesalers market.

## VI.2 First Recommendations and Wholesaler Orders

As established in the previous section, first-time analyst recommendations are linked to reductions in effective spreads for both exchange orders and wholesaler orders. Though wholesalers provide a lower effective spread before the recommendations, the reduction in percentage is close between exchange orders and wholesaler orders (9.19% for exchange orders and 7.79% for wholesaler orders). This section takes a deeper look at the wholesaler market.

As I discussed earlier in the paper, the wholesalers market is highly concentrated - Citadel and Virtu take more than 70% of the market share.[25] This concentration has raised concerns from the SEC regarding the level of competition and pricing transparency in the retail execution space. If the two leading wholesalers (top two wholesalers thereafter) have a high market share and maintain some market power, we are likely to see a difference between the spread charged by them and by other wholesalers.

If limited competition prevents retail investors from receiving the best possible prices, then improvements in competition could lead to better execution outcomes. The first analyst recommendation can potentially improve the competition: if some market participants maintain an information advantage over others, the release of public information can level the playing field.

To illustrate this point, consider a simplified analogy: suppose several lemonade companies compete in a market, but a few have access to a secret recipe that allows them to produce superior lemonade. These firms dominate the market because of their informational

[25]For more details, see Table 1

advantage. However, once the recipe becomes public, the playing field levels—no single firm retains a competitive edge, and prices become more competitive as a result.

The wholesaler market bears resemblance to the 'lemonade' market described above. The two dominant wholesalers, Citadel and Virtu, are likely possess informational advantages over their competitors when executing retail orders. One potential source of this advantage lies in the multiple roles these firms play within the broader financial ecosystem. Take Citadel, for example: in addition to being a leading wholesaler, Citadel also operates as a high-frequency trader (HFT), a major market maker in the options market, a co-founder of the Members Exchange (MEMX), and a designated market maker (DMM) on the NYSE.

These diverse roles allow Citadel to aggregate and process vast volumes of market data across asset classes and trading venues in real time. As an HFT, Citadel can continuously analyze order flow to detect short-term supply and demand imbalances. Its presence in the options market further enhances its information advantage, given that options trading often reveals expectations about future volatility and price movements. Moreover, its infrastructure and connectivity via MEMX and its role of designated market maker at the NYSE provide additional visibility into exchange-level trading activity. Collectively, these roles may grant Citadel a significant informational edge in executing orders. The other leading wholesaler, Virtu, is also an HFT, DMM, and a leading market in the option market.

However, this advantage is not exclusive. Other wholesalers also participate in multiple segments of the market. For instance, Jane Street is both a high-frequency trader and an active player in the options market, while firms such as Merrill Lynch and Morgan Stanley have wholesaler market-making and investment banking services. While firms are required to maintain information barriers across departments, it is difficult to observe whether any intra-firm information flow occurs in practice. Because the extent of each wholesaler's information set at the time of execution is unobservable, it is difficult to measure these advantages directly. Nonetheless, if certain wholesalers consistently charge higher effective spreads and the reduction in effective spread following first-time analyst recommendations is disproportionately large for these firms, this would provide indirect evidence that their pricing previously reflected an informational advantage.

To test this Hypothesis, I focus especially on the wholesalers market. Given that Citadel and Virtu are the two largest wholesalers and are likely to possess informational advantages, I examine whether the top two wholesalers charge a higher effective spread on average and whether the association between first-time analyst recommendations and effective spread is particularly pronounced for these two firms. To do so, I estimate the following regression:

$$\textit{Effective Spread}_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{ijt}, \quad (3)$$

where $Top2_j$ is a dummy variable equal to 1 if the order is executed by Citadel or Virtu, and 0 if the order is executed by other wholesalers. Besides the controls I included in Table 5, I include one additional control, $\textit{Exchange } ES_{it}$, which represents the volume-weighted effective spread on exchanges for stock i, given a specific order type and order size in month t. This variable captures the prevailing execution cost on exchanges for comparable orders. I include $\textit{Exchange } ES_{it}$ to account for the possibility that the observed reduction in retail order effective spreads may, in part, reflect a spillover effect from the exchange-traded segment of the market. By controlling for this broader market condition, the specification isolates the incremental effect of first-time analyst recommendations on wholesaler-executed orders. Correspondingly, I control the exchange price impact, realized spread, and effective-over-quoted spread in the following regressions.

Column (1) in Table 6 presents the baseline regression results without the interaction term. The main focus of the analysis, however, lies in Column (2), which includes the interaction between the first recommendation and the top two wholesalers. The results in column (2) indicate that Citadel and Virtu, collectively referred to as the top two wholesalers, charge significantly higher effective spreads than other wholesalers before the first analyst recommendation. The coefficient on $Top2_j$ is 1.270 and statistically significant at the 1%

level, suggesting that orders executed by these two firms carry an effective spread that is 1.27 cents higher, on average.

Table 6: First Recommendations and Retail Order Execution Quality

The table estimates the effect of First Analyst Recommendation on four measures of order execution quality - Effective Spread, Realized Spread, Price Impact, and EFQ (effective-over-quoted spread) for wholesaler orders. Regression (1), (3), and (5) report coefficient estimates from regressions of the following form:

$$Order\ Execution\ Quality_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + Controls + \varepsilon_{ijt}$$

where $Order\ Execution\ Quality_{ijt}$ is the $Effective\ Spread_{ijt}$, $Price\ Impact_{ijt}$, $Realized\ Spread_{ijt}$, or $EFQ_{ijt}$. $FR$, log(*PRC*), *Volatility*, log(*Volume*), log(*Mktcap*), and log(*# of Analysts*) are as previously defined. *Exchange ES* (*Exchange Price Impact*, *Exchange RS*, *Exchange EFQ*) is the share volume weighted Effective spread (Price Impact, Realized Spread, EFQ) for stock i with a certain order type and order size on exchanges. Regressions (2), (4), and (6) report coefficient estimates from regressions of the following form:

$$Order\ Execution\ Quality_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{it}$$

$Top2_j$ takes a value of 1 if the order is executed by Citadel or Virtu and 0 if the order is executed by any other wholesalers. All models are estimated with stock, order type, order size, and month fixed effects, and the standard errors are double-clustered across stocks and year-months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | Effective Spread | | Price Impact | | Realized Spread | | EFQ | |
|---|---|---|---|---|---|---|---|---|
| $FR_{it}$ | -0.4864*** | -0.2794*** | -0.5549*** | -0.3910*** | -0.2464*** | -0.1762* | -0.0031 | -0.0061** |
| | (0.0988) | (0.0949) | (0.1240) | (0.1255) | (0.0896) | (0.0903) | (0.0026) | (0.0026) |
| $Top2_j$ | | 1.269*** | | 0.9997*** | | 0.2914*** | | 0.0267*** |
| | | (0.0861) | | (0.1184) | | (0.1008) | | (0.0035) |
| $FR_{it}$ x $Top2_j$ | | -0.6355*** | | -0.5021*** | | -0.2177** | | 0.0101*** |
| | | (0.0749) | | (0.1093) | | (0.0946) | | (0.0034) |
| $Log(PRC)_{it-1}$ | 1.084*** | 1.088*** | 1.277*** | 1.279*** | 0.6155*** | 0.6163*** | 0.0146*** | 0.0145*** |
| | (0.1347) | (0.1347) | (0.1472) | (0.1471) | (0.1047) | (0.1047) | (0.0020) | (0.0020) |
| $Vol_{it-1}$ | 2.670*** | 2.672*** | 2.699*** | 2.698*** | 1.794*** | 1.794*** | 0.0521*** | 0.0519*** |
| | (0.3169) | (0.3168) | (0.3813) | (0.3811) | (0.2768) | (0.2767) | (0.0068) | (0.0068) |
| $Log(Mktcap)_{it-1}$ | 0.4959*** | 0.4918*** | 0.4955*** | 0.4918*** | 0.2627*** | 0.2615*** | -0.0094*** | -0.0095*** |
| | (0.1042) | (0.1038) | (0.1275) | (0.1271) | (0.0849) | (0.0850) | (0.0023) | (0.0022) |
| $Log(Volume)_{it-1}$ | -0.6303*** | -0.6203*** | -0.6727*** | -0.6641*** | -0.4540*** | -0.4521*** | -0.0087*** | -0.0083*** |
| | (0.0478) | (0.0474) | (0.0570) | (0.0564) | (0.0454) | (0.0455) | (0.0011) | (0.0011) |
| $Log(\#\ of\ Analysts)_{it-1}$ | -0.6061*** | -0.6127*** | -0.7733*** | -0.7781*** | -0.1608** | -0.1620** | -0.0046** | -0.0047** |
| | (0.0921) | (0.0918) | (0.1106) | (0.1103) | (0.0770) | (0.0769) | (0.0022) | (0.0022) |
| $Ret_{it-1}$ | 0.6690*** | 0.6692*** | 0.9027*** | 0.9021*** | 0.2514*** | 0.2513*** | 0.0148*** | 0.0148*** |
| | (0.1364) | (0.1366) | (0.1795) | (0.1795) | (0.0850) | (0.0850) | (0.0021) | (0.0021) |
| Exchange $ES_{it}$ | 0.4419*** | 0.4409*** | | | | | | |
| | (0.0146) | (0.0146) | | | | | | |
| Exchange Price $Impact_{it}$ | | | 0.0985*** | 0.0982*** | | | | |
| | | | (0.0056) | (0.0055) | | | | |
| Exchange $RS_{it}$ | | | | | 0.0303*** | 0.0304*** | | |
| | | | | | (0.0034) | (0.0034) | | |
| Exchange $EFQ_{it}$ | | | | | | | 0.1377*** | 0.1376*** |
| | | | | | | | (0.0032) | (0.0032) |
| Fixed-Effects: | | | | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Order Type | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Order Size | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,331,316 | 1,331,316 | 1,330,767 | 1,330,767 | 1,330,833 | 1,330,833 | 1,330,958 | 1,330,958 |
| Adjusted R2 | 0.59023 | 0.59215 | 0.11460 | 0.11506 | 0.03227 | 0.03230 | 0.31741 | 0.31925 |

While Citadel and Virtu charge a higher effective spread, the reduction in effective spread following the first analyst recommendation is more pronounced for them. The interaction term $FR_{it} \times Top2_j$ is negative and statistically significant, indicating that spreads decline more for these two firms following the first analyst recommendation. Specifically, the first analyst recommendation is associated with a 0.28 cent reduction in effective spreads for other wholesalers, compared to a 0.91 cent reduction (0.2794 + 0.6355) for Citadel and Virtu.

In terms of the reduction in percentage, the effective spread for the top two wholesalers before the recommendations is 9.37 cents, and thus, the reduction is 9.71% (0.91/9.37). The effective spread for other wholesalers is 7.47 cents before recommendations, so the reduction for other wholesalers is 3.75% (0.28/7.47). Taken together, these findings suggest that orders executed by Citadel and Virtu are more sensitive to the information shock introduced by first-time analyst coverage.

The top two wholesalers have a higher price impact than other wholesalers. This is likely driven by the clientele difference two leading wholesalers and other wholesalers; Citadel and Virtu's clients are more sophisticated than those of other wholesalers (Dyhrberg et al., 2025). However, the reduction in price impact is more pronounced for the two leading wholesalers than for others after the analyst recommendations - the reduction in price impact is 0.89 for the top two wholesalers and 0.39 for other wholesalers, both ar 1% significance level. These results suggest that the first analyst recommendation has meaningful influence in reducing the 'toxicity' of the orders received by the top two wholesalers. I found a similar result in realized spread: the top two wholesalers charge a higher realized spread, and the reduction in realized spread is also more pronounced for them after the first analyst recommendation. The top two wholesalers have a worse EFQ spread than the others (a higher effective-over-quoted spread means worse price improvement). The EFQ declines following the first recommendation for other wholesalers, and slightly increases for the top two wholesalers. The next section provides a detailed analysis examining the variation in EFQ among wholesalers and orders in different size buckets.

This section examines changes in effective spread within the wholesalers market and finds a more pronounced reduction in effective spread for the top two wholesalers. This evidence supports the view that the first analyst recommendation mitigate the market power of these dominant firms and help level the playing field. To further investigate this mechanism, the next section analyzes changes in the market shares of the top two wholesalers.

## VI.3 Top Two Wholesalers' Market Share

If the more pronounced reduction in the effective spread charged by the top two wholesalers is because of the enhanced competition, we should expect the top two wholesalers lose market shares to their competitors. To access top two wholesalers' market share changes, I estimate the following regression:

$$\textit{Top2 Market Share}_{it} = \alpha_i + \gamma_t + \beta_1 FR_{it} + Controls + \varepsilon_{it}. \tag{4}$$

The variable $Top2\ Market\ Share_{it}$ is calculated in two ways. In the first specification, it is defined as the number of executed shares (SHS)[26] by the top two wholesalers divided by the total number of executed shares by fourteen exchanges and eight wholesalers for stock i, given a specific order type and order size. This captures the top two wholesalers' share of the total market in my sample. I incorporate exchanges' share in the denominator because brokers always have an outside option to route the orders to exchanges. In the second specification, the denominator includes only executed shares by eight wholesalers, providing a measure of the top two firms' share relative to their wholesaler peers. All other variables are defined as in earlier regressions.

The results are shown in Table 7. Following the first analyst recommendation, the top two wholesalers lose market shares to the overall market by 1.97% and lose shares by 0.37% in the wholesalers market. These results provide suggestive evidence that the top two wholesalers lose some competitive advantages after the first analyst recommendation. Since the competition primarily occurs among wholesalers, it is worthwhile to examine the market share changes in the wholesalers market more closely.

[26]For more details, see Table A3 for the definition of SHS.

In Table 6, I show that the top two wholesalers' effective spread reduces more than that of other wholesalers. In this section, I examine which groups of orders exhibit the most pronounced reduction in effective spread for the top two wholesalers. The Rule 605 reports categorize orders into size buckets: 100–499, 500–1,999, 2,000–4,999, and 5,000 shares or more.

Table 7: First Recommendations and Top 2 Wholesalers' Market Share

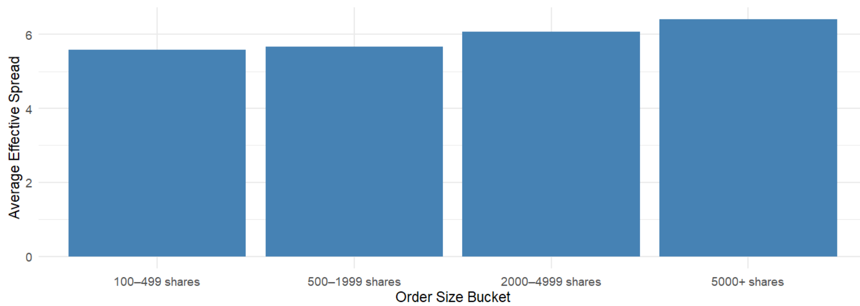
To examine whether the market share of the top 2 wholesalers changes after the first recommendations, I estimate the following regression:

$$Top2\ Market\ Share_{it} = \alpha_i + \gamma_t + \beta_1 FR_{it} + Controls + \varepsilon_{it}$$

where $Top2\ Market\ Share_{it}$ is the number of total executed shares by Citadel and Virtu to total executed shares in the overall market (both exchanges and wholesalers markets) for stock i with certain order type and order size at month t. $FR$, $Log(PRC)$, $Volatility$, $Log(Mktcap)$, $Ret$, and $Log(\#\ of\ Analysts)$ are as previously defined. I include the stock, order type, order size, and year-month fixed effect. The standard error is double-clustered across stocks and months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | Top 2 Market Share (Overall Market) | Top 2 Market Share (Wholesaler Market) |
|---|---|---|
| $FR_{it}$ | -0.0197*** | -0.0037** |
| | (0.0028) | (0.0018) |
| $Log(PRC)_{it-1}$ | 0.0408*** | -0.0023 |
| | (0.0043) | (0.0021) |
| $Vol_{it-1}$ | -0.0902*** | 0.0065* |
| | (0.0102) | (0.0033) |
| $Log(Mktcap)_{it-1}$ | -0.0622*** | -0.0032* |
| | (0.0043) | (0.0018) |
| $Log(\#\ of\ Analysts)_{it-1}$ | -0.0011 | 0.0041*** |
| | (0.0026) | (0.0015) |
| $Ret_{it-1}$ | 0.0133*** | 0.0055*** |
| | (0.0032) | (0.0018) |
| Fixed-Effects: | | |
| Stock | Yes | Yes |
| Time | Yes | Yes |
| Order Type | Yes | Yes |
| Order Size | Yes | Yes |
| Observations | 277,830 | 277,815 |
| Adjusted R2 | 0.67753 | 0.33007 |

This categorization is essential to my study, as the effective spread can vary substantially across different order sizes. In particular, large orders tend to incur higher effective spreads than small orders because they are more difficult to execute. I plot a histogram of the average effective spread across the different order size buckets in Figure 2.




The figure presents the average Effective Spread for four different order size buckets: 100-499, 500-1999, 2000-4999, and above 5000.

Figure 2: The Average Effective Spread by Order Size

The average effective spread for orders in the 100–499 share bucket and the 500–1,999 share bucket are very similar, at 5.58 cents and 5.66 cents, respectively. The average effective spreads for orders in the two larger order-size buckets are higher, at 6.08 cents and 6.41 cents. The top two wholesalers could have varying effective spreads in different order size buckets because of their economies of scale. The influence of the first analyst recommendations on the top two wholesalers' effective spread could also be different for different order size buckets. To investigate potential heterogeneous effects by order size, I conduct a subsample analysis across size categories and estimate the following regression:

$$Effective\ Spread_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{ijt}, \quad (5)$$

Based on Table 8, the effect of the first analyst recommendation on the top two wholesalers' effective spread is the most pronounced in the smallest order size bucket (100-499 shares). In that smallest order size bucket, I do not find a significant result showing that the first analyst recommendation has an influence on other wholesalers' effective spread. However, the top two wholesalers' effective spread significantly declines by 0.82 cents at 1% significance level following the first analyst recommendation.

The additional effect of the first analyst recommendation on the effective spread charged by the top two wholesalers, as captured by the coefficient of $FR_{it} \times Top2_j$, gradually diminishes as order size increases. In the largest order size bucket (5,000+ shares), the coefficient of

$FR_{it} \times Top2_j$ is not statistically significant. As shown in Table 8, the first analyst recommendation has the strongest impact on the effective spread charged by the top two wholesalers for small orders, which are most likely placed by retail investors, while its influence on large orders is negligible.

Table 8: First Recommendations and Effective Spread by Order Size

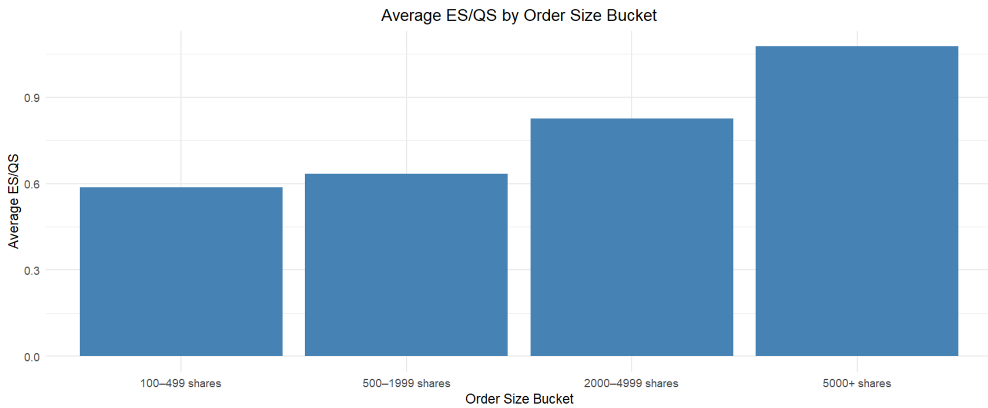
The table estimates the effect of First Analyst Recommendation on Price Improvement for different order size categories.

$$Effective\ Spread_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{ijt}$$

where *Effective Spread*$_{ijt}$ is the effective-over-quoted spread for stock i with a certain order type executed by market center j in month t. $FR$, log(*PRC*), *Volatility*, log(*Volume*), log(*Mktcap*), *Ret*, and log(*# of Analysts*) are as previously defined. *Exchange ES to QS* is the share volume-weighted effective-to-quoted spread on exchanges for stock i with certain order type and order size in year-month t. The columns from left to right present coefficient estimates for progressively larger order size buckets, ranging from the smallest (100–499 shares) to the largest (5,000+ shares). All models are estimated with stock, order type, and year-month fixed effects, and the standard errors are double-clustered across stocks and year-months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | Effective Spread (100–499) | Effective Spread (500–1999) | Effective Spread (2000–4999) | Effective Spread (5000+) |
|---|---|---|---|---|
| $FR_{it}$ | -0.1306 | -0.2717*** | -0.4509*** | -0.5569*** |
| | (0.0902) | (0.0980) | (0.1347) | (0.1522) |
| $Top2_j$ | 1.499*** | 1.674*** | 0.7515*** | 0.1288 |
| | (0.1261) | (0.0990) | (0.0976) | (0.0996) |
| $FR_{it}$ x $Top2_j$ | -0.8191*** | -0.7425*** | -0.3591*** | -0.1329 |
| | (0.1004) | (0.0842) | (0.0897) | (0.0988) |
| $\text{Log(PRC)}_{it-1}$ | 0.9247*** | 1.143*** | 1.171*** | 1.247*** |
| | (0.1315) | (0.1434) | (0.1611) | (0.1809) |
| $\text{Vol}_{it-1}$ | 2.573*** | 2.829*** | 2.693*** | 2.432*** |
| | (0.2932) | (0.3427) | (0.3934) | (0.4110) |
| $\text{Log(Mktcap)}_{it-1}$ | 0.5153*** | 0.5417*** | 0.4805*** | 0.3558** |
| | (0.0978) | (0.1096) | (0.1211) | (0.1523) |
| $\text{Log(Volume)}_{it-1}$ | -0.6025*** | -0.6648*** | -0.6476*** | -0.6113*** |
| | (0.0449) | (0.0524) | (0.0579) | (0.0659) |
| $\text{Log(\# of Analysts)}_{it-1}$ | -0.5813*** | -0.6246*** | -0.6629*** | -0.5957*** |
| | (0.0763) | (0.1009) | (0.1203) | (0.1503) |
| $\text{Ret}_{it-1}$ | 0.6213*** | 0.6002*** | 0.7635*** | 0.8550*** |
| | (0.1177) | (0.1594) | (0.1759) | (0.1594) |
| Exchange $\text{ES}_{it}$ | 0.5066*** | 0.3903*** | 0.3874*** | 0.4130*** |
| | (0.0172) | (0.0173) | (0.0176) | (0.0191) |
| Fixed-Effects: | | | | |
| Time | Yes | Yes | Yes | Yes |
| Stock | Yes | Yes | Yes | Yes |
| Order Type | Yes | Yes | Yes | Yes |
| Observations | 507,042 | 389,173 | 260,108 | 174,993 |
| Adjusted R2 | 0.62273 | 0.59574 | 0.58152 | 0.57441 |

To see a more complete picture of the competition among wholesalers, I investigate the influence of the first analyst recommendation on the effective-over-quoted spread in each order size bucket. One interesting finding in Table 6 is that the EFQ decreases for other wholesalers after the first analyst recommendation. However, it slightly increases for the two leading wholesalers. Ernst et al. (2023) find that economies of scale are more relevant for large-cap stocks, large orders, and actively traded securities—groups where execution quality (as measured by EFQ) exhibits greater variation. Since there is a great variation in order size in my sample, we are likely to observe a large difference in EFQ across different order sizes. Figure 3 presents the average ES/QS for four different order size buckets.




The figure presents the average ES/QS for four different order size buckets: 100-499, 500-1999, 2000-4999, and above 5000.

Figure 3: The Average ES/QS by Order Size

The EFQ increases monotonically with order size. The orders in the smallest size bucket have the lowest average EFQ, 0.5872, and the orders in the largest size bucket have the highest EFQ, 1.0773. The figure of EFQ above 1 means those orders are executed at a spread even worse than the quoted spread. The two leading wholesalers could provide different EFQ from others in the four order size buckets because the economies of scale are different among wholesalers. Furthermore, the effect of the first analyst recommendation on price improvement may also vary across different order sizes. To examine whether the effects vary across different order sizes, I perform a subsample analysis by order size category and estimate the following regression model:

$$EFQ_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{ijt}, \tag{6}$$

The results are shown in Table 9. I found the top two wholesalers offer superior price improvement for large orders in my sample (2,000–4,999 and 5,000+ share buckets). Specifically, they provide 0.0304 better EFQ in the 2000 - 4900 shares bucket, and 0.0806 better

EFQ in the 5000+ shares bucket. However, they offer worse price improvement for small orders—in the 100–499 and 500–1,999 share buckets: 0.0666 worse EFQ in the 100 - 499 share bucket and 0.0458 worse EFQ in the 500 - 1,999 share bucket. The two leading wholesalers provide better price improvement on large orders that are more difficult to execute, while at the same time offering relatively less favorable pricing on small orders.

Following the first analyst recommendation, the EFQ declines for other wholesalers in all size buckets, except the smallest order size bucket (100 - 499). One interesting finding in this table is that the top two wholesalers' EFQ increases following the first analyst recommendation in the two largest order size buckets. Specifically, the top two wholesalers' EFQ increases by 0.0127 (0.0258 - 0.0131) in the 2000 - 4,999 size bucket, and increases by 0.0227 (0.0363 - 0.0136) in the 5,000+ size bucket. Even though the top two wholesalers' EFQ increases after the recommendation, they still have a better EFQ compared with others. However, the gap in EFQ between the top two and the others narrows after the recommendation.

In sum, Table 8 shows that the effect of the first analyst recommendation on the effective spread is the most pronounced for the top two wholesalers on small orders they execute, but it barely has an effect on large orders they execute. Table 9 shows that the top two wholesalers' price improvement gets worse in the two large order size buckets (2000-4999 and 5000+) following the first analyst recommendation. Altogether, these two tables suggest that the top two wholesalers reduce their effective spread more than others to maintain their competitive advantage in the two small order size buckets. However, in the two large order size buckets, they lose their competitive advantage in providing price improvement following the first analyst recommendation.

Then, if other wholesalers catch up in providing better price improvement, and the top two wholesalers lose their competitive advantage in the two large order size buckets, I expect to see the two leading wholesalers lose some market share in the two large order size buckets. To investigate this, I estimate the influence of the first analyst recommendation on the top two wholesalers' market share in each order size bucket.

The results are shown in Table 10. Within the wholesalers market, the two leading wholesalers lose market shares in the largest order size bucket (above 5000 shares), where other wholesalers enhance their price improvement, and the top two wholesalers get worse price improvement after the analyst recommendation. This result provides suggestive evidence that the top two wholesalers lose market shares on orders where they lose their competitive advantage.

Table 9: First Recommendations and ES/QS by Order Size

The table estimates the effect of First Analyst Recommendation on Price Improvement for different order size categories.

$$EFQ_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{ijt}$$

where $EFQ_{ijt}$ is the effective-over-quoted spread for stock i with a certain order type executed by market center j in month t. *FR*, log(*PRC*), *Volatility*, log(*Volume*), log(*Mktcap*), *Ret*, and log(# *of Analysts*) are as previously defined. *Exchange ES to QS* is the share volume-weighted effective-to-quoted spread on exchanges for stock i with certain order type and order size in year-month t. The columns from left to right present coefficient estimates for progressively larger order size buckets, ranging from the smallest (100–499 shares) to the largest (5,000+ shares). All models are estimated with stock, order type, and year-month fixed effects, and the standard errors are double-clustered across stocks and year-months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | EFQ (100–499) | EFQ (500–1999) | EFQ (2000–4999) | EFQ (5000+) |
|---|---|---|---|---|
| $FR_{it}$ | -0.0035 | -0.0082*** | -0.0131*** | -0.0136* |
| | (0.0022) | (0.0027) | (0.0043) | (0.0073) |
| $Top2_j$ | 0.0666*** | 0.0458*** | -0.0304*** | -0.0806*** |
| | (0.0046) | (0.0043) | (0.0058) | (0.0092) |
| $FR_{it}$ x $Top2_j$ | 0.0048 | 0.0067* | 0.0258*** | 0.0363*** |
| | (0.0047) | (0.0037) | (0.0050) | (0.0084) |
| $Log(PRC)_{it-1}$ | -0.0100*** | -0.0007 | 0.0322*** | 0.0829*** |
| | (0.0019) | (0.0023) | (0.0030) | (0.0050) |
| $Vol_{it-1}$ | 0.0319*** | 0.0467*** | 0.0548*** | 0.0928*** |
| | (0.0042) | (0.0062) | (0.0125) | (0.0168) |
| $Log(Mktcap)_{it-1}$ | -0.0014 | -0.0059** | -0.0130*** | -0.0189*** |
| | (0.0019) | (0.0022) | (0.0033) | (0.0056) |
| $Log(Volume)_{it-1}$ | -0.0033*** | -0.0062*** | -0.0163*** | -0.0230*** |
| | (0.0008) | (0.0012) | (0.0019) | (0.0030) |
| Log(# of Analysts)$_{it-1}$ | -0.0047*** | -0.0062*** | -0.0057 | -0.0049 |
| | (0.0017) | (0.0021) | (0.0038) | (0.0065) |
| $Ret_{it-1}$ | 0.0102*** | 0.0125*** | 0.0186*** | 0.0134** |
| | (0.0018) | (0.0026) | (0.0041) | (0.0061) |
| Exchange $EFQ_{it}$ | 0.0357*** | 0.0128*** | 0.0335*** | 0.0752*** |
| | (0.0029) | (0.0023) | (0.0038) | (0.0061) |
| Fixed-Effects: | | | | |
| Time | Yes | Yes | Yes | Yes |
| Stock | Yes | Yes | Yes | Yes |
| Order Type | Yes | Yes | Yes | Yes |
| Observations | 506,991 | 389,109 | 259,976 | 174,882 |
| Adjusted R2 | 0.45159 | 0.29331 | 0.08079 | 0.07050 |

Table 10: Top Two Wholesalers' Market Shares by Order Size

To examine whether the market share of the top 2 wholesalers changes within each order size bucket after the first recommendations, I estimate the following regression:

$$Top2\ Market\ Share_{it} = \alpha_i + \gamma_t + \beta_1 FR_{it} + Controls + \varepsilon_{it}$$

where $Top2\ Market\ Share_{it}$ is the number of total executed shares by Citadel and Virtu to total executed shares in the wholesalers' market for stock i with a certain order type at month t. $FR$, $Log(PRC)$, $Volatility$, $Log(Mktcap)$, $Ret$ and $Log(\#\ of\ Analysts)$ are as previously defined. I include the stock, order type, order size, and month fixed effect. The standard error is double-clustered across stocks and year-months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | Top2 Shares (100–499) | Top2 Shares (500–1999) | Top2 Shares (2000–4999) | Top2 Shares (5000+) |
|---|---|---|---|---|
| $FR_{it}$ | -0.0029 | -0.0013 | -0.0043 | -0.0074** |
| | (0.0023) | (0.0023) | (0.0027) | (0.0036) |
| $Log(PRC)_{it-1}$ | -0.0077** | -0.0096*** | 0.0030 | 0.0074** |
| | (0.0032) | (0.0023) | (0.0024) | (0.0030) |
| $Vol_{it-1}$ | 0.0067 | 0.0101** | 0.0123** | -0.0116 |
| | (0.0053) | (0.0039) | (0.0055) | (0.0078) |
| $Log(Mktcap)_{it-1}$ | 0.0008 | -0.0018 | -0.0064*** | -0.0053* |
| | (0.0025) | (0.0020) | (0.0023) | (0.0029) |
| $Log(\#\ of\ Analysts)_{it-1}$ | 0.0043* | 0.0058*** | 0.0042** | 0.0013 |
| | (0.0023) | (0.0019) | (0.0020) | (0.0029) |
| $Ret_{it-1}$ | 0.0071*** | 0.0097*** | 0.0052* | -0.0016 |
| | (0.0025) | (0.0021) | (0.0028) | (0.0038) |
| Fixed-Effects: | | | | |
| Stock | Yes | Yes | Yes | Yes |
| Time | Yes | Yes | Yes | Yes |
| Order Type | Yes | Yes | Yes | Yes |
| Observations | 74,549 | 73,983 | 69,571 | 59,712 |
| Adjusted R2 | 0.52098 | 0.48325 | 0.30340 | 0.22107 |

In sum, this section explores the changes in the market share of the top two wholesalers. I found that the top two wholesalers lose market share to exchanges and other wholesalers. Within the wholesalers segment, the top two wholesalers lose market share in the largest order size buckets.

## VI.4 Pre-trends and Treatment Effect Dynamics

Analysts do not randomly choose which stocks to cover. The prior literature identifies several factors that influence analyst coverage decisions. For example, Brown et al. (2015) conducts a survey and finds that client demand for information about a company is the most important determinant. Other relevant factors include trading volume, market capitalization, and growth prospects. Since the main measure of transaction cost in this paper is the effective spread, which serves as a proxy for liquidity, these incentives are likely to be correlated with liquidity characteristics. For instance, stocks with higher client demand are often more liquid. Therefore, it is plausible that liquidity may already be improving before the release of an analyst recommendation.

However, the focus of this paper is to see the differential effect of the first analyst recommendation on different orders and to explore the potential mechanisms behind any heterogeneous effects. The key identifying assumption is that the difference in effective spreads across orders executed by different venues (exchanges versus wholesalers, and top two wholesalers versus other wholesalers) follows parallel trends in the absence of the first analyst recommendation.

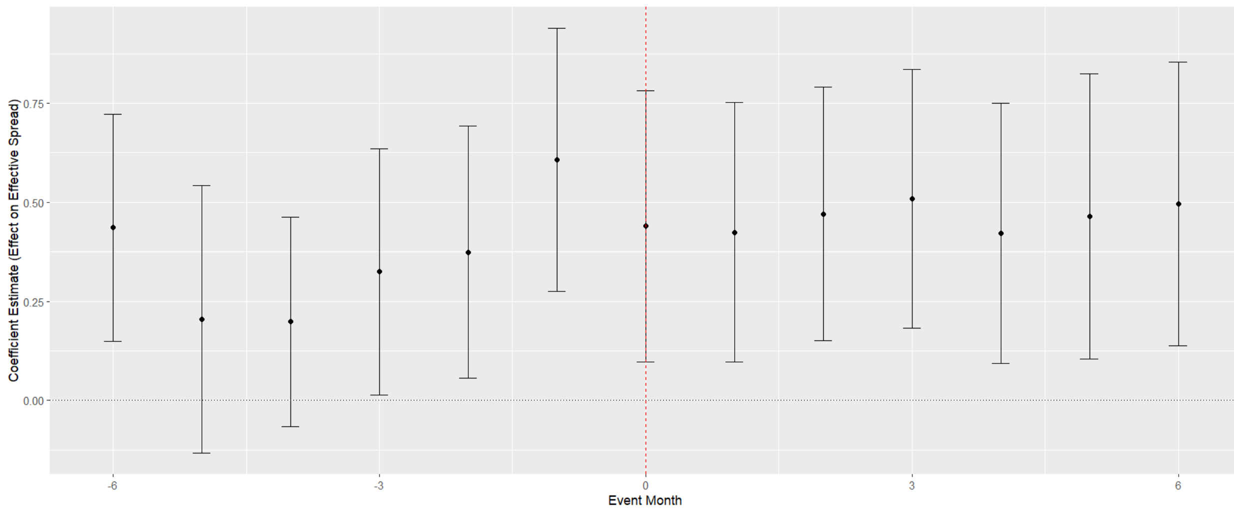
To assess this assumption in the context of exchange versus wholesaler orders, I estimate the following event-study regression:

$$\textit{Effective Spread}_{ijt} = \alpha_i + \gamma_t + \beta_1 \, \textit{WHOL}_j + \sum_{\tau} \beta_{\tau}^{(1)} T_{\tau,i} + \sum_{\tau} \beta_{\tau}^{(2)} \left( T_{\tau,i} \times \textit{WHOL}_j \right) + \text{Controls} + \varepsilon_{ijt}, \quad (7)$$

where $T_{\tau,i}$ is an indicator equal to one if observation i falls in month $\tau$ relative to the public release of the first analyst recommendation, and zero otherwise. I use a symmetric event window from $t-6$ to $t+6$ months and treat the 6-month pre-event period as the reference group (any months $< -6$). I plot the coefficients of the interaction terms in equation (7), with 95% confidence intervals Figure 4.

There is a spike in the coefficient of the interaction term at the event month. However, it does not mean the effective spread increases for wholesaler orders. It means the magnitude of reduction in effective spread is more pronounced for exchange orders than for wholesaler orders.[27] One plausible reason the spike happens one month before the recommendation is the information leakage.

[27] Table 5 shows that effective spread declines for both exchange and wholesaler orders, and the reduction is more pronounced for exchange orders.



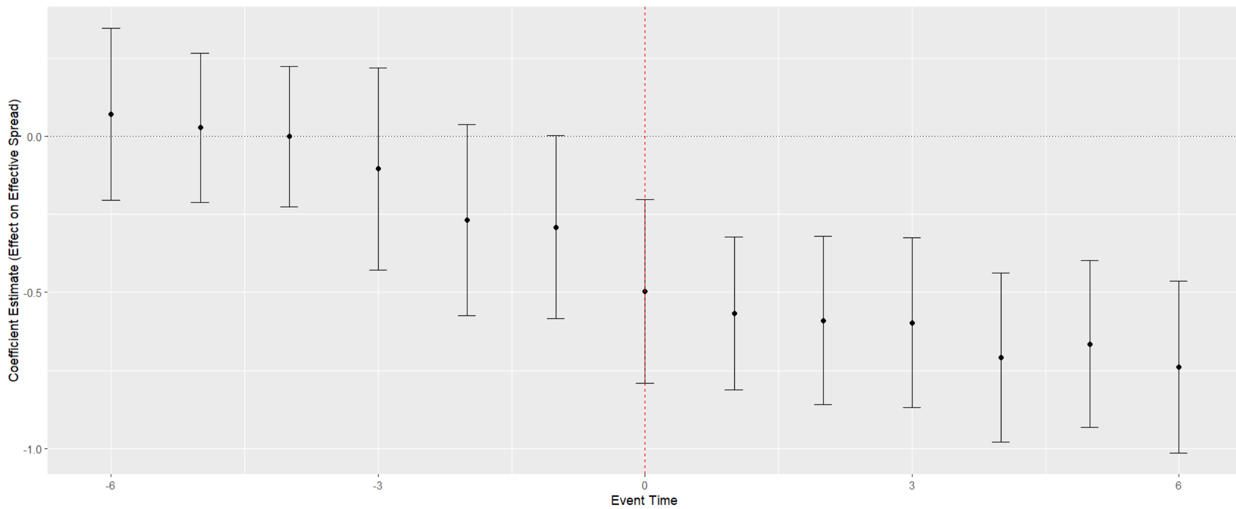

This figure reports the coefficient estimate of the effect of the first analyst recommendation on effective spread in wholesaler markets relative to exchange markets, 6 months before and after the first recommendations. The reference group in this event study is all effective spreads 6 months prior to the first recommendation (any months $< -6$).

Figure 4: Event Study on Effective Spread (Wholesalers vs Exchanges)

I next focus on the wholesalers market, and examine whether there are differential trends between the top two wholesalers and other wholesalers. To do so, I estimate the following specification:

$$Effective\ Spread_{ijt} = \alpha_i + \gamma_t + \beta_1 Top2_j + \sum_{\tau} \beta_{\tau}^{(1)} T_{\tau,i} + \sum_{\tau} \beta_{\tau}^{(2)} \left(T_{\tau,i} \times Top2_j\right) + Controls + \varepsilon_{ijt}. \tag{8}$$

Figure 5 plots the interaction coefficients. The reduction is more pronounced for the two leading wholesalers. There is a slight pre-trend before the event month. However, the coefficient does not become significant at the event month.




This figure reports the estimated coefficients of the effect of the first analyst recommendation on the effective spreads of the top two wholesalers, relative to those of other wholesalers, 6 months before and after the first recommendations. I control the share volume weighted effective spread on exchanges in the regression. The reference group in this event study is all effective spreads 6 month prior to the first recommendation (any months $< -6$).

Figure 5: Event Study on Retail Orders' Effective Spread (Top 2 vs Others)

# VII Conclusion

This paper investigates whether the first analyst recommendation influences retail investors' trading costs. Using 605 reports from 2019 to 2022, I find that the first analyst recommendations are associated with a substantial improvement in retail execution quality, specifically, a 7.79% reduction in effective spread for wholesaler orders. My finding suggests that traditional analyst reports remain a valuable information source for retail investors, even in a market increasingly shaped by social media and alternative information channels.

I explore the wholesalers market, and find the two leading wholesalers (Citadel and Virtu) experience a more pronounced reduction in effective spread compared with other wholesalers (9.71% versus 3.75%). I provide suggestive evidence that the reduction in retail trading costs is driven by improved competition among wholesalers - two leading wholesalers lose market shares to their competitors following the first recommendation. These findings highlight the potential of stock analyst reports to mitigate the effects of market concentration and information asymmetry in retail trading. While structural reforms, such as the SEC's proposed Order Competition Rule, aim to improve transparency and pricing fairness in the wholesaler market, my results suggest that expanding analyst coverage could serve as a complementary mechanism.

My paper sheds light on the role of analyst recommendations in improving pricing outcomes for retail investors, while also raising important questions for future research. For example, what specific information do some wholesalers possess that others do not, and why is this information unavailable or previously unknown to certain wholesalers? Exploring these questions would provide deeper insights into market dynamics and represents a promising avenue for future study.

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# Appendix

## Robustness Check

In the main regression, I use the effective spread in cents as my outcome variable. For completeness, here I use the effective spread in cents scaled by the closing monthly price as my outcome variable and report the regression analysis for equation (3).

Table A1: First Recommendations and Retail Order Execution Quality (Scaled by Price)

This table reports coefficient estimates from regressions of the following form:

$$Order\ Execution\ Quality_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{ijt}$$

$Top2_j$ takes a value of 1 if the order is executed by Citadel or Virtu and 0 if the order is executed by any other wholesalers. Effective Spread, Realized Spread, and Price Impact are scaled by the monthly closing price. All other variables are as previously defined.

| | Effective Spread | Price Impact | Realized Spread |
|---|---|---|---|
| $FR_{it}$ | 0.0098 | 0.0076 | -0.0058 |
| | (0.0129) | (0.0104) | (0.0090) |
| $Top2_j$ | 0.1022*** | 0.0738*** | 0.0254*** |
| | (0.0072) | (0.0105) | (0.0093) |
| $FR_{it}$ x $Top2_j$ | -0.0387*** | -0.0233** | -0.0154* |
| | (0.0073) | (0.0100) | (0.0087) |
| $Log(PRC)_{it-1}$ | -0.0912*** | 0.0270* | -0.0901*** |
| | (0.0181) | (0.0156) | (0.0135) |
| $Vol_{it-1}$ | 0.5495*** | 0.3616*** | 0.2454*** |
| | (0.0457) | (0.0474) | (0.0380) |
| $Log(Mktcap)_{it-1}$ | -0.0600*** | -0.0532*** | -0.0045 |
| | (0.0176) | (0.0162) | (0.0099) |
| $Log(Volume)_{it-1}$ | -0.1830*** | -0.1152*** | -0.0830*** |
| | (0.0108) | (0.0090) | (0.0065) |
| $Log(\#\ of\ Analysts)_{it-1}$ | -0.0067 | -0.0132 | -0.0039 |
| | (0.0120) | (0.0107) | (0.0075) |
| $Ret_{it-1}$ | 0.0851*** | 0.0594*** | 0.0396*** |
| | (0.0160) | (0.0133) | (0.0129) |
| Exchange $ES_{it}$ | 0.0129*** | | |
| | (0.0009) | | |
| Exchange Price $Impact_{it}$ | | 0.0031*** | |
| | | (0.0003) | |
| Exchange $RS_{it}$ | | | 0.0024*** |
| | | | (0.0002) |
| Fixed-Effects: | | | |
| Time | Yes | Yes | Yes |
| Stock | Yes | Yes | Yes |
| Order Type | Yes | Yes | Yes |
| Order Size | Yes | Yes | Yes |
| Observations | 1,328,480 | 1,327,931 | 1,327,997 |
| Adjusted R2 | 0.47458 | 0.06650 | 0.03097 |

Since the firms in my sample went public not long ago, there is a concern that the effect comes from the IPO rather than the first analyst recommendation. To address this concern, I control for the logarithm of the year from the firms' IPO date to the observed date.

Table A2: First Recommendations and Retail Order Execution Quality (Control for age)

This table reports coefficient estimates from regressions of the following form:

$$Order\ Execution\ Quality_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{ijt}$$

$Top2_j$ takes a value of 1 if the order is executed by Citadel or Virtu and 0 if the order is executed by any other wholesalers. Effective Spread, Realized Spread, and Price Impact are scaled by the monthly closing price. Log(Firm Age) is calculated as the logarithm of the year from the IPO date to the observed date. All other variables are as previously defined.

| | Effective Spread | Price Impact | Realized Spread |
|---|---|---|---|
| $\text{FR}_{it}$ | 0.2396*** | 0.2028 | 0.0860 |
| | (0.0884) | (0.1274) | (0.0985) |
| $\text{Top2}_j$ | 1.280*** | 1.011*** | 0.2961*** |
| | (0.0863) | (0.1186) | (0.1009) |
| $\text{FR}_{it}$ x $\text{Top2}_j$ | -0.6469*** | -0.5143*** | -0.2229** |
| | (0.0755) | (0.1104) | (0.0945) |
| $\text{Log(PRC)}_{it-1}$ | 1.059*** | 1.235*** | 0.5959*** |
| | (0.1349) | (0.1447) | (0.1053) |
| $\text{Vol}_{it-1}$ | 2.616*** | 2.608*** | 1.752*** |
| | (0.3130) | (0.3716) | (0.2781) |
| $\text{Log(Mktcap)}_{it-1}$ | 0.4927*** | 0.4886*** | 0.2598*** |
| | (0.1051) | (0.1264) | (0.0859) |
| $\text{Log(Volume)}_{it-1}$ | -0.6229*** | -0.6600*** | -0.4496*** |
| | (0.0477) | (0.0556) | (0.0457) |
| $\text{Log(\# of Analysts)}_{it-1}$ | -0.3608*** | -0.4871*** | -0.0330 |
| | (0.0953) | (0.1101) | (0.0721) |
| $\text{Ret}_{it-1}$ | 0.7045*** | 0.9357*** | 0.2652*** |
| | (0.1353) | (0.1765) | (0.0838) |
| $\log(Frim\ Age)_{it}$ | -1.284*** | -1.458*** | -0.6429*** |
| | (0.1260) | (0.1591) | (0.1282) |
| Exchange $\text{ES}_{it}$ | 0.4354*** | | |
| | (0.0146) | | |
| Exchange Price $\text{Impact}_{it}$ | | 0.0970*** | |
| | | (0.0055) | |
| Exchange $\text{RS}_{it}$ | | | 0.0304*** |
| | | | (0.0034) |
| Fixed-Effects: | | | |
| Time | Yes | Yes | Yes |
| Stock | Yes | Yes | Yes |
| Order Type | Yes | Yes | Yes |
| Order Size | Yes | Yes | Yes |
| Observations | 1,331,316 | 1,330,767 | 1,330,833 |
| Adjusted R2 | 0.59328 | 0.11564 | 0.03242 |

Table A3: Variable Definitions

| Variable | Description |
|---|---|
| **Effective Spread** | The share-weighted average effective spread in cents (605 reports record the effective spread in dollars. I convert them to cents. Effective Spread, Price Impact, and Realized Spread are all reported in cents in my paper.). |
| **Realized Spread** | The share-weighted average realized spread in cents using a five-minute horizon. |
| **Price Impact** | The Price Impact is not reported in the 605 reports. I calculated it as: $Effective\ Spread\ - Realized\ Spread$ |
| **Executed Shares (EXshs)** | The cumulative number of shares executed at the receiving market center. |
| **Away Executed Shares (AWshs)** | The cumulative number of shares executed at another venue. |
| **The Shares Executed (SHS)** | $EXshs + AWshs$ |
| **Price Improved Shares (PIshs)** | The cumulative number of shares executed with a price improvement. |
| **Price Improved Average Amount ($PI)** | The per share share-weighted average dollar amount by which prices were improved |
| **At the Quote Shares (AQshs)** | The cumulative number of shares executed at the quote. |
| **Outside the Quote Shares (OQshs)** | The cumulative number of shares executed outside the quote. |
| **Outside the Quote Average Amount ($OQ)** | The per share share-weighted average dollar amount by which prices were outside the quote. |
| **Quoted Spread** | Quoted Spread is not reported in 605 reports. I calculated the quoted spread by using the formula: $Effective\ Spread\ + 2 \cdot \frac{1}{SHS} \cdot (\$PI \cdot PIshs + 0 \cdot AQshs - \$OQ \cdot OQshs) \cdot 100$ |
| **EFQ** | Effective Spread/ Quoted Spread |
| **FR** | Indicator variable equal to 1 starting from the month the stock is first covered by an analyst, and 0 otherwise. |
| **Log(PRC)** | Natural logarithm of the stock price at the end of each month, from CRSP. |
| **Volatility** | The difference between the monthly high and low price, scaled by the monthly high price. |
| **Log(Volume)** | Natural logarithm of monthly trading volume, from CRSP. |
| **Log(Mktcap)** | Natural logarithm of market capitalization (share price multiplied by share outstanding), from CRSP. |
| **Log(# of Analysts)** | Natural logarithm of 1 plus the number of recommendations from unique analysts. |
| **Top2 Market Share (Measure 1)** | The number of executed shares (SHS) by the top two wholesalers (Citadel and Virtu), scaled by the total number of executed shares across both exchanges and wholesalers. |
| **Top2 Market Share (Measure 2)** | The number of executed shares (SHS) by the top two wholesalers (Citadel and Virtu), scaled by the total number of executed shares in the wholesaler market. |

Note: I use the same variable description as Dyhrberg et al. (2025) for EXshs, AWshs, SHS, PIshs, $PI, AQshs, OQshs, $OQ, and Quoted Spread.

## Table A4: Data Availability for Exchanges and Wholesalers

This table reports the data coverage periods for exchange and wholesaler market centers. Some market centers are missing observations because their Rule 605 reports were not available on their website during certain periods.

| **Exchange** | **Coverage Period** | **Wholesaler** | **Coverage Period** |
|---|---|---|---|
| NYSE | Jan 2020 to Aug 2020 and Jan 2022 to Dec 2022 | Citadel | Apr 2019 to Dec 2022 |
| NYSE AMER | Jan 2020 to Aug 2020 and Jan 2022 to Dec 2022 | Virtu | Jan 2020 to Dec 2022 |
| NYSE ARCA | Jan 2019 to Dec 2022 | G1 | Aug 2020 to Dec 2022 |
| BATS Exchange | Jan 2019 to Dec 2022 | UBS | Jan 2019 to Dec 2022 |
| NYSE Chicago | Nov 2019 to August 2020 and Feb 2022 to Dec 2022 | Jane Street | Jan 2019 to Dec 2022 |
| NYSE National | Jan 2020 to Aug 2020 and Feb 2022 to Dec 2022 | Two Sigma | July 2020 to Dec 2022 |
| NASDAQ | Jan 2019 to Dec 2022 | Merrill Lynch | Jan 2019 to Dec 2022 |
| NASDAQ BX | Jan 2019 to Dec 2022 | Morgan Stanley | Jan 2019 to Dec 2022 |
| NASDAQ PSX | Jan 2019 to Dec 2022 | | |
| Cobe EDGX | Jan 2019 to Dec 2022 | | |
| Cobe EDGA | Jan 2019 to Dec 2022 | | |
| Cobe BYX | Jan 2019 to Dec 2022 | | |
| IEX | Jan 2019 to Dec 2022 | | |
| MEMX | Sep 2020 to Dec 2022 | | |