Clearing the Murky Waters: The First Analyst Recommendations and Retail Trading Costs

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Abstract

Retail trading has been on the rise for the past few decades, with the COVID-19 pandemic accelerating this trend. However, there is a growing concern that stocks with high retail interest often lack analyst coverage, leaving social media—a relatively noisy source—as the primary information source for them. My research shows that the first analyst recommendations are associated with lower investors' trading costs, with a more substantial reduction in effective spreads for orders executed by wholesalers than the ones executed on exchanges. I investigate the underlying mechanism and find that the decrease in transaction costs charged by wholesalers is likely due to reduced effective spreads from the top two wholesalers—Citadel and Virtu—who lose market share relative to exchanges following these recommendations. These findings suggest that analyst recommendations provide valuable information that changes the trading environment and potentially reduces the information rents that the largest wholesalers can extract from retail traders.

JEL codes: G20, G23, G24

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

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 opaque 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 first-time analyst recommendations, as these represent a structural change in a stock's information environment.

In the classic information asymmetry model of Kyle (1985), the market maker charges a spread to compensate for the risk of trading against the insider. Since the market maker cannot distinguish between informed and noise traders, the noise traders also bear the cost

[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 exhibit high skill.

[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`

of information asymmetry through higher spreads. One assumption in the model is that the market maker can only observe the aggregated order flows and can not differentiate between informed orders and uninformed orders.

Modern markets are highly segmented. Retail orders are largely separated from institutional flows and are primarily executed off-exchange through wholesalers (Dyhrberg et al., 2025). Wholesalers, the market makers in the retail market, know the venues of the orders. Although retail orders can be informed or 'toxic', 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.

Several papers compare order execution quality in the wholesaler market versus on exchanges and find that wholesalers generally provide superior execution quality to retail orders (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 wholesaler market, where a few dominant players execute a large share of order flow. When some wholesalers possess significant market power, they may be able to charge retail investors 'unfair' prices, suggesting there is still room for retail investors to achieve better pricing.

The SEC made a lot of effort to enhance the competition and enhance pricing for retail investors, including requiring more detailed disclosure of order execution quality,[6] proposing order-by-order auctions,[7] reforming trading fees and tick sizes,[8] and a new "best execution" rule requiring brokers to execute customer trades at the most favorable terms reasonably

[6] U.S. Securities and Exchange Commission Press Release, "SEC Adopts Amendments to Enhance Disclosure of Order Execution Information," March 6, 2024. Available at: `https://www.sec.gov/newsroom/press-releases/2024-32`

[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`

[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`

available under the circumstances.[9]

My paper suggests that, in addition to restructuring and refining industry practices, encouraging analyst coverage can enhance competition and improve pricing for retail investors. I document that the trading costs decrease for both orders routed to wholesalers and orders routed to exchanges. However, the reduction is more pronounced for orders routed to wholesalers, which are mainly retail orders, than for those routed to exchanges (19.74% versus 8.12%). I also show that within the wholesalers market, the trading costs charged by the two leading wholesalers (Citadel and Virtul) decline more than the rest of the wholesalers (16.99% versus 10.27%). In other words, the first analyst recommendations lead to a more substantial reduction in trading costs for orders executed by the leading wholesalers which may maintain market power.

I use the effective spread in dollars, as reported in Rule 605 reports, 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 routed to wholesalers, while orders executed on exchanges are more likely to originate from institutional investors.[11] However, not all orders handled by wholesalers are retail, and not all exchange orders are institutional. 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".

I start my analysis by comparing the effective spread of wholesaler orders versus exchange

[9]For more details, see:
`https://www.sec.gov/rules-regulations/2025/06/regulation-best-execution`

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

[11]Dyhrberg et al. (2025)

orders. Wholesaler orders have a larger effective spread than exchange orders. This result looks counterintuitive at first glance, since the separated orders are expected to receive a lower effective spread because of the lower adverse selection costs. However, the timing of order placement likely differs between wholesaler orders and exchange orders. Exchange orders—largely from institutional investors—are often placed strategically when quoted spreads are narrower. In contrast, wholesaler orders—primarily from retail investors—are less likely to be strategically timed. According to industry participants, wholesalers do not selectively choose when and what orders to execute. Thus, the timing of these orders reflects investor decisions rather than actions taken by wholesalers.

Following the first-time analyst recommendations, the effective spread for orders routed to wholesalers decreased by nearly twice as much as for orders routed to exchanges. This difference is not merely driven by a greater reduction in quoted spreads for wholesaler orders. When I scale the effective spread by the quoted spread (the effective-over-quoted spread), I find that the decline remains more pronounced for wholesaler orders. These results highlight two important points: traditional analyst recommendations still play a significant role in today's market, and their impact is especially pronounced for wholesaler orders.

To understand why the reduction is more pronounced for 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 orders. 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 1.17 cents higher effective spread than the rest of the wholesalers. It doesn't seem like the timing difference between different groups of investors, as Citadel and Virtu 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 4% 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 others, the reduction in their effective spread following the first analyst recommendations is also more pronounced than others. 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 recommendations. I find that these wholesalers lose market share to exchanges after the first analyst recommendations. 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, the shift in market share toward exchanges suggests that the dominant wholesalers lose some of their execution advantage after the information environment improves.

Among the eight wholesalers in my sample, I find that the two leading wholesalers lose market share on orders for which they do not provide price improvement after the analyst recommendations. Citadel and Virtu provide superior price improvement on large orders, likely because of their economies of scale. However, they provide worse price improvement on small orders. After the first analyst recommendations, these two wholesalers provide more price improvement than others on small orders. However, I do not find evidence showing that they provide any price improvement on large orders. As a result, Citadel and Virtu gain market share on small orders but lose share on large orders. These results indicate that the analyst recommendations may force the dominant players to provide price improvement on orders they previously underperformed.

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

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 perfect competition, 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 examine wholesaler competition across the broad universe of stocks. In contrast, I focus on stocks which have an opaque 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. 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 et al. (2007) 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.[12] 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 focuses on the interaction between first analyst recommendations and order execution across these two distinct market segments. I find that the impact of first analyst recommendations on trading costs is heterogeneous: the reduction in trading costs following recommendations is significantly more pronounced for orders executed by wholesalers, particularly for those routed to the two leading wholesalers. This pattern provides suggestive evidence of limited competition for these stocks in the wholesaler market.

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.[13] According to industry consensus, Rule 605 reports submitted by

[12] 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.

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

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.

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. To ensure consistency and avoid autocorrelation, I restrict the sample to Class A shares.

Moreover, I focus exclusively on liquidity-demanding orders—namely, market orders and marketable limit orders—because wholesalers are required to forward liquidity-providing orders to exchanges. I trim the top and bottom 10% of the distributions for the three key execution metrics—effective spread, realized spread, and price impact—to mitigate the influence of outliers. The dataset includes 11,421 unique PERMNOs,[14] which I refer to as 'stocks'. I further restrict my sample to stocks experiencing their first analyst recommendation, which reduces the sample to 1,385 stocks. Although exchange orders are included in the analysis, the primary focus of this paper is on retail order execution. Among stocks that receive a first-time analyst recommendation, 49.56% of orders are executed by wholesalers, while 50.44% are executed on exchanges.

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 all stocks versus the subset of stocks with first analyst coverage. Panel A of Table 2 shows that Citadel and Virtu dominate retail order execution, jointly accounting for 70.31% of all retail trading volume from 2019 to 2022. The third-largest wholesaler, G1,

[14]PERMNOs are company identifiers used in CRSP.

executes 9.86% 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 70.75%. 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 (4.45%) slightly surpasses UBS (4.13%).

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: All Stocks

Wholesalers	Shares Executed, bil	Market Shares, %.
Citadel	667.32	41.18
Virtu	471.97	29.13
G1	159.85	9.86
Jane Street	124.87	7.71
UBS	87.41	5.39
Two Sigma	60.12	3.71
Merrill Lynch	31.63	1.95
Morgan Stanley	17.27	1.07

Panel B: First Covered Stocks

Wholesalers	Shares Executed, bil	Market Shares, %.
Citadel	127.51	40.35
Virtu	96.09	30.40
G1	34.51	10.92
Jane Street	23.69	7.50
Two Sigma	14.05	4.45
UBS	13.05	4.13
Merrill Lynch	5.54	1.75
Morgan Stanley	1.60	0.51

B. Measures of Order Execution Quality

The main outcome variable in this study is effective spread, 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. In contrast, 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 twice the difference between the transaction price and the midquote; for seller-initiated trades, it is twice the difference between the midquote and 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 first-time analyst recommendations affect 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. I infer price impact as the difference between the effective spread and the realized spread. This component 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 may also be interpreted as 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, we hope the ratio to be as low as possible.

In my regression analysis, I use effective spread as the primary outcome variable, as the focus of this paper is on the actual trading costs incurred by retail investors. I include effective-over-quoted spread and price impact in the tables to aid in the interpretation of the main findings based on effective spread.

B. 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). Although I follow similar filtering criteria, my definition of the first recommendation differs slightly from the concept of 'analyst initiation' in Irvine (2003) and Irvine et al. (2007). Their definition classifies an initiation as the first recommendation on a stock by a given brokerage firm and analyst, allowing for cases where a new brokerage and analyst cover the same stock, so the recommendation may not be the first recommendation a stock receives. In contrast, my study focuses on the '0 to 1' effect. Thus, I apply a stricter definition than that used in the prior literature: the first instance of a given recommendation for a stock.

Before identifying the first recommendations, I apply several filters. 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 and those made within five trading days of an earnings release ($t-5$ to $t+5$ days). The last 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 of stocks receiving first coverage and compares them with stocks listed on the NYSE, NASDAQ, and NYSE American. The analysis is conducted on stocks executed by wholesalers. This comparison helps to contextualize the sample of first covered stocks and provides a better understanding of their distinguishing features relative to the overall market. Generally, NYSE stocks are large, established blue-chip companies, while NASDAQ stocks tend to be tech-heavy and growth-oriented. In contrast, NYSE American primarily lists small to mid-cap firms.

Among these groups, the first covered stocks have the lowest median price at 10.21. The median market capitalization of the first covered stocks is actually not small; it is 419.51

million, which is higher than that on NASDAQ AND NYSE American. This is because the analysts do not random pick stocks to cover - they typically pick the large stocks with high growth prospects. While these are not the typical ‘small-cap’ stocks that retail investors often trade, my finding that analyst initiations improve liquidity for larger-cap stocks suggests the potential for even greater impact on smaller firms, whose information environments are more opaque. Notably, 71.60% of first covered stocks are listed on NASDAQ, 27.17% on NYSE, and 2.23% on NYSE American, further confirming that these firms are not disproportionately small by nature.[15]

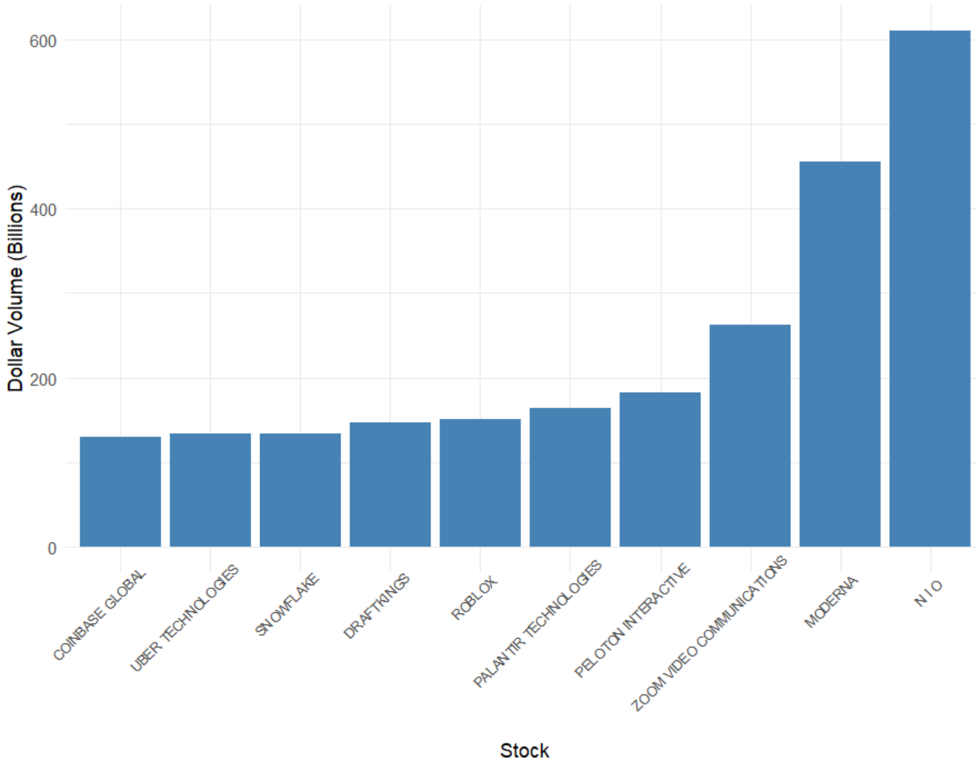
Table 2: Sample Description (Median)

The table compares some stock characteristics among stocks listed on NYSE, NASDAQ, NYSE American, and First-covered stocks.

Variable	NYSE	NASDAQ	NYSE American	First-ever Covered Stocks
Stock Price	20.10	11.01	3.91	10.21
Market Capitalization, mil.	1484.98	323.93	102.50	419.51
Total Assets, mil.	4179.00	443.06	87.23	395.46
Total Liabilities, mil.	2622.10	192.55	22.49	120.33
Capital Expenditures, mil.	84.90	3.79	1.16	3.31
Revenue, mil.	2015.48	121.86	21.36	87.37
Book to Market Ratio	1469.70	202.96	51.07	237.18

Figure 1 presents the top 10 most traded stocks by dollar volume, reflecting retail trading interest. NIO leads the list with the highest dollar volume, indicating strong engagement from retail investors. As a Chinese electric vehicle manufacturer specializing in smart, high-performance EVs, NIO is often viewed as a competitor to Tesla in the premium EV market, particularly in China. Moderna and Zoom follow in second and third place, respectively, 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. The list is dominated by technology-related stocks, including Roblox, Palantir, Snowflake, and DraftKings, which are known for their high growth potential and volatility. In addition to tech firms, retail investors also exhibit interest in fintech (Coinbase Global) and consumer-tech companies (Peloton, Uber).

[15] A similar analysis using average values is provided in the Appendix to complement the median-based results. However, as average can be inflated by mega firms, the median is a more representative figure.



This figure displays the ten most actively traded stocks by total dollar volume in the wholesaler market over the sample period. The x-axis represents the stock ticker symbols, and the y-axis shows the corresponding dollar trading volume (in billions of USD).

Figure 1: Top 10 Most Traded Stocks

Figure 2 presents the top 10 most executed stocks by share volume for each wholesaler. I use share volume instead of dollar volume to highlight the differences in market share across wholesalers in executing specific stocks. Wholesalers may specialize in executing certain stocks for various reasons, such as their role as Designated Market Makers (DMMs) on exchanges, high-frequency trading (HFT) operations, or dominance in options market-making.

The Figure reports the top 10 most executed stocks by share volume for each wholesaler.

Figure 2: Top 10 Most Executed Stocks by Wholesaler

For instance, Citadel Securities previously served as a DMM on the NYSE but exited that role in 2021. Virtu Financial acquired KCG Holdings in 2017, which was a DMM on the NYSE. In addition, both Citadel Securities and Virtu Financial are major HFT firms, leveraging ultra-fast trading strategies. Beyond equities, some wholesalers are also leading options market makers, such as Citadel Securities, Virtu Financial, and Jane Street. These factors—being a DMM, HFT firm, or options market maker—can provide certain wholesalers with informational advantages in trading specific stocks.

From Figure 2, we observe that Citadel Securities and Virtu Financial dominate in executed share volume, capturing the largest market share. However, there is notable variation in the specific stocks each wholesaler specializes in. Citadel Securities, Virtu Financial, and G1 have significantly higher execution volumes in NIO and Sundial Growers, suggesting strong engagement in these stocks. In contrast, the other wholesalers distribute their executions more evenly across different stocks, including some stocks that are not among the top 10 most traded by Citadel and Virtu. This suggests that some wholesalers concentrate on high-volume stocks, while others engage more diversely across a broader range of securities.

Table 3 presents the pairwise difference in three measures of order execution quality: effective spread (Panel A), realized spread (Panel B), and price impact (Panel C). Citadel offers a significantly lower effective spread than G1 and Jane Street but does not show a significant difference from other wholesalers. Jane Street exhibits the highest effective spread and realized spread. The reason Jane Street offers a high realized that it is earning a high profit. Instead, Jane Street, a new player who entered the market in mid-2019, has a high liquidity generation cost. Citadel and Virtu show significantly higher realized spread than Merrill Lynch and Morgan Stanley. In terms of price impact, Citadel incurs significantly higher costs than G1, Jane Street, Merrill Lynch, and Morgan Stanley, implying that Citadel faces more toxic order flow. Conversely, Merrill Lynch and Morgan Stanley experience the lowest price impact, suggesting they handle less informed order flow. It is important to note that the summary statistics are based on stock-level aggregated observations and do not control for any stock characteristics. As a result, the insights drawn from these pairwise comparisons may differ from those obtained through the formal regression analysis, which accounts for various fixed effects and control variables.

Table 3: Pairwise Difference in Order Execution Quality

The table presents pairwise comparisons across the eight wholesalers in terms of average effective spread, realized spread, and price impact. These comparisons are based on stock-level aggregated data and do not control for order type, order size, or any stock-level characteristics. Fixed effects are not included.

Panel A: Effective Spread

	Citadel	G1	Jane Street	Merrill Lynch	Morgan Stanley	Two Sigma	UBS	Virtu
Citadel	-	-	-	-	-	-	-	-
G1	-0.0095 **	-	-	-	-	-	-	-
Jane Street	-0.0119 ***	-0.0024	-	-	-	-	-	-
Merrill Lynch	-0.0041	0.0053	0.0078 *	-	-	-	-	-
Morgan Stanley	-9e-04	0.0086 **	0.011 ***	0.0033	-	-	-	-
Two Sigma	0.0023	0.0117 ***	0.0142 ***	0.0064	0.0031	-	-	-
UBS	-5e-04	0.009 **	0.0114 ***	0.0036	4e-04	-0.0028	-	-
Virtu	-0.0018	0.0076	0.01 ***	0.0023	-0.001	-0.0041	-0.0014	-

Panel B: Realized Spread

	Citadel	G1	Jane Street	Merrill Lynch	Morgan Stanley	Two Sigma	UBS	Virtu
Citadel	-	-	-	-	-	-	-	-
G1	5e-04	-	-	-	-	-	-	-
Jane Street	-0.0095 ***	-0.01 ***	-	-	-	-	-	-
Merrill Lynch	0.0073 ***	0.0069 ***	0.0169 ***	-	-	-	-	-
Morgan Stanley	0.0051 **	0.0046 *	0.0146 ***	-0.0023	-	-	-	-
Two Sigma	0.0037	0.0032	0.0132 ***	-0.0036	-0.0014	-	-	-
UBS	0.0014	9e-04	0.0109 ***	-0.006 ***	-0.0037	-0.0024	-	-
Virtu	-6e-04	-0.0011	0.0089 ***	-0.008 ***	-0.0057 ***	-0.0043	-0.002	-

Panel C: Price Impact

	Citadel	G1	Jane Street	Merrill Lynch	Morgan Stanley	Two Sigma	UBS	Virtu
Citadel	-	-	-	-	-	-	-	-
G1	-0.009 ***	-	-	-	-	-	-	-
Jane Street	-0.0021	0.0069 *	-	-	-	-	-	-
Merrill Lynch	-0.0122 ***	-0.0032	-0.0101 ***	-	-	-	-	-
Morgan Stanley	-0.0062	0.0028	-0.0041	0.006	-	-	-	-
Two Sigma	-0.001	0.008 ***	0.0011	0.0112 ***	0.0052	-	-	-
UBS	-0.0021	0.0068 **	-1e-04	0.01 ***	0.004	-0.0011	-	-
Virtu	-0.001	0.008 **	0.0011	0.0112 ***	0.0052	0	0.0012	-

V Hypotheses

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. 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 is whether the reduction in effective spread is more pronounced for retail orders or institutional orders. On one hand, institutional order flow is typically more informed than retail flow. As such, public information should reduce asymmetric information more effectively for institutional trades, leading to a larger decrease in spreads. On the other hand, there are concerns that the top two wholesalers maintain significant market power in the retail segment. If analyst recommendations reduce their informational advantage and increase competition, we may observe a larger reduction in effective spreads for retail orders. In particular, if enhanced competition is the driving force, we should see a sharper decline in the spreads charged by the top two wholesalers relative to others. The next section tests these hypotheses.

VI Regression Results

VI.1 First Recommendations and All Orders

Under the current circumstances, where there is a lot of information from social media, it is not certain that the traditional analyst recommendations still play a role. To assess the average effect of the first analyst recommendations on all orders from fourteen exchanges and eight wholesalers, I run the following regression:

$$\textit{Effective Spread}_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + Controls + \varepsilon_{ijt}, \qquad (1)$$

where *Effective Spread*$_{ijt}$ is the effective spread for stock i with certain order type and order size[16] in month t. As the focus of this paper the actual cost that retail investors incurred, I

[16] 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

chose the effective spread in dollars as my main outcome variable.

FR_{it} is a dummy variable equal to 1 starting from the month a stock is first covered by an analyst, and 0 otherwise. The control variables are $Log(PRC)_{it}$, $Volatility_{it}$, $Log(Volume)_{it}$, $Log(Mktcap)_{it}$, and $Log(\#\text{ of Analysts})_{it}$. $Log(PRC)_{it}$ is the natural log of the price at the end of each month. $Volatility_{it}$ is the difference between the highest daily price and the lowest daily price or the Bid/Ask average during the month. $Log(Volume)_{it}$ is the natural log of the market-wide trading volume in each month. $Log(\#\text{ of Analysts})_{it}$ is the natural log of 1 plus the number of unique analysts covering the stock in each month. I calculate all control variables by using the data from CRSP to capture the market-wide activity. α_i is stock plus order type and order size fixed effect. γ_t is the month fixed effect.

The control variables I add are linked to the effective spread. Higher stock prices are typically associated with lower effective spreads due to the fixed tick sizes. Greater volatility often reflects increased information flow; as a result, it tends to reduce adverse selection costs and is generally associated with lower effective spreads. Higher trading volume is indicative of greater market liquidity and is usually correlated with narrower spreads. Larger firms, measured by market capitalization, generally exhibit greater liquidity. The higher number of analysts following the firm provides more information and is related to a lower effective spread.

The results are shown in equation (1) in Table 4. The coefficient on the first recommendation indicator suggests that analyst initiations are associated with a 1.09-cent reduction in the effective spread. Given that the average effective spread in the sample is 5.39 cents, this corresponds to a 20.22% decline in execution costs. This sizable reduction highlights the economically significant role that first-time analyst recommendations can play in improving market liquidity.

In order to see the heterogeneous effect of first recommendations on effective spread of retail orders and institutional orders, I introduce a dummy variable $WHOL_j$ in the regression

- '23'; 5000 or more shares - '24'.

and interact it with FR_{it}:

$$Effective\ Spread_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 WHOL_j + \beta_3 FR_{it} \times WHOL_j + Controls + \varepsilon_{ijt}, \quad (2)$$

where $WHOL_j$ is a dummy variable equals 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.

The results in equation (2) indicate that first-time analyst recommendations are associated with a lower effective spread for both institutional and retail orders. However, the magnitude of the reduction is greater for retail orders. Specifically, the effective spread for institutional orders decreases by 0.56 cents, while the spread for retail orders declines by 1.56 cents (0.56 + 1.00). This reduction for retail orders is more than twice that observed for institutional orders. Given that the average effective spread is 5.06 cents for institutional orders and 5.70 cents for retail orders, the percentage reduction is approximately 11.07% for institutional orders and 27.37% for retail orders. These findings suggest that retail investors benefit more, in relative terms, following an analyst's first recommendation.

Table 4: First Recommendations and Order Execution Quality

The table estimates the effect of First Analyst Recommendation on three measures of order execution quality - effective spread, effective-over-quoted spread, and price impact. 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 $Effective\ Spread_{ijt}$ (ES/QS_{ijt}, $Price\ Impact_{ijt}$) is the effective spread (effective-over-quoted spread, price impact) 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 unique analysts covering the stock. I use CRSP value for $Volatility$ and $Log(Volume)$ to capture the market-wide activity. Regressions (2), (4), and (6) report coefficient estimates from regressions of the following form:

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

$WHOL_j$ 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 month fixed effects, and the standard errors are double-clustered across stocks and months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Effective Spread (Dollars)		ES/QS		Price Impact (Dollars)	
	(1)	(2)	(3)	(4)	(5)	(6)
FR_{it}	-0.0109***	-0.0056***	-0.0009	0.0084***	-0.0086***	-0.0091***
	(0.0013)	(0.0011)	(0.0009)	(0.0012)	(0.0011)	(0.0010)
$WHOL_j$		0.0190***		-0.1487***		-0.0115***
		(0.0021)		(0.0026)		(0.0013)
FR_{it} x $WHOL_j$		-0.0100***		-0.0166***		0.0008
		(0.0017)		(0.0019)		(0.0012)
$Log(PRC)_{it}$	0.0178***	0.0171***	0.0051***	0.0045***	0.0158***	0.0161***
	(0.0024)	(0.0024)	(0.0013)	(0.0010)	(0.0018)	(0.0018)
$Volatility_{it}$	0.0659***	0.0682***	0.0538***	0.0232***	0.0621***	0.0607***
	(0.0048)	(0.0050)	(0.0038)	(0.0022)	(0.0043)	(0.0042)
$Log(Mktcap)_{it}$	0.0098***	0.0108***	0.0052***	-0.0036***	0.0086***	0.0080***
	(0.0014)	(0.0015)	(0.0014)	(0.0009)	(0.0012)	(0.0012)
$Log(Volume)_{it}$	-0.0130***	-0.0129***	-9.52e-6	0.0006	-0.0088***	-0.0090***
	(0.0007)	(0.0007)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
$Log(\#\ of\ Analysts)_{it}$	-0.0016	-0.0014	-0.0041***	-0.0050***	-0.0002	-0.0003
	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0008)	(0.0008)
QS			-0.1979***	-0.0543***		
			(0.0125)	(0.0065)		
Fixed-Effects:						
Time	Yes	Yes	Yes	Yes	Yes	Yes
Stock	Yes	Yes	Yes	Yes	Yes	Yes
Order Type	Yes	Yes	Yes	Yes	Yes	Yes
Order Size	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,548,378	3,548,378	3,548,378	3,548,378	3,548,378	3,548,378
Adjusted R2	0.42668	0.43165	0.43935	0.45545	0.37973	0.49022

One interesting finding in column (2) is the positive coefficient on $WHOL_j$, indicating that retail orders tend to have higher effective spreads than institutional orders. At first glance, this result appears counterintuitive. Retail investors are generally considered less informed than institutional investors, so market makers should, in theory, charge them lower spreads. One plausible reason for this result is the timing of the trades. The institutional investors are more likely to time the market and place their orders when the quoted spread is narrow. However, retail investors are less likely to time the market and thus place their orders while the quoted spread is wide (?). Thus, if retail investors place their orders while the quoted spread is wide, they are likely to receive a higher effective spread than institutional orders.

To take into account contemporaneous quoted spreads, I introduce an alternative execution quality measure: the effective-over-quoted spread (hereafter EFQ), a standard metric for price improvement. Basically, I scale the effective spread by using the quoted spread.[17] EFQ scales the effective spread by the quoted spread, where the quoted spread reflects the advertised cost and the effective spread captures the realized cost. Thus, EFQ measures the extent to which actual trading costs deviate from advertised costs, and a lower EFQ indicates better price improvement.

Regression results are presented in columns (3) and (4). While column (3) shows no significant impact of first-time analyst recommendations on EFQ overall, column (4) reveals a differential effect by investor type: EFQ declines for retail orders but increases for institutional orders following the recommendation. This suggests that retail investors benefit from improved price execution, whereas institutional investors face worsened price improvement after the event. And this is likely because the retail orders are less informed than institutional orders - in column (6), I show that retail orders have a lower price impact than institutional orders. Thus, wholesalers are willing to give retail investors a better price improvement as their orders are less 'toxic'.

A natural question arises: why is the EFQ on exchanges not equal to 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 may 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

[17] See appendix for the definition of quoted spread

average, it can fall below 1 when such price improvements occur.

Given this context, the result in column (4) is not trivial: wholesalers offer a 14.78% lower EFQ than exchanges, even if exchanges benefit from hidden liquidity. Moreover, wholesalers provide even greater price improvement for retail orders following analyst initiations, highlighting the role of the first analyst recommendations in enhancing execution quality for retail investors.

VI.2 First Recommendations and Retail Orders

As established in the previous section, first-time recommendations are linked to reductions in effective spreads for both institutional and retail orders, with a notably larger effect for retail trades. This section takes a deeper look at the wholesalers market and investigates the plausible explanations for the disproportionate impact on retail orders.

As I discussed earlier in the paper, the wholesaler market is rather concentrated - Citadel and Virtu take 70% of the market share.[18] This concentration has raised concerns from the SEC regarding the level of competition and pricing transparency in the retail execution space. If limited competition prevents retail investors from receiving the best available prices, then improvements in competition could lead to better execution outcomes. This raises the question of whether first-time analyst recommendations can play a role in enhancing competition among wholesalers—and if so, through what mechanisms.

The wholesaler market bears resemblance to the 'lemonade' market described above. The two dominant wholesalers—Citadel and Virtu—may 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 is also a leading market maker in the option market (Bryzgalova et al., 2023), a high-frequency trade (HFT), a co-founder of the Members Exchange (MEMX), and was previously a designated market maker (DMM)

[18]For more details, see Table 1.

on 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 historical role at the NYSE provide additional visibility into exchange-level trading activity. Collectively, these roles may grant Citadel a significant informational edge in executing orders.

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 combine wholesale market making with institutional execution 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 charge consistently higher effective spreads—and if 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 specifically on the wholesaler market. Given that Citadel and Virtu are the two largest wholesalers and are likely to possess informational advantages, I examine whether the association between first-time analyst recommendations and trading costs 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. I include an additional control variable, $Exchange\ ES_{it}$, 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 $Exchange\ ES_{it}$ 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 retail orders.

Equation (1) in Table 5 presents the baseline regression results without the interaction term. The positive coefficient of FR_{it} in column (1) indicates that the first analyst recommendations reduce the effective spread for overall orders. The main focus of the analysis, however, lies in Equation (2), which includes the interaction between first-time recommendations and the top two wholesalers. The results indicate that Citadel and Virtu—collectively referred to as the top two wholesalers—charge significantly higher effective spreads than other wholesalers. The coefficient on $Top2_j$ is 0.0143 and statistically significant at the 1% level, suggesting that orders executed by these two firms carry an effective spread that is 1.43 cents higher, on average.

While Citadel and Virtu tend to charge higher spreads on average, the association between first-time analyst recommendations and reduced spreads is also more pronounced for them. The interaction term $FR_{it} \times Top2_j$ is negative and statistically significant, indicating that spreads charged by these two firms decline more following analyst initiations. Specifically, first-time recommendations are associated with a 0.75 cent reduction in effective spreads for other wholesalers, compared to a 1.58 cent reduction (0.75 + 0.83) for Citadel and Virtu. 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.

Table 5: First Recommendations and Retail Order Execution Quality

The table estimates the effective of First Analyst Recommendation on three measures of order execution quality - Effective Spread, Realized Spread, and Price Impact for retail 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 *Effective Spread*$_{ijt}$ (*Realized Spread*$_{ijt}$, *Price Impact*$_{ijt}$), FR, log(*PRC*), *Volatility*, log(*Volume*), log(*Mktcap*), and log(*# of Analysts*) are as previously defined. *Exchange ES* is the share volume weighted Effective spread on exchanges, *Exchange RS* is the share volume weighted Realized Spread on exchanges, and *Exchange PI* is the share volume weighted Price Impact on exchanges. *QS* is the contemporaneous quoted spread. Regressions (2), (4), and (6) report coefficient estimates from regressions of the following form:

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

$Top2_j$ 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. All models are estimated with stock, order type, order size, and month fixed effects, and the standard errors are double-clustered across stocks and months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Effective Spread (Dollars)		ES/QS		Price Impact (Dollars)	
	(1)	(2)	(3)	(4)	(5)	(6)
FR_{it}	-0.0101***	-0.0075***	-0.0115***	-0.0101***	-0.0104***	-0.0086***
	(0.0018)	(0.0017)	(0.0034)	(0.0030)	(0.0016)	(0.0016)
Top2		0.0143***		0.0399***		0.0111***
		(0.0010)		(0.0038)		(0.0013)
FR_{it} x Top2		-0.0083***		-0.0043		-0.0058***
		(0.0009)		(0.0061)		(0.0012)
Log(PRC)_{it}	0.0093***	0.0093***	0.0139**	0.0138**	0.0123***	0.0123***
	(0.0021)	(0.0021)	(0.0064)	(0.0064)	(0.0019)	(0.0019)
Volatility_{it}	0.0338***	0.0338***	0.0698***	0.0699***	0.0371***	0.0371***
	(0.0041)	(0.0041)	(0.0139)	(0.0139)	(0.0045)	(0.0044)
Log(Mktcap)_{it}	0.0078***	0.0078***	-0.0059	-0.0059	0.0065***	0.0065***
	(0.0014)	(0.0014)	(0.0047)	(0.0047)	(0.0013)	(0.0013)
Log(Volume)_{it}	-0.0080***	-0.0078***	-0.0076***	-0.0069***	-0.0078***	-0.0077***
	(0.0007)	(0.0007)	(0.0025)	(0.0025)	(0.0006)	(0.0006)
$\text{Log(\# of Analysts)}_{it}$	2.58e-5	5.12e-5	-0.0134***	-0.0132***	0.0004	0.0004
	(0.0010)	(0.0010)	(0.0046)	(0.0046)	(0.0013)	(0.0013)
Exchange ES_{it}	0.6965***	0.6943***				
	(0.0232)	(0.0232)				
$\text{Exchange ES to QS}_{it}$			0.0848**	0.0842**		
			(0.0359)	(0.0360)		
QS			-0.1641***	-0.1672***		
			(0.0487)	(0.0485)		
$\text{Exchange Price Impact}_{it}$					0.2021***	0.2013***
Fixed-Effects:						
Time	Yes	Yes	Yes	Yes	Yes	Yes
Stock	Yes	Yes	Yes	Yes	Yes	Yes
Order Type	Yes	Yes	Yes	Yes	Yes	Yes
Order Size	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,408,060	1,408,060	1,407,930	1,407,930	1,408,060	1,408,060
Adjusted R2	0.55326	0.55505	0.00552	0.00555	0.10345	0.10391

So far, I have shown that first-time analyst recommendations reduce the effective spread for retail orders overall, with a more pronounced reduction observed for orders executed by the top two wholesalers. This finding is consistent with the notion that such recommendations diminish the information advantage previously held by these dominant wholesalers, thereby increasing market competition and lowering the spreads they charge. However, the results in column 6 suggest an alternative interpretation. Orders routed to the top two wholesalers exhibit a higher price impact compared to those routed to other wholesalers, indicating that these orders are more informed. This is plausible, as the client base of the top two wholesalers is likely more sophisticated than that of their competitors (?). Consequently, first-time analyst recommendations may enhance the information set of the top wholesalers to a greater extent, which could explain the more substantial decline in spreads. To further explore these mechanisms, I examine the market share changes for the top two wholesalers in the next section.

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' market share to decrease after the first analyst recommendations. To access top two wholesalers' market share changes, I estimate the following regression:

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

The variable $Top2\ Market\ Share_{it}$ is calculated in two ways. In the first specification, it is defined as the number of shares executed (SHS)[19] by the top two wholesalers divided by the total number of shares executed by both exchanges and wholesalers for stock i, conditional on a specific order type and order size. This captures the top two wholesalers' share of the total market. In the second specification, the denominator includes only shares executed by all wholesalers, providing a measure of the top two firms' share relative to their wholesaler peers. All other variables are defined as in earlier regressions.

Under the first specification, Table 6 shows that the top two wholesalers' market share declines by 1 percentage point following the first recommendation. However, under the second specification—restricted to wholesaler activity—the effect is not statistically significant.

[19] For more details, see appendix for the definition of SHS.

These results suggest that, conditional on order type and size (controlled via fixed effects), Citadel and Virtu Financial lose market share to exchanges, but not to other wholesalers.

However, does this imply that the top two wholesalers are not losing market share within the wholesaler segment at all? 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. The Rule 605 reports categorize orders into size buckets: 0–499, 500–1,999, 2,000–4,999, and 5,000 shares or more. Figure displays the average EFQ across these size buckets. The EFQ increases monotonically with order size, indicating that larger orders tend to receive worse price improvement.

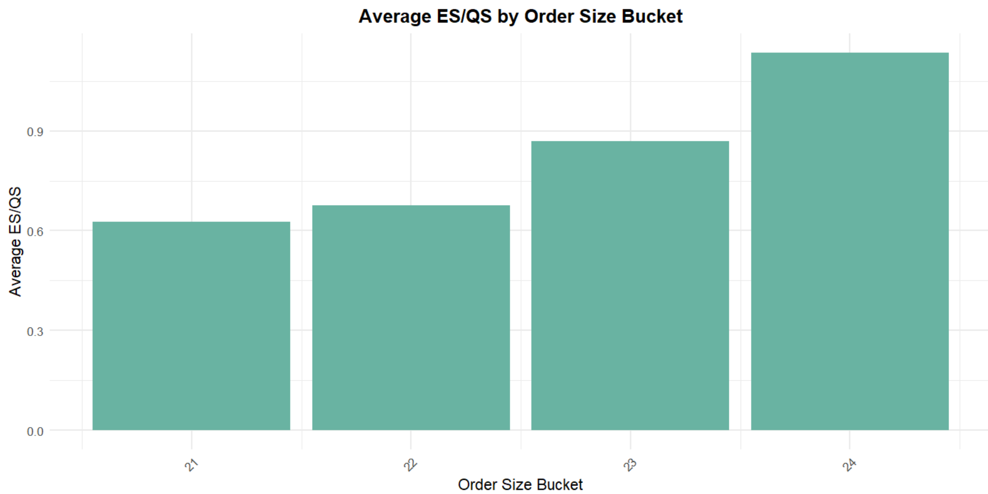
Table 6: First Recommendations and Top 2 Wholesalers' Market Share

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

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

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, $Log(PRC)$, $Volatility$, $Log(Volume)$, $Log(Mktcap)$, and $Log(\#\ of\ Analysts)$ are as previously defined. I incorporated a new control variable $Log(Retail\ Volume)$, which is the natural log of retail trading volume in stock i at month t. I control for the total retail trading volume instead of the total CRSP trading volume because the changes in the retail trading volume likely drive the changes in the top 2 wholesalers' market shares. I use the stock, order type, order size, and 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}	-0.0109***	-9.59e-6
	(0.0023)	(0.0020)
$Log(PRC)_{it}$	0.0344***	-0.0004
	(0.0044)	(0.0018)
$Volatility_{it}$	-0.0588***	0.0257***
	(0.0091)	(0.0072)
$Log(Mktcap)_{it}$	-0.0520***	-0.0012
	(0.0046)	(0.0017)
$Log(\#\ of\ Analysts)_{it}$	-0.0168***	-0.0002
	(0.0032)	(0.0016)
$Log(Volume)_{it}$	-0.0072***	-0.0028***
	(0.0012)	(0.0010)
Fixed-Effects:		
Time	Yes	Yes
Stock	Yes	Yes
Order Type	Yes	Yes
Order Size	Yes	Yes
Observations	300,815	298,467
Adjusted R2	0.67052	0.27457



The figure present the average ES/QS for four different order size buckets: 1-499, 500-1999, 2000-4999, and above 5000.

Figure 3: The Average ES/QS by Order Size

Then, it is likely that the top two wholesalers provide different price improvements than others across different size buckets. Furthermore, the effect of first-time analyst recommendations on price improvement may also vary across different order sizes. To investigate potential heterogeneous effects by order size, I conduct a subsample analysis across size categories and estimate the following regression:

$$\frac{\mathrm{ES}_{ijt}}{\mathrm{QS}_{ijt}} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{ijt}, \tag{5}$$

The results are presented in Table 7. I find that the top two wholesalers offer worse price improvement for small orders—in the 0–499 and 500–1,999 share buckets—but provide better price improvement for larger orders in the 2,000–4,999 and 5,000+ share buckets. In particular, they deliver 9.85% and 7.02% worse price improvement for the two smallest buckets, while offering 3.56% and 13.12% better price improvement for the two largest buckets. These results suggest that the top two wholesalers tend to offer more favorable pricing for orders that are harder to execute, while offering less favorable pricing for small orders, which are easier to improve upon.

Regarding the effect of first-time analyst recommendations, I find that they reduce the

ES/QS ratio for the first three order size buckets, but not significantly for the largest bucket—though the coefficient remains negative. Moreover, the interaction term reveals that the price improvement effect is particularly pronounced for the smallest orders executed by the top two wholesalers.

In summary, the top two wholesalers provide better price improvement for larger, more difficult-to-execute orders, but worse improvement for smaller, easier orders. First-time analyst recommendations generally enhance price improvement for orders up to 5,000 shares, with the strongest additional effect observed among small orders handled by the top two wholesalers.

Table 7: 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.

$$\frac{\text{ES}_{ijt}}{\text{QS}_{ijt}} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 Top2_j + \beta_3 FR_{it} \times Top2_j + Controls + \varepsilon_{ijt}$$

where ES/QS_{ijt} is the effective-over-quoted spread for stock i with a certain order type 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. $Top2_j$ 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. $log(PRC)$ 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 unique analysts covering the stock. I use CRSP value for $Volatility$ and $Log(Volume)$ to capture the market-wide activity. QS is the contemporaneous quoted spread. *Exchange ES to QS* is the share volume-weighted effective-to-quoted spread on exchanges. The columns from left to right present coefficient estimates for progressively larger order size buckets, ranging from the smallest (0–499 shares) to the largest (5,000+ shares). All models are estimated with stock, order type, and month fixed effects, and the standard errors are double-clustered across stocks and months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	ES/QS (0–499)	ES/QS (500–1999)	ES/QS (2000–4999)	ES/QS (5000+)
FR_{it}	-0.0061***	-0.0114***	-0.0189**	-0.0096
	(0.0021)	(0.0027)	(0.0092)	(0.0203)
Top2	0.0985***	0.0702***	-0.0356***	-0.1312***
	(0.0040)	(0.0032)	(0.0084)	(0.0208)
FR_{it} x Top2	-0.0085**	-0.0010	0.0200*	0.0087
	(0.0032)	(0.0030)	(0.0119)	(0.0423)
Volatility_{it}	0.0286***	0.0221***	0.0495	0.2331***
	(0.0051)	(0.0081)	(0.0484)	(0.0614)
Log(PRC)_{it}	-0.0071***	0.0040*	0.0021	0.0734***
	(0.0023)	(0.0024)	(0.0231)	(0.0140)
Log(Mktcap)_{it}	-0.0012	-0.0057***	0.0108	-0.0046
	(0.0023)	(0.0018)	(0.0119)	(0.0072)
Log(Volume)_{it}	-0.0005	-0.0013	-0.0245***	-0.0765**
	(0.0009)	(0.0013)	(0.0072)	(0.0355)
$\text{Log(\# of Analysts)}_{it}$	-0.0113***	-0.0096***	-0.0251**	0.0101
	(0.0019)	(0.0023)	(0.0100)	(0.0217)
Exchange ES to QS_{it}	0.0487***	0.0073	-0.0277	0.1642
	(0.0063)	(0.0111)	(0.0187)	(0.2080)
QS	-0.0019	0.0065	-0.2062***	-1.313**
	(0.0089)	(0.0101)	(0.0316)	(0.5216)
Fixed-Effects:				
Time	Yes	Yes	Yes	Yes
Stock	Yes	Yes	Yes	Yes
Order Type	Yes	Yes	Yes	Yes
Observations	534,923	418,106	275,470	179,431
Adjusted R2	0.37531	0.30109	0.00044	0.00450

Although Table 6 shows no evidence that these wholesalers are losing market share to their peers, it is possible they lose shares on the orders that they do not offer additional price improvement. To check the top two wholesalers' market share changes, I estimate equation (4) again within each order size bucket. The results are shown in Table 8.

I find that the top two wholesalers' market share increases by 0.66% in the smallest order size bucket, where they offer significantly better price improvement, and by 0.37% in the second bucket. In contrast, their market share declines by 1.05% in the largest size bucket, where they do not provide price improvement. These results suggest that although there is no overall evidence of market share loss for the top two wholesalers, they do lose share in segments where they do not provide additional price improvement after the first analyst recommendations.

Table 8: 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:

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

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 a certain order type at month t. FR, $Log(PRC)$, $Volatility$, $Log(Volume)$, $Log(Mktcap)$, and $Log(\#\ of\ Analysts)$ are as previously defined. I incorporated a new control variable $Log(Retail\ Volume)$, which is the natural log of retail trading volume in stock i at month t. I control for the total retail trading volume instead of the total CRSP trading volume because the changes in the retail trading volume likely drive the changes in the top 2 wholesalers' market shares. I use the stock, order type, order size, and 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.

	Top2 Shares (0–499)	Top2 Shares (500–1999)	Top2 Shares (2000–4999)	Top2 Shares (5000+)
FR_{it}	0.0066**	0.0037*	-0.0040	-0.0105***
	(0.0030)	(0.0019)	(0.0025)	(0.0031)
$Log(PRC)_{it}$	-0.0089***	-0.0031	0.0044*	0.0070**
	(0.0027)	(0.0020)	(0.0023)	(0.0028)
$Volatility_{it}$	0.0299***	0.0213***	0.0249***	0.0268**
	(0.0079)	(0.0078)	(0.0083)	(0.0101)
$Log(Mktcap)_{it}$	0.0039*	-0.0021	-0.0042*	-0.0010
	(0.0021)	(0.0017)	(0.0021)	(0.0028)
$Log(Volume)_{it}$	-0.0062***	-0.0010	-0.0005	-0.0066***
	(0.0016)	(0.0012)	(0.0011)	(0.0014)
Fixed-Effects:				
Stock	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Order Type	Yes	Yes	Yes	Yes
Observations	80,441	79,801	74,786	63,439
Adjusted R2	0.47345	0.44355	0.24197	0.16852

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.

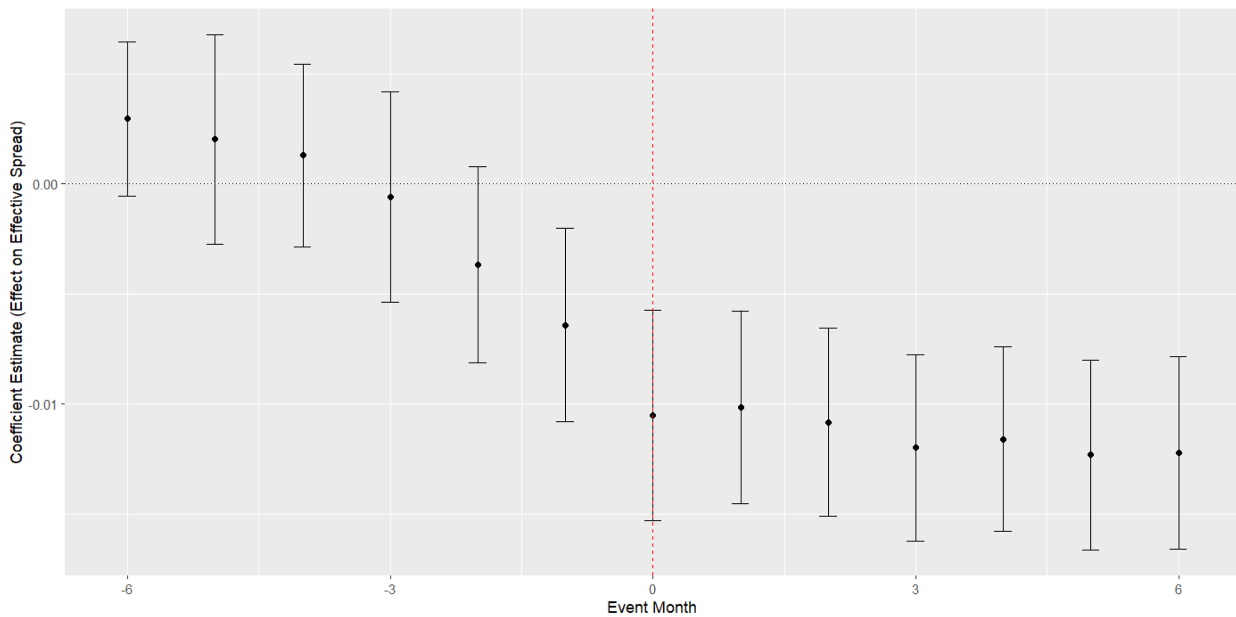
However, the goal of this paper is not to establish a general causal relationship between analyst initiations and effective spreads. Instead, the objective is to identify which group of investors is more affected by first-time analyst coverage and to explore the potential mechanisms behind any heterogeneous effects. The key identifying assumption is that the difference in effective spreads across investor groups follows parallel trends in the absence of the analyst initiation.

To assess this assumption in the context of exchange-routed versus wholesaler-executed orders (Model 2), I estimate the following event-study regression:

$$\textit{Effective Spread}_{ijt} = \alpha_i + \gamma_t + \beta_1 \, WHOL_j + \sum_{\tau} \beta_\tau^{(1)} T_{\tau,i} + \sum_{\tau} \beta_\tau^{(2)} \left(T_{\tau,i} \times \, WHOL_j\right) + \text{Controls} + \varepsilon_{ijt}, \tag{6}$$

where $T_{\tau,i}$ is an indicator equal to one if observation i falls in month τ 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 also include an additional indicator equal to one for all observations beyond +6 months to account for long-term trends. I plot the coefficients of the interaction terms in Figure 4.

The interaction coefficients $T_{\tau,i} \times WHOL_j$ exhibit some pre-trend, but they do not become statistically significant until one month prior to the public release of the recommendation. One potential explanation is that brokerages may share reports with institutional clients before making them publicly available. Since I define the event month as the month of public dissemination, some of the observed effects could begin earlier.



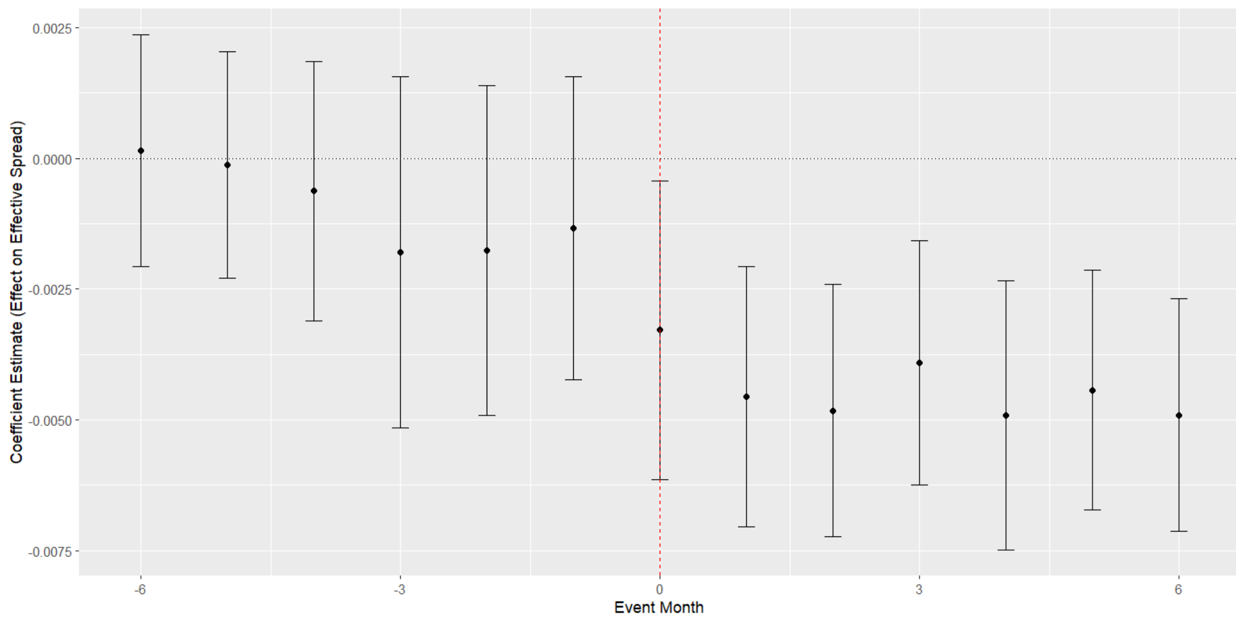
This figure reports the coefficient estimate of the effect of first recommendations on effective spread in wholesaler markets relative to exchange markets, 6 months before and after the first recommendations. The reference group in this event study is all effective spreads 6 months prior to the first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

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

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

$$Effective\ Spread_{ijt} = \alpha_i + \gamma_t + \beta_1 Top2_j + \sum_{\tau} \beta_{\tau}^{(1)} T_{\tau,i} + \sum_{\tau} \beta_{\tau}^{(2)} \left(T_{\tau,i} \times Top2_j\right) + Controls + \varepsilon_{ijt}. \tag{7}$$

Figure 5 plots the interaction coefficients. After controlling for the volume-weighted effective spread on exchanges, there is no statistically significant difference in effective spreads between the top two wholesalers and other wholesalers prior to the analyst initiation. However, at the event month, the effective spread for the top two wholesalers drops sharply and remains lower in subsequent months.



This figure reports the estimated coefficients of the effect of first analyst recommendations 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 months prior to the first recommendations.

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

VII Conclusion

This paper investigates whether first-time analyst recommendations influence retail investors' trading costs. Using Rule 605 order-level data from 2019 to 2022, I find that the first analyst recommendations are associated with a substantial improvement in retail execution quality—specifically, a 27.37% reduction in effective spreads for retail orders, compared to a 11.07% reduction for institutional orders. These findings suggest 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 provide suggestive evidence that this reduction in retail trading costs is driven by improved competition among wholesalers. Citadel and Virtu, which dominate the retail execution landscape, exhibit the most pronounced declines in effective spreads following analyst recommendations. Moreover, their relative market share declined after the first recommendations, consistent with the competition mechanism. 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.

However, this paper has several limitations. Since we cannot observe the wholesalers' information sets, it is difficult to identify exactly what information some wholesalers possess that others do not. While I argue that analyst reports help inform the less informed wholesalers, I am unable to pinpoint the specific content of that information or explain why it was previously unknown to certain wholesalers. These are important and interesting questions that warrant further investigation in future research.

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Appendix

Robustness Check

In the main regression, I use the effective spread in dollars as my outcome variable. For completeness, here I use the effective spread scaled by closing monthly price as my outcome variable and report the regression analysis for equations (1) and (2).

Table A1: First Recommendations and Effective Spread (scaled by price)

The table estimates the effect of First Analyst Recommendation effective spread scaled by price. Regression (1) report coefficient estimates from regressions of the following form:

$$\textit{Effective Spread}_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + Controls + \varepsilon_{ijt}$$

where $\textit{Effective Spread}_{ijt}$ is the effective 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 unique analysts covering the stock. I use CRSP value for $Volatility$ and $Log(Volume)$ to capture the market-wide activity. Regressions (2), (4), and (6) report coefficient estimates from regressions of the following form:

$$\textit{Effective Spread}_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + \beta_2 WHOL_j + \beta_3 FR_{it} \times WHOL_j + Controls + \varepsilon_{ijt}$$

$WHOL_j$ 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 month fixed effects, and the standard errors are double-clustered across stocks and months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Effective Spread over Price	
	(1)	(2)
FR_{it}	7.71e-5	0.0004***
	(0.0001)	(0.0001)
$WHOL_j$		-0.0002
		(0.0001)
$FR_{it} \times WHOL_j$		-0.0007***
		(0.0001)
$Log(PRC)_{it}$	-0.0031***	-0.0031***
	(0.0003)	(0.0003)
$Volatility_{it}$	0.0094***	0.0094***
	(0.0005)	(0.0005)
$Log(Volume)_{it}$	-0.0023***	-0.0023***
	(0.0001)	(0.0001)
$Log(Mktcap)_{it}$	0.0003	0.0003
	(0.0002)	(0.0002)
$Log(\#\ Analysts)_{it}$	-0.0005***	-0.0005***
	(0.0001)	(0.0001)
Fixed Effects:		
Time	Yes	Yes
Stock	Yes	Yes
Order Type	Yes	Yes
Order Size	Yes	Yes
Observations	3,674,903	3,674,903
Adjusted R^2	0.4365	0.4383

Table A2 shows the scaled effective spread in the retail market.

Table A2: First Recommendations and Retail Order Execution Quality (scaled by price)

The table estimates the effect of First Analyst Recommendation effective spread scaled by price. Regression (1) report coefficient estimates from regressions of the following form:

$$\textit{Effective Spread}_{ijt} = \alpha_i + \gamma_t + \beta_1 FR_{it} + Controls + \varepsilon_{ijt}$$

where $\textit{Effective Spread}_{ijt}$ is the effective 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 unique analysts covering the stock. I use CRSP value for $Volatility$ and $Log(Volume)$ to capture the market-wide activity. Regressions (2), (4), and (6) report coefficient estimates from regressions of the following form:

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

$WHOL_j$ 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 month fixed effects, and the standard errors are double-clustered across stocks and months. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Effective Spread (bps)	
	(1)	(2)
FER_{it}	-6.52e-5	6.84e-6
	(8.96e-5)	(8.56e-5)
Top2		0.0002***
		(5.22e-5)
$\text{FER}_{it} \times$ Top2		-0.0002***
		(5.02e-5)
Log(PRC)_{it}	-0.0006***	-0.0006***
	(0.0001)	(0.0001)
Volatility_{it}	0.0055***	0.0055***
	(0.0003)	(0.0003)
Log(Mktcap)_{it}	-2.72e-5	-2.8e-5
	(0.0001)	(0.0001)
Log(Volume)_{it}	-0.0017***	-0.0017***
	(0.0001)	(0.0001)
$\text{Log(\# Analysts)}_{it}$	-0.0002***	-0.0002***
	(6.33e-5)	(6.34e-5)
Exchange ES_{it}	0.2808***	0.2807***
	(0.0133)	(0.0133)
Fixed Effects:		
Time	Yes	Yes
Stock	Yes	Yes
Order Type	Yes	Yes
Order Size	Yes	Yes
Observations	1,493,899	1,493,899
Adjusted R^2	0.4886	0.4886

Table A3: Variable Definitions

Variable	Description
Effective Spread	For buy orders, twice the difference between the execution price and the NBBO midpoint at the time of order receipt; for sell orders, twice the difference between the NBBO midpoint and the execution price. Reported in Rule 605 reports.
Quoted Spread	605 reports do not require wholesalers to report the contemporaneous NBBO. I implied the NBBO by using the equation used in **?**
Price Impact	Calculated as the difference between the effective spread and the realized spread.
FR (First Recommendation)	Indicator variable equal to 1 after a stock receives its first analyst recommendation, 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 low price.
Log(Volume)	Natural logarithm of monthly trading volume, from CRSP.
Log(Mktcap)	Natural logarithm of market capitalization, from CRSP.
Log(# of Analysts)	Natural logarithm of 1 plus the number of unique analysts covering the stock.
SHS	Total number of shares received by the receiving market center, including shares executed away from receiving market center.
Top2 Market Share (Measure 1)	The number of shares executed by the top two wholesalers (Citadel and Virtu), scaled by the total number of shares across both exchanges and wholesalers.
Top2 Market Share (Measure 2)	Number of shares executed by the top two wholesalers (Citadel and Virtu), scaled by the total number of shares in the wholesaler market.

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 2020 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		

Table A5: Sample Description (Mean)

The table compares some stock characteristics among stocks listed on NYSE, NASDAQ, NYSE American, and First-covered stocks.

Variable	NYSE	NASDAQ	NYSE American	First Covered Stocks
Stock Price	50.68	33.17	24.34	18.11
Market Capitalization, mil.	10461.88	5487.54	506.30	2054.40
Total Assets, mil.	44168.92	4408.65	891.78	2143.04
Total Liabilities, mil.	36731.97	3077.29	622.90	1405.49
Capital Expenditures, mil.	653.34	141.35	39.66	40.18
Revenue, mil.	9541.59	2040.03	416.84	771.17
Book to Market Ratio	7712.91	1439.91	309.03	759.09

Table A6: Distribution of Recommendation Ratings

Rating	**Count**	**Percentage**
Buy	721	51.7%
Hold	338	24.3%
Strong Buy	282	20.2%
Underperform	50	3.6%
Sell	3	0.2%

Table A7: Distribution of the First-ever Recommendations Rating

Rating	**Count**	**Percentage**
Buy	860	59.4%
Strong Buy	370	25.6%
Hold	195	13.5%
Underperform	19	1.3%
Sell	3	0.2%

Table A8: Execution Quality Before and After First Recommendation

Metric	**Before**	**After**
Effective Spread	0.0799	0.0488
Effective-over-Quoted Spread	0.7844	0.7732
Price Impact	0.0520	0.0323