

Payment for Order Flow And Asset Choice*

Thomas Ernst[†] and Chester Spatt[‡]

March 13, 2022

Abstract

The paper documents important differences in payment for order flow (PFOF), spreads, and price improvement across asset classes. In stocks, we show that PFOF is small. While many retail trades are executed off-exchange, we find that they receive meaningful price improvement, particularly when spreads are at their minimum. In single-name equity options, we show that PFOF is large. While all option trades are executed on-exchange, option exchanges have rules that facilitate internalization. We exploit variation in the Designated Market Maker (DMM) assignments at option exchanges to show that retail traders receive less price improvement, and worse prices, from those DMMs who pay PFOF to brokers, costing retail investors billions per year. Current debate concerning PFOF has focused on equity routing. We show that option routing is comparatively worse, and this gives rise to a second potential conflict of interest of brokers: encouraging customers to trade assets offering higher PFOF. As fintech has eliminated retail commissions, these cross-asset differences in PFOF have become far more consequential to broker incentives.

*First Draft: October 2021. For helpful comments, we are thankful to Zhi Da, Michael Golding, Terrence Hendershott, Steve Heston, Pete Kyle, Robert Van Ness, and seminar participants at Carnegie Mellon University, the University of Maryland, and the University of Mississippi.

[†]University of Maryland, Robert H. Smith School of Business: ternst@umd.edu

[‡]Carnegie Mellon University, Tepper School of Business: cspatt@andrew.cmu.edu

I. Introduction

Financial technology has drastically expanded access to the stock market. Today, a retail investor can effortlessly trade stocks on a smartphone, access news on social media, and pay zero fees for either service. While the automation of trading has been a decades-long process, the coronavirus pandemic further accelerated this evolution. Robinhood, LLC (a zero-commission brokerage firm) currently reports 18 million users, and earns over 80% of its revenue from payment for order flow (PFOF). These are payments from market makers (such as “Citadel”) to brokers (such as “Robinhood”), on the condition that the broker privately routes orders to the market maker, rather than to the public markets. This practice has raised a series of concerns from both market participants and the U.S. Securities and Exchange Commission (SEC), which has a mandate to maintain fair, orderly, and efficient markets. The first concern is that these trades may not receive the best prices. The second is that the practice of routing customer orders away from markets may lead to wider bid-ask spreads on exchanges. The third is that retail brokerages will have incentives to encourage excess trading.

Across all these concerns, our paper highlights a novel cross-asset difference between stocks and options. In equity markets, we find that broker routing to wholesalers *also benefits retail equity traders*, as wholesalers offer smaller bid-ask spreads than the exchanges. Moreover, this occurs even when exchange spreads are at the minimum allowable width, in which case PFOF cannot be leading to artificially wide spreads. In option markets, we find the opposite result: broker routing to wholesalers *harms retail option traders*. Thanks to randomized assignments of Designated Market Makers (DMM) across options exchanges, we are able to show that PFOF-paying DMMs are causally associated with wider bid-ask spreads on retail orders. When we look at the PFOF payments made directly to brokers, we show that a similar cross-asset difference occurs: routing options trades pays brokers substantially more, both in aggregate and per-share, than equity trades. Brokers have more than just an incentive to encourage excess trading of any asset, rather, they have a particular incentive *to encourage excess trading of options*.

This cross-asset difference is magnified by the zero-commission trading environment. From SEC Rule 606 reports, we estimate the typical PFOF paid to a broker for routing a 100 share options trade at 40 cents, while the typical payment for routing a 100 share equity trade is around 20 cents.

In an era of \$5 commissions, an options trade would give a market maker 4% more revenue than an equity trade. With \$0 commissions, an options trade would give a market maker 100% more revenue than an equity trade. Differences in prices between stocks and options provide further amplification. The average retail stock trade is in a \$25 stock, while the average retail option trade is in a \$5 option. A nominal investment of \$1,000 in a \$25 stock would generate a 40-share equity order, worth 8 cents in equity PFOF, while a nominal investment of \$1,000 in a \$5 option would generate a 200-share options order, worth 80 cents in option PFOF. In other words, the same nominal investment in options will generate 10 times as much PFOF as the equity investment. When PFOF is the only source of broker income, this discrepancy in per-asset PFOF creates a very powerful potential incentive misalignment for brokers, with options trades producing substantially more income for the broker than equity trades.

The traditional concern about payment for order flow has not been over asset choice, but instead over execution quality. In equity markets, we carefully document the quality of execution for internalized orders. We identify internalized orders following Boehmer, Jones, Zhang, and Zhang (2021), who highlight subpenny price improvements. These subpenny price improvements are offered by market makers to attract retail trades, and are distinct from PFOF.¹ While PFOF accrues to the broker, subpenny price improvement accrues to the customer. We show that the total value of these subpenny improvements is substantial. In our sample of all U.S. equity trades from January 1, 2019 to October 31, 2021, retail investors receive between \$20 and \$30 million per month in price improvement. Per trade, subpenny improvement saves retail investors an average of .5 basis points, a substantial reduction in transaction costs for equity markets, given that most stocks trade at a one penny bid-ask spread.

We find that these subpenny improvements are a considerable portion of equity market maker's revenue. We estimate realized spreads² with and without subpenny price improvement. We find that around 10% of market maker revenue on retail trades goes to providing subpenny price im-

¹Boehmer et al. (2021) note that subpenny improvement is not allowed on exchanges, nor is it allowed for institutional trades. Subpenny price improvements therefore offer a method of identifying retail trades which were internalized off-exchange. This method misses retail trades executed on public markets or crossed at the midquote, but trades crossed at the midquote execute at a zero bid-ask spread while trades crossed on public equity markets are clearly not subject to internalization.

²A realized spread compares the trade price with the midquote 1 minute after the trade. We consider the trade price as well a hypothetical trade price with no subpenny improvement. We also consider the midquote 3 milliseconds or 30 seconds after the trade.

provement to customers. These subpenny price improvements to customers are even larger than the payment for order flow provided to brokers, with customers receiving more financial benefit from off-exchange routing than their brokers. Against the concern that internalization leads to wide bid-ask spreads on exchanges, we document that over 50% of subpenny improvement occurs when bid-ask spreads are at the minimum tick size. In panel regressions, we show that internalization is negatively correlated with volatility and off-exchange trading, suggesting subpenny improvements are associated with *narrower* bid-ask spreads.

We also rule out that subpenny trades are sensitive to execution timing. Our trade-level data from NYSE's Trade and Quote (TAQ) database contains two timestamps, one provided by exchanges or market makers and one provided by the Securities Information Processor (SIP). For exchange trades, execution quality will differ considerably between one measure and the alternative. For internalized trades, however, we demonstrate that quote discrepancies are less common, even several milliseconds before or after the trade. Price changes—and any associated predatory high-frequency trading—occur in very short bursts. Retail trades, which are not sent with high-frequency timing considerations, are unlikely to encounter these short bursts in which execution quality is sensitive to timing.

In options markets, we document that price improvement is substantially more common, but of lower quality. Due to clearing considerations, options markets do not have off-exchange internalization. Instead, all trading happens on-exchange, but there are exchange-provided price improvement mechanisms. Via these mechanisms, a market maker brings a retail trade and proposes a price, after which other participants can enter the auction and propose better prices. These auctions are commonplace, comprising 15% of all trades, and the improvement that the auction generates against the prevailing bid-ask spread ranges from \$200 to \$600 million per month. These internalization mechanisms appear to generate substantial savings for investors.

The bar for improvement in options, however, is much lower than the bar in equity markets. Bid-ask spreads are substantially wider, with minimum ticks on some exchanges ranging from 5 to 10 cents.³ Options exchanges can also attract wholesalers looking to internalize by adopting rules which favor internalizers. For example, a market maker who brings a retail trade can receive

³For reference, the minimum tick size in equity markets is 1 cent. While option market making costs are higher (Battalio and Schultz (2011)), the preponderance of price-improving auctions in options reflects that the quotes can be improved for many trades.

a reduced take fee or gain a price-match option against any competitor in the auction. These rules reduce the competition to reduce spreads, allowing wholesalers to more profitably internalize trades.

We use variation in designated market makers to conduct a novel test of the impact of PFOF on execution quality. Most U.S. option exchanges have designated market makers (DMM), who are market makers with both a special obligation to quote securities and special privileges in trading. Each asset will have an assigned DMM, and these DMM assignments vary both across assets and across exchanges. As an example, at the Chicago Board Options Exchange, Global Trading Systems is the DMM in Coca-Cola, while Citadel is the DMM in Walgreen's. At the Miami Options Exchange, Global Trading Systems is the DMM in Walgreen's, while Citadel is the DMM in Coca-Cola. We compare price improvement in option trades in Coca-Cola at CBOE vs. Miami against price improvement in option trades in Walgreen's at CBOE vs. Miami. Our goal in comparing these price improvements is to examine systemic differences based on whether the exchange's DMM pays PFOF, and we exploit the asset-exchange level pairings to allow us to fit fixed effects for each asset and each exchange.

We compare execution quality when the specialist does not pay PFOF against execution quality when the specialist does. On an option priced at \$2, we estimate that having a PFOF specialist leads to a price that is 100 basis points (or 2 cents) worse per share, while the broker collects 0.4 cents per share in payment for order flow. Across 26 months of data, we identify \$770 billion dollars in price improvement mechanism trades; consequently, a 1 percent increase would amount to more than \$7 billion dollars in increased costs to retail investors. Total options PFOF (for a broader set of trades) over that time period was between \$2 billion and 3 billion dollars, so the transaction cost increase to investors greatly exceeds any potential savings from reduced broker commissions.

Finally, we compare the performance of retail equity and option portfolios to highlight the dangers of over-trading different assets. From observed retail option trades, we construct portfolios of 50 assets each. We calculate portfolio returns, assuming the options are held to maturity, and compare against an equivalent portfolio that only trades options. Across over 400,000 samples, the option portfolios have a standard deviation 10 times higher than that of the stock portfolio—and half of the option portfolios lose more than 90% of their value. Thus the differences across assets for clients are no less stark than the differences for brokers. While a small amount of excess equity

trading produces a small PFOF benefit to brokers, the client returns will also generally be similar to the market portfolio return. By contrast, a small amount of excess option trading produces a large PFOF benefit to brokers, and the client will see a return substantially different from the market portfolio return.

While “best execution” can be difficult to define, the goal is straightforward: buying (or selling) at the best available price. In the equity markets, the tight bid-ask spread gives a high bar for price improvement. In the option markets, bid-ask spreads are much wider. While price improvement is common, we show that PFOF-paying DMMS are associated with consistently lower price improvement compared to non-PFOF paying DMMS. Evaluating broker performance is not just a matter of comparing to one benchmark (like the National Best Bid or Offer), but rather to the best price available.⁴ When trades frequently execute at prices better than the best quotes, brokers should deliver such execution quality to their customers.

Options routing is of lower quality than equity routing, and gives higher payment to brokers. We note that this gives rise to a second conflict of interest for brokers, over which assets the customer should trade. While the SEC has scrutinized the “gamification” of trading smartphone apps, the concern has been focused on the overall volume of trading, and not the asset choice. Deviating from a mean-variance optimal portfolio takes a great many equity trades, but just a few option trades. Broker conflicts over asset recommendations are comparatively more difficult to regulate. Rather than a simple goal of getting the best price, recommending “the best” assets for a client is not a clearly defined target. Some clients may prefer riskier securities or a more volatile portfolio. Investors with an idiosyncratic risk preference may only be drawn into investing by the allure of potential large positive returns. For these investors, the choice may not be between holding a risky portfolio and the market portfolio, but between having a risky investment or not investing at all.⁵ It is difficult to say whether a broker does a disservice by catering to these types of investors, and bringing them into investing.

⁴It also is useful to note that some interpretations of Best Execution standards even suggest that any inducement for order flow (PFOF) should not be taken into account (netted) in assessing the market quality obtained for the customer. Furthermore, it also bears emphasizing that meeting Best Execution responsibilities should reflect the extent of price improvement rather than just simply respecting the NBBO quotes. Indeed, under Best Execution standards brokers are responsible for detecting weaknesses in their own routing at a security and order type level.

⁵In questioning by House Committee on Financial Services member Jim Himes (D-CT) suggesting the proper benchmark should be the market portfolio, Robinhood CEO Vladimir Tenev argued instead that the proper benchmark for these investors is not investing at all. (February 18,2021: Game Stopped? Who Wins and Loses When Short Sellers, Social Media, and Retail Investors Collide)

II. Literature Review

Payment for order flow dates back to the 1990s, with regional exchanges attracting order flow from brokers Chordia and Subrahmanyam (1995). In part led by Bernard Madoff, payment for order flow was soon expanded to cover payments from market makers to brokers to attract retail flow, as these traders are typically less informed than the general population of investors. Under a Glosten and Milgrom (1985) style model, the exchange bid-ask spreads will give the market maker substantial profits when trading against retail traders; as a result, market makers are willing to pay for retail order flow.⁶ Market makers may also pay for order flow in order to obtain information, and use this information to execute on-exchange trades, as in Ernst, Sokobin, and Spatt (2021). In recent years, payment for order flow has re-emerged as a particularly salient issue in the era of zero-commission trading. As Jain, Mishra, O'Donoghue, and Zhao (2020) note, equity execution in this environment is of high quality. Robinhood, LLC, first introduced unlimited zero-commission trading, and earns 80% of its revenue from payment for order flow. Our paper highlights the importance of cross-asset differences in payments.⁷ We show that brokers have a powerful incentive to encourage not just more trading of all assets, but in particular trading of options due to their higher payment for order flow.

The negative relationship between trading and returns has long been studied, from the institutional setting in Jensen (1968) to the individual-investor setting of Barber and Odean (2000). Robinhood investors, in particular, have earned lower profits with their trading, as documented in Barber, Huang, Odean, and Schwarz (2021). Our paper highlights the significant asset-choice side dimension to over-trading. We document that while a portfolio drawn from observed retail equity trades delivers close to the market return, a portfolio drawn from observed retail option trades delivers a substantially lower return and higher variance.

Payment for order flow is related to off-exchange execution, including both broker-affiliated venues and alternative trading systems. Routing to broker-affiliated venues for institutional orders

⁶Easley, Kiefer, and O'Hara (1996) present evidence of cream-skimming with payment for order flow. Battalio, Jennings, Selway, and Archipelago (1998) find brokers can reduce commissions, while Parlour and Rajan (2003) model social welfare effects.

⁷Typical payment for a 100 share trade is 40 cents in options markets and 20 cents in equity markets. On a fixed \$5 commission, the option trade earns brokers 4% more than the stock. With a \$0 commission, the option pays a broker 100% more than the stock. These differences are per-share, so if the investment is in nominal terms, these price differences can be further amplified by the lower nominal price of options.

typically produces poor execution quality, as Battalio, Corwin, and Jennings (2016a) and Anand, Samadi, Sokobin, and Venkataraman (2021) show. We show, however, that retail traders receive fairly good execution quality in equity markets. Unlike institutions, retail traders are more likely to execute single small trades, and which are smaller than the available quantities at the national best bid or offer. Our work makes extensive use of microsecond timestamps in our analysis of execution quality. Against the standard practice of matching trades and quotes with SIP timestamps (Holden and Jacobsen (2014)), we explore an alternative of using the participant timestamps. In part, we are motivated by Hasbrouck (2018)'s documentation of local exchange liquidity, and Bartlett and McCrary (2019), who document occasional differences between the SIP and proprietary feed of the national best bid and offer. Methodologically, we show that SIP and proprietary feed differences are important for exchange trades, but less important for retail trades. In recent work, Bernhardt, Barardehi, Da, and Warachka (2022) show that sub-penny price improvement occurs not just with retail trades, but in particular when market makers decide internalization is profitable. Consistent with that, we document overwhelmingly positive spreads for internalized trades, but we also note that these trades mostly frequently occur when spreads are at the minimum tick size.

The minimum tick size has come under scrutiny. Li, Wang, and Ye (2021) connect much HFT size to tick-constrained stocks, while Li and Ye (2022) show that some stocks are round-lot constrained, and not tick constrained. Bartlett, McCrary, and O'Hara (2022) highlight how significant information is contained in odd-lot quotes. In our work, we note that when stocks are tick-constrained, internalization is better for investors than crossing the spread, and that banning internalization could not lead to narrower spreads in stocks which are already tick constrained.

Options markets typically have higher trading costs than equity markets, in part due to greater difficulty market makers face in hedging Battalio and Schultz (2011). While option spreads are wide, investors can time their trades Muravyev and Pearson (2020) or explore differences in make-take pricing Battalio, Shkilko, and Van Ness (2016b). More recently, Battalio, Griffith, and Van Ness (2021) examine the switch of the PHLX options exchange from make-take to PFOF as a pricing mode. We add new analysis on price improvement auctions, which facilitate the on-exchange internalization of option trades. These internalized options trades comprise around 15% of all options trades, and receive over \$12.4 billion in improvement during our sample. These PIM auctions represent significant savings for investors over the prevailing quotes, but the frequency

of PIM trades also indicates that improvement is expected. Investors should expect to frequently receive prices which are better than the best bid or ask.

III. Internalization in U.S. Equities

Brokers have a best execution requirement on behalf of their clients. The Financial Industry Regulatory Authority (FINRA) explicitly defines this best-execution requirement via Rule 5310, which requires that members “shall use reasonable diligence to ascertain the best market for the subject security, and buy or sell in such market so that the resultant price to the customer is as favorable as possible under prevailing market conditions.”

In modern U.S. equity markets, determining the best market for a security is a sophisticated process. Trading takes place across several exchanges and in other platforms, with data centers located hundreds of miles apart. This physical distance complicates the market search; while brokers can view the current best quotes at each exchange, sending an order to any exchange will take time. Even at the speed of light, during the transit time, quotes may change. Thus the routing decision of a broker must take into account not just the market now, but also latency in the current pricing as well as what the market may be milliseconds into the future.

Against this challenge finding the best exchange quote, brokers may route to an off-exchange trading venue (or internalize the order). This carries the potential advantage of receiving price improvement compared to the prevailing quotes, either from a mid-quote matching facility like a dark pool, or wholesale liquidity provider offering reduced spreads to retail clients.

We measure the price improvement and execution quality provided by brokers. We evaluate broker performance with a careful technical analysis of the markets. First, we measure prices against both the exchange timestamps, and the slower Securities Information Processor (SIP) timestamps. We find that differences are common for exchange trades, but less common for off-exchange trades. Differences are uncommon for likely retail trades with de minimis price improvement. These likely retail trades are also far less likely to see changes in the price both before and after the trade, suggesting no incentive to artificially delay execution by a few microseconds. We also find that even the de-minimis price improvement of 20 or 30 hundredths of a cent add up to substantial savings for investors, and most stocks are quoted close to the minimum 1 cent bid-ask spread.

A. Data

We collect NYSE TAQ (Trade and Quote) data from January 1, 2019 to October 31, 2021. We use all securities which appear in have a closing price of at least \$1 and trade on at least three-fourths of the days of our sample; this yields a sample of 6,009 individual securities. All trades and quotes are cleaned according to the techniques described in Holden and Jacobsen (2014).

B. Price Improvement

Brokers have flexibility in routing their client orders, and an obligation to obtain the best price possible for their clients. Wholesalers can internalize trades off-exchange, provided brokers route to them. To induce brokers, wholesalers can offer payment for order flow and sub-penny price improvement. We examine the payments for order flow in Section VI, and analyze the sub-penny price improvements here. Boehmer et al. (2021) document these sub-penny price improvements, and use them to identify retail trades. While their focus is on the predictive power of retail trades, our focus will be on the execution quality of retail traders as well as the level of sub-penny improvements.

Sub-penny trades are defined as trades in which the price has a sub-penny component, but is not a mid-quote trade. As an example, a trade price of \$10.2515 has a sub-penny component of 15 hundredths of a cent. Following Boehmer et al. (2021), we define a trade as a sub-penny improvement if the sub-penny component falls between (0, 40) and (60, 100). These trades are overwhelmingly retail trades, as institutions trade either on-exchange or at the mid-quote or even penny increments.

Market makers offer sub-penny price improvement to attract retail flow. Under a Glosten and Milgrom (1985) model, bid-ask spreads depend on the ratio of informed to uninformed traders. If retail traders are less informed than the general population of traders, market makers could charge a smaller bid-ask spread to retail traders. We directly confirm this with observed realized spreads, comparing the price at the time of trade to the mid-quote one second after the trade. These realized spreads reflect the potential profits of a market maker; positive values indicate market makers make money, while negative values indicate market makers lose money. We measure realized spreads for all stock-day observations in our sample. Figure 1 plots the distribution of

realized spreads, both for all trades and for the subset of trades which receive sub-penny price improvement. Realized spreads are overwhelmingly positive for retail trades, with positive values at the 25%, 50%, and 75% quantiles of realized spreads. Across all trades, the 25% quantile is frequently negative, suggesting market makers lose money on these trades. As a result, the retail trades appear to be far more profitable for market makers in the short run, and providing a sub-penny price improvement provides a way for market makers to induce brokers to route more of these profitable retail trades.

We calculate the combined value of all sub-penny improvements, and find that the sub-penny improvements have total substantial value. Figure 2 plots the monthly total improvements, with most months having between \$50 and \$150 million in sub-penny price improvement. By total improvement, we calculate the total value of only the sub-penny portion of improvement. For example, if a trade executes at \$10.2515, the total improvement is \$0.0015, or fifteen hundredths of a cent. For a trade which executes at \$10.2595, the total improvement is \$0.0005, or five hundredths of a cent. It is these fractional cents which we add up to arrive at the monthly totals.

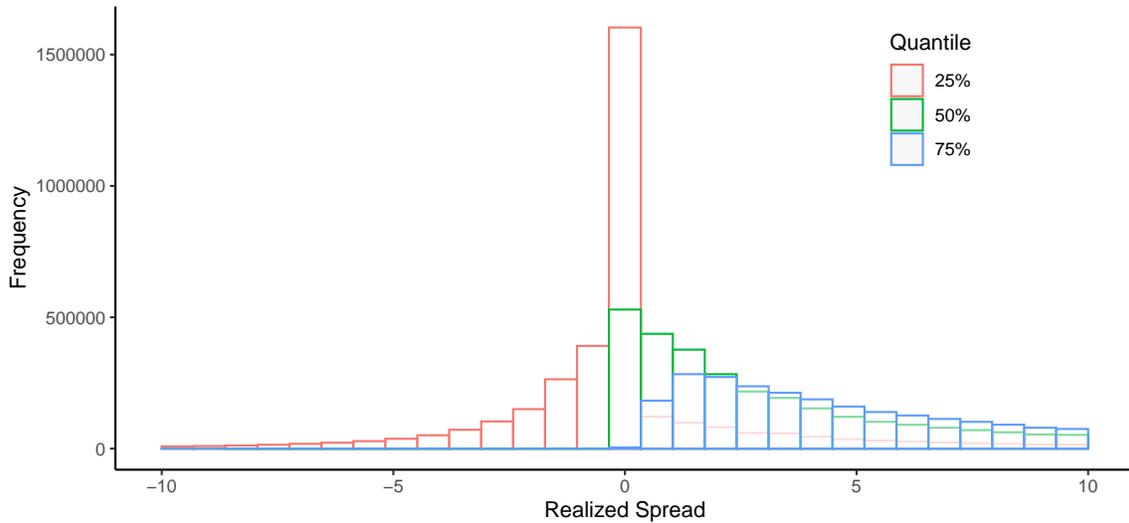
While these volumes are substantial in part due to the tremendous volume of U.S. equities trades, they also represent a meaningful portion of transaction costs. With monthly transaction volumes of sub-penny trades ranging between \$300 billion and \$1 trillion, the average sub-penny price improvement is around half a basis point of improvement. This is a substantial amount of price improvement, considering the liquidity of U.S. equity markets. As Figure 2 shows, around half of the total sub-penny price improvement occurs when stocks are at the minimum one-tick spread, i.e. a single penny bid-ask spread.

In Appendix A we estimate improvement by comparing the execution price to the best bid or offer at the time of trade. This risks errors in timing. Consider, for example, a trade to buy stock in a rising market. If the timestamp on the trade is delayed (relative to timestamps on quotes), the buy order will appear to have executed at a very low price and received generous improvement. If we do measure improvements against the prevailing spread, we get substantially larger estimates of improvement.

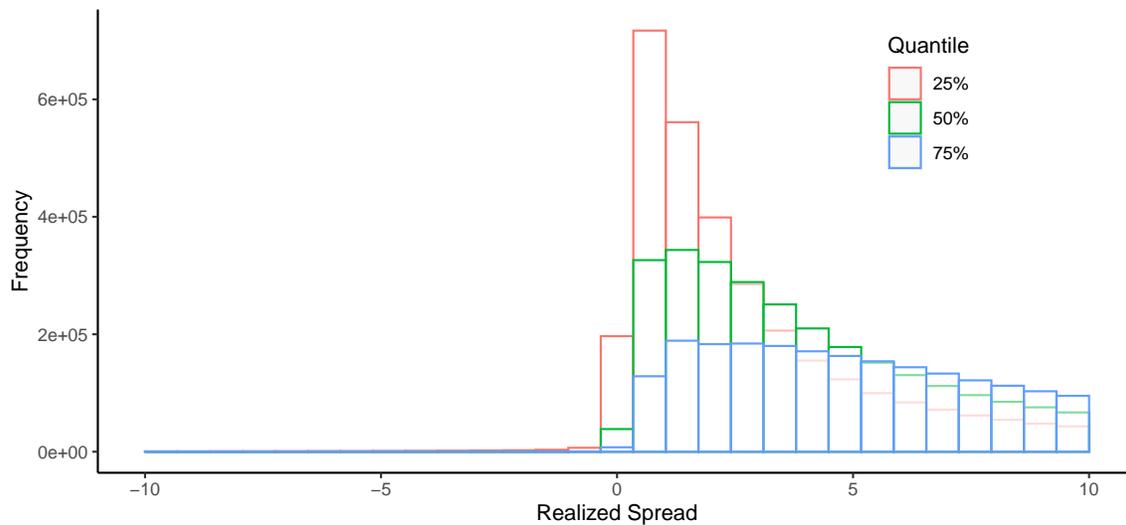
To further capture the value of these price improvements, we consider how market-making profits would be impacted if there were to be no sub-penny price improvements. We use realized spreads as a measure of market-making profits, as the realized spread compares the signed trade

Figure 1. Comparison of Realized Spreads. For each stock-day observation, we measure realized spreads at the 25%, 50%, and 75% quantiles. Realized Spreads are measured as the signed price difference between the order price and the mid-quote one second after the trade, and reflect the short-term profit available to market-making. Panel A plots the distribution of realized spreads for all trades, while Panel B plots the distribution of realized spreads for trades which receive sub-penny price improvement.

Panel A: Realized Spreads for All Trades



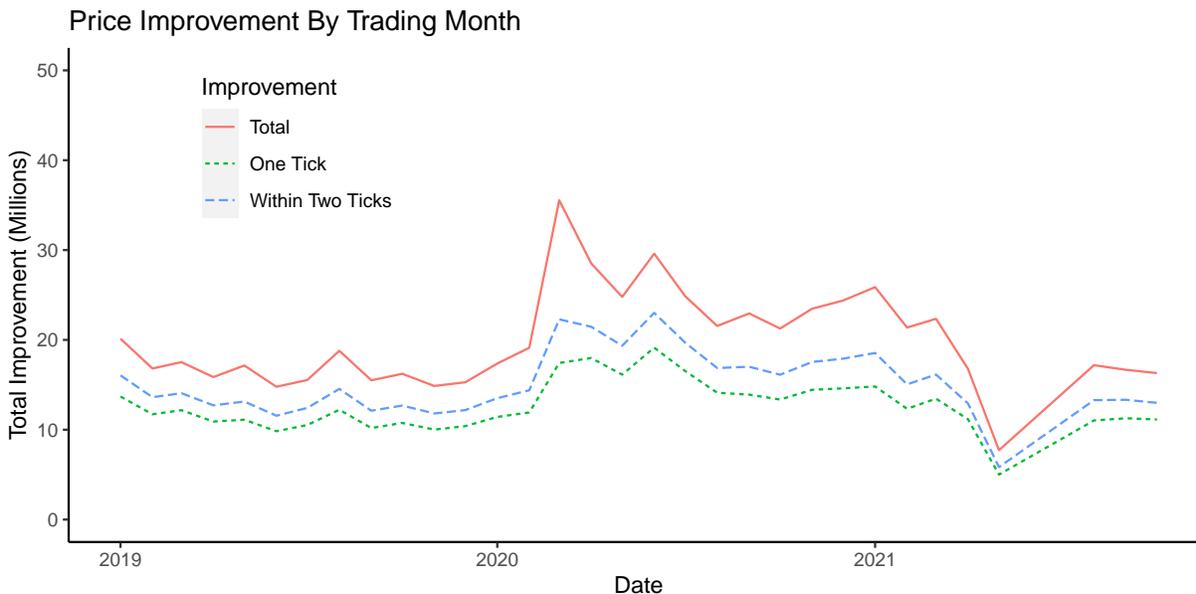
Panel B: Realized Spreads for Sub-penny Trades



price against the mid-quote some time interval after the trade.

For each sub-penny price-improved trade, we also consider the national best bid or offer, *NBBO*,

Figure 2. Price Improvement By Month. Total price improvement for sub-penny trades, by month. Following Boehmer et al. (2021), sub-penny trades are defined as trades in which the price has a sub-penny component between (0, 40) and (60, 100). For example, a trade price of \$10.2515 has a sub-penny price improvement of 15 hundredths of a cent. We calculate the total dollar value of all such sub-penny price improvements, and plot the monthly total with the red solid line. We separately calculate the total value of sub-penny improvements which occur when the quoted spread is at one tick (green dashed line) or at two ticks (blue dashed line).



at the time of the trade. We compare two different measures of realized spreads: one measured against the actual trade price, and one measured using the trade price inflated by the sub-penny improvement. That is, for a trade price of \$10.2585, the realized spread without improvement would be calculated with a price of \$10.26. This measure of realized spreads without subpenny price improvement could be thought of as the total potential revenue available to a market maker, while the measure of realized spreads using the actual trade price is the total profit. If sub-penny price improvement is viewed as an expense, the ratio of the two realized spread measures captures the share of total revenue devoted to sub-penny price improvement.

Formally, for a trade price P_T , trade sign Y , subpenny improvement Sub_t , and midquote m

which occurs X seconds after the trade, we define the two possible definitions of a realized spread:

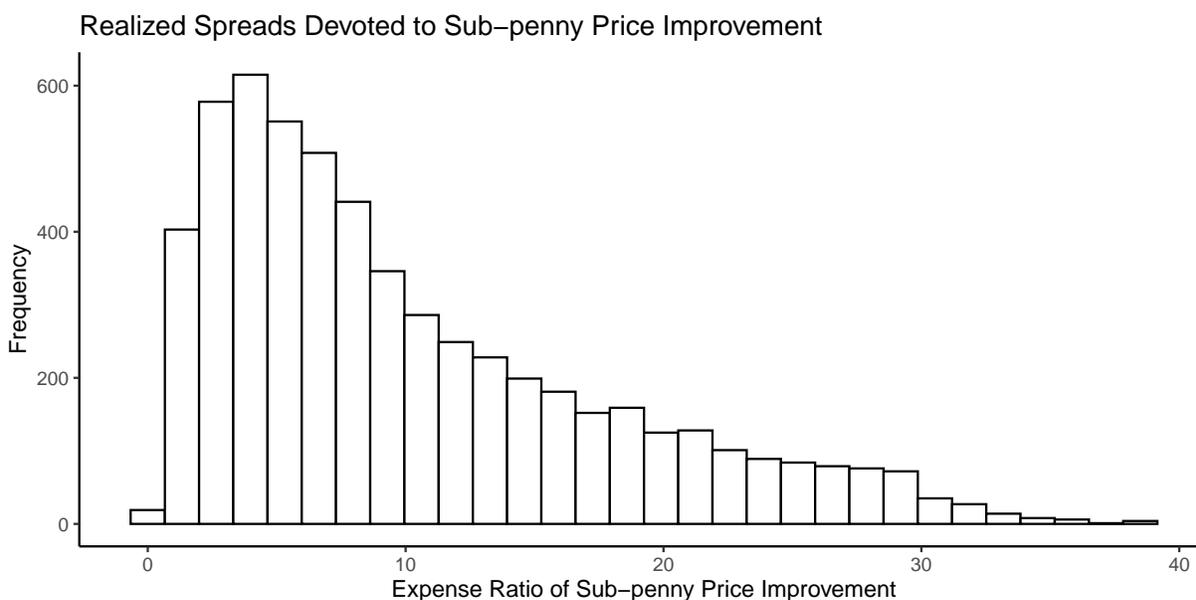
$$\text{Realized_With_Improvement}_t = Y(P_t - m_{t+X}) \quad (1)$$

$$\text{Realized_No_Improvement}_t = Y(P_t - m_{t+X}) + \text{Sub}_t \quad (2)$$

$$\text{Expense_Ratio} = 1 - \frac{\sum \text{Realized_With_Improvement}}{\sum \text{Realized_No_Improvement}} \quad (3)$$

For each stock, we calculate the value of this expense ratio, and plot the distribution of this ratio across stocks in Figure 3. The average stock has around a 25% difference between the two measures. If we consider the total revenue from retail trades to be the realized spread on these trades calculated using the price without sub-penny improvement, around 25% of this total revenue goes to offering sub-penny price improvements.

Figure 3. Price Improvement As Fraction of Realized Spreads. Realized spreads for sub-penny price-improved trades are as much as 60% lower than a realized spread measured against the contemporaneous national best bid or offer. For all subpenny trades, we calculate the realized spreads using both the trade price and the NBBO (Equation 3). The realized spread using the trade price reflects market maker profits, while the realized spread using the NBBO reflects market maker revenue. Total realized spreads in sub-penny in most stocks are between 5% and 30% lower than the total realized spreads on those same trades using the NBBO rather than the trade price. This suggests roughly 10 to 15% of the total revenue market makers make from retail trades is allocated to sub-penny price improvement.



These calculations of market maker profits do not take into account how the NBBO itself

depends on market maker behavior. Ernst et al. (2021) examine how the off-exchange trades can influence on-exchange trading. This element of the value of off-exchange trades will not be captured in the analysis of this paper, but we do examine the relationship between sub-penny price improvement and quoted spreads. As Figure 2 shows, much improvement already occurs when spreads are at the minimum allowed spread. For these trades when spreads are already at the minimum, no alternative routing or internalization could lead to narrower spreads.

C. Time Sensitivity of Trades

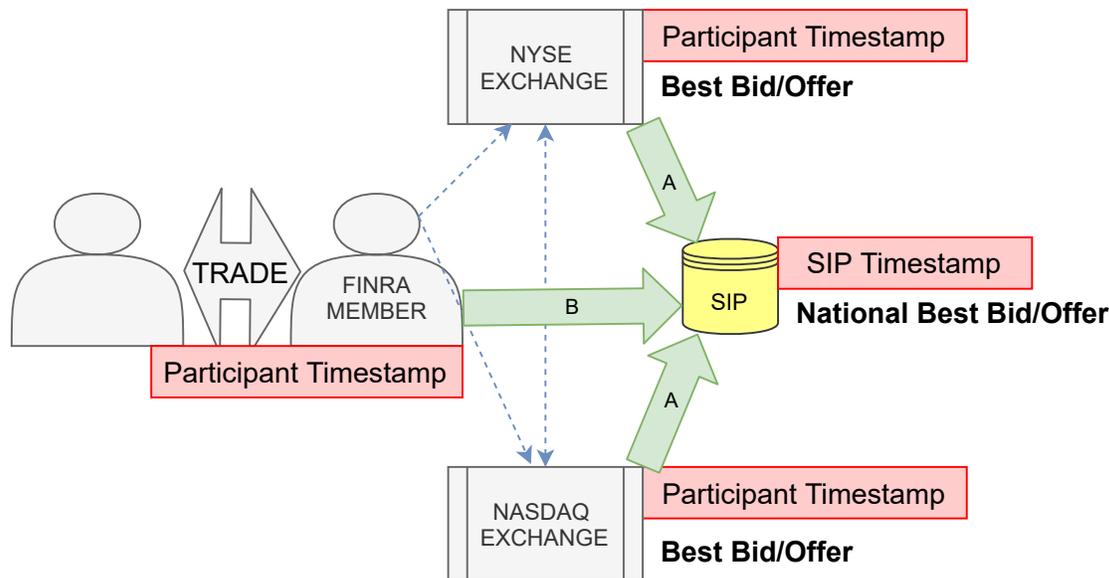
Evaluating whether a price is a good price depends on the other prices available in the market. At very short time horizons, the geography of the market plays a critical role. Prices at a specific point in time are only available from a specific location. In this subsection, we analyze the timing of trades, using a technical analysis of the timestamps available in TAQ. We find that the differences in timestamps are crucial for exchange trades, with sizable price changes occurring over small time horizons. We find, however, that the retail trades with sub-penny price improvement occur almost exclusively at times when prices are not changing. For these retail trades, executing slightly earlier or later would make a difference only for a small share of trades.

The Securities Information Processor (SIP) calculates, disseminates, and records the official National Best Bid or Offer (NBBO). TAQ data, which this study will use, comes from SIP records. All trades and quotes in TAQ are timestamped twice, with a participant timestamp and a SIP timestamp.⁸ Trades and quotes are first stamped with a participant timestamp at the facility at which they occur. For example, a trade occurring at the NYSE would be stamped by NYSE according to the time displayed on the NYSE's clock. All trades and quotes are reported to the SIP, where the SIP timestamp is assigned according to the SIP's clock.

There are two SIP facilities: the Consolidated Tape Association (CTA) and the Unlisted Trading Privileges (UTP). The CTA SIP, historically associated with the NYSE and co-located in the current NYSE data center, processes data for any securities listed at the NYSE's family of exchanges, including Tape A and Tape B securities. The UTP SIP, historically associated with NASDAQ and co-located in the current NASDAQ data center, processes data for any securities listed at

⁸There is a third timestamp field in the data, the TRF Timestamp. For a detailed discussion and analysis of the TRF timestamp, see Ernst et al. (2021).

Figure 4. Timestamps and Data Map. All trades and quotes in TAQ are first timestamped by the participant, and second by the SIP. Exchanges report both trades and quotes to the SIP (Green Arrows A). FINRA members report off-exchange trades to the SIP (Green Arrow B). While the SIP disseminates an official National Best Bid or Offer, each exchange or broker can monitor market conditions via direct feeds (blue dotted arrows).



NASDAQ's family of exchanges, including Tape C securities.

The multiplicity of timestamps and SIPs presents several possibilities for matching trades and quotes. Holden and Jacobsen (2014) match trades and quotes according to their SIP timestamps. This works well conditional on trades and quotes being reported to the SIP with equal latencies. When the trade and quote updates occur at different exchanges, however, the latency to report either to the SIP will be unequal. As an example, consider a NASDAQ-listed stock. If there is a trade at NYSE, and a few microseconds later a quote update at NASDAQ, the update will reach the UTP SIP long before the trade. Matching this NASDAQ quote with the NYSE trade according to the SIP timestamps will lead to matching a trade with a quote that happened after the trade.

We explore an alternative, that of matching trades and quotes according to their participant timestamps. This has the advantage of eliminating discrepancies in the exchange-to-SIP latency, as the participant timestamps record when a trade or quote took place, not when it was recorded by the SIP. We feel this presents a plausibly more accurate comparison of a trade price against prevailing market conditions.

No approach, however, is perfect. For example, matching participant timestamps fails to take

into both the time and geographic position at which the market participant send a trade message. In addition to matching trades to the nearest quote under either timestamp, we explore matching trades to quotes slightly before or after the trade.

The SIP and participant-timestamp matched quotes differ around 40% of the time. This means effective spreads, quoted spreads, and price impacts will differ depending on the method used, and the execution quality a customer receives may be sensitive to the microsecond-level routing decision made by a broker. For sub-penny trades, however, we find that differences between the SIP and participant-timestamp matched quotes are far less likely, averaging below 10% per day. Differences in quotes before the trade are more common than differences in quotes after the trade, with the midquote 1 to 3 microseconds before a trade differing from the participant-matched quote around 60% of the time for non-sub-penny trades, and 35% of the time for sub-penny trades. Differences in quotes after a trade are less likely, with the midquote 1 to 3 microseconds after the SIP-matched quote averaging 40% of the time for non-sub-penny trades and below 10% for sub-penny trades.

Across stocks, differences in the matched quotes are more common in higher-priced stocks. Figure 6 plots the percentage of trades for which the SIP-matched quote differs from the participant-matched quote across stock-day observations. Higher-priced stocks differ on a larger percentage of days than low-priced stocks, reflecting the greater likelihood of many small price changes in the higher-priced stocks.

As a further test of timing differences, we examine differences in the SIP and participant timestamp matched quotes for each of Tape A, Tape B, and Tape C securities. Tapes A and B are both processed by the CTA SIP, while Tape C securities are processed by the UTP SIP. During our sample period, the UTP SIP disseminated trades for broadcast less than 20 microseconds after receiving them, while the CTA SIP disseminated trades for broadcast between 100 and 200 microseconds in 2019 and most of 2020, and less than 30 microseconds for 2021. There is also a geographic difference, with the UTP located in central New Jersey, next to the NASDAQ exchange, and the CTA SIP located in northern New Jersey, next to the NYSE exchange. Despite these differences, however, the percentage of trades with a difference between the SIP-matched quote and participant-timestamp matched quote is similar across Tapes A and C (Figure 7). Tape B has substantially fewer differences between the SIP-timestamp-matched quote and participant-timestamp-matched quote. Tape B is far more likely to have ETF listings than either Tape A or Tape C, and the lower

Figure 5. Midquote Differences by Venue Type. Trades can be matched against quotes according to one of two timestamps (described in Figure 4). On a typical day, the midquote matched via participant timestamps differs from the midquote matched via SIP timestamps around 35% of the time for non-sub-penny trades, but less than 10% of the time for sub-penny trades. We also measure how often the quotes differ 1 or 3 milliseconds prior, and 1 or 3 milliseconds after the trade. Across all time horizons, differences in quotes are far less likely for sub-penny trades.

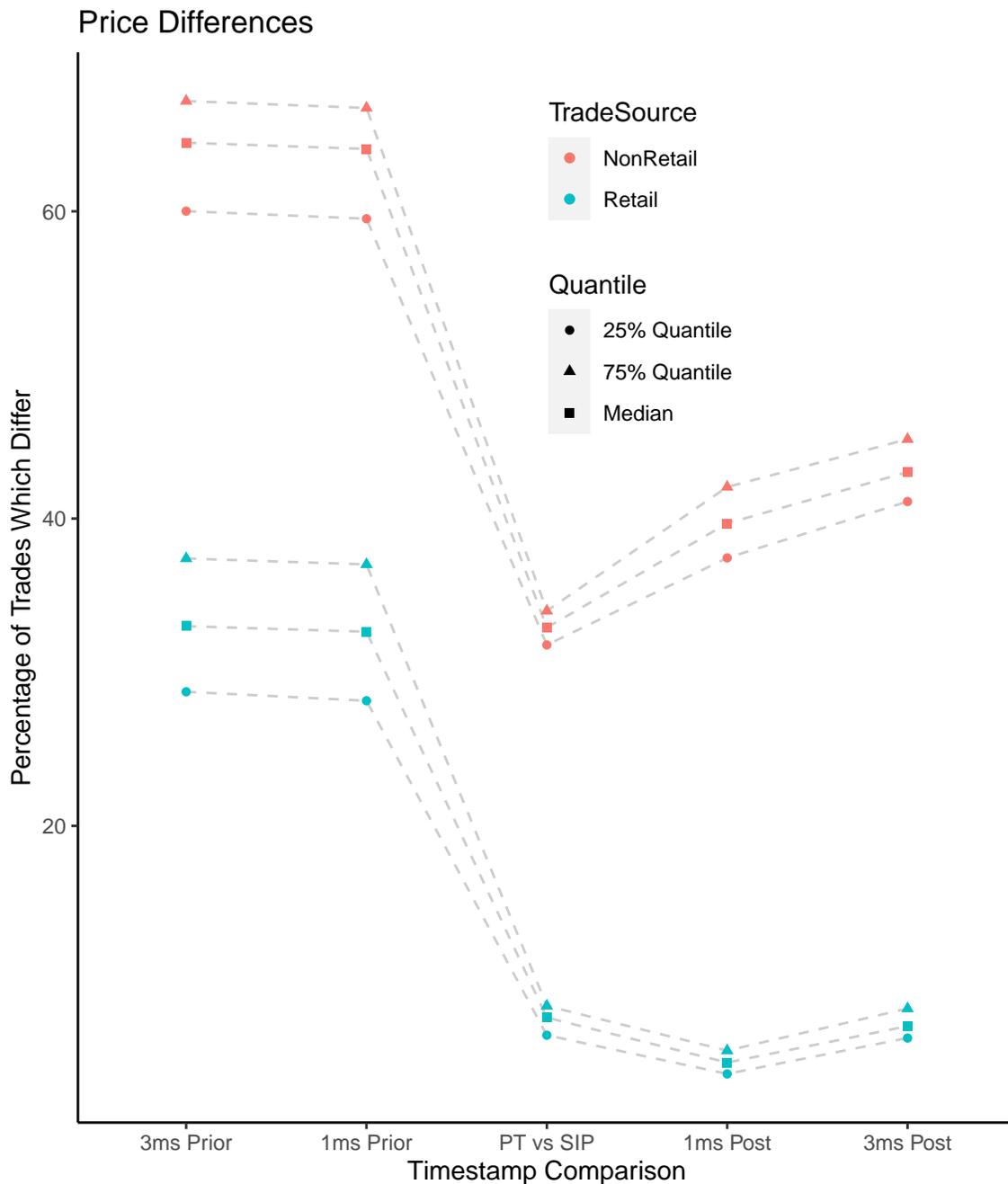


Figure 6. Midquote Differences By Stock Characteristics.. We plot the percentage of trades for which the SIP-timestamp-matched quotes differ from the participant-timestamp-matched quotes across stock-day observations. Stocks with a share price greater than \$100 (dashed purple) have far more days with a high number of differences between the timestamps compared to stocks with a share price less than \$15 (solid red line), reflecting the fact that small price changes are more frequent in higher-priced stocks.

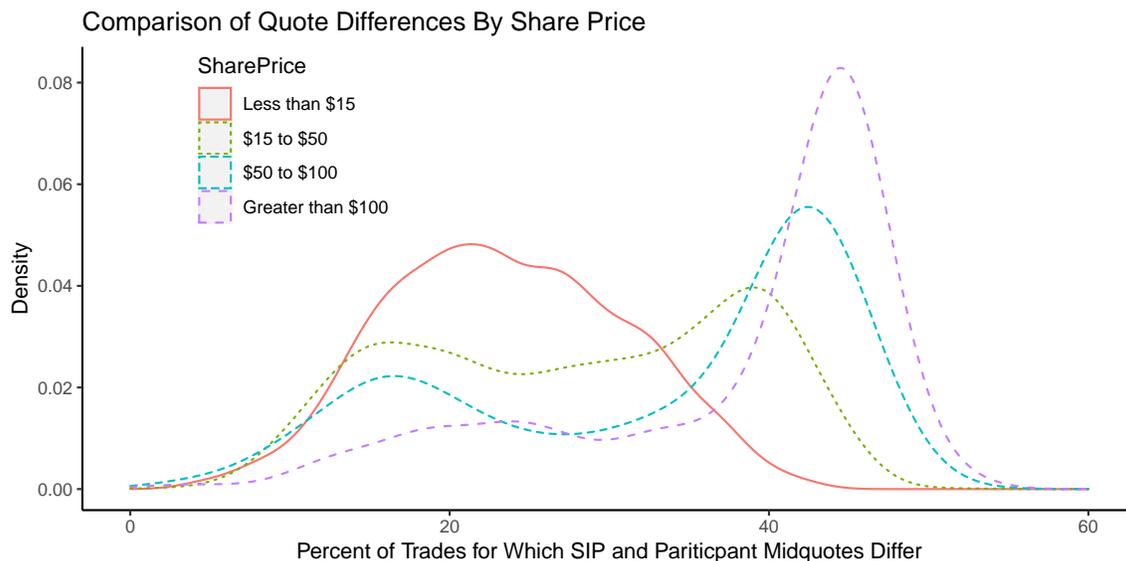
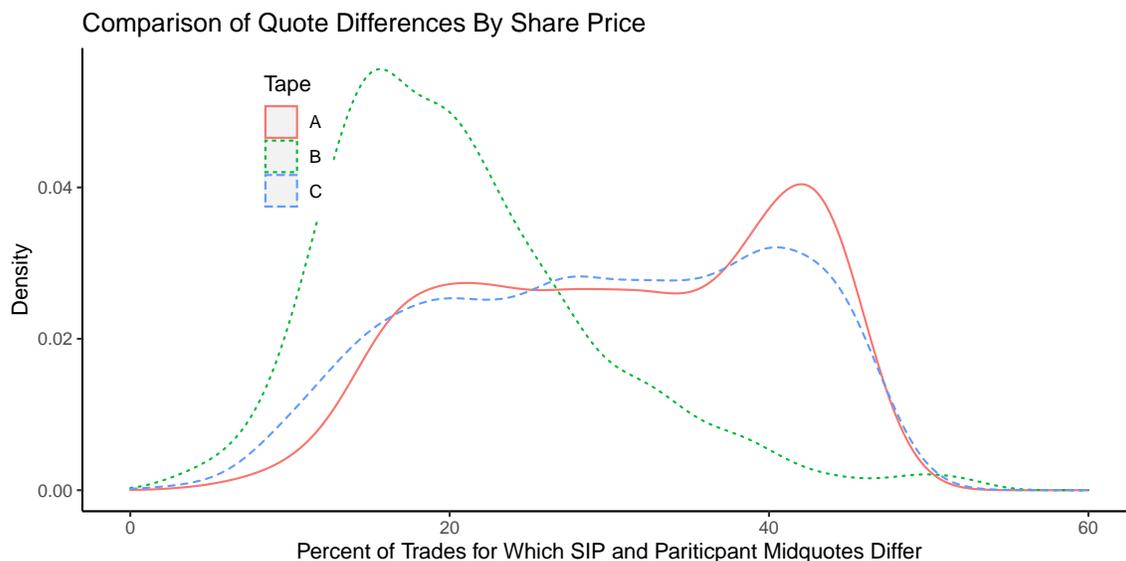


Figure 7. Midquote Differences By Tape. We plot the percentage of trades for which the SIP-timestamp-matched quotes differ from the participant-timestamp-matched quotes across stock-day observations. Stocks listed on Tapes A and C (solid red and dashed blue lines) are far more likely to have differences between the SIP-matched quotes and Participant-matched quotes compared to Tape B securities. Tapes A and B are both processed by the CTA SIP, while Tape C trades are processed by the UTP SIP.



(portfolio) volatility of ETF shares would explain the substantially decreased likelihood of a price difference between the SIP-matched and participant-matched quotes.

D. Regression Analysis of Equity Price Improvement

To formally measure the relationship between retail improvement and market conditions, we estimate three regressions. Regression 1 estimates the relationship between the share of trades receiving price improvement and market conditions. Regression 2 estimates the relationship between the share of realized spreads devoted to sub-penny price improvement. Regression 3 estimates the relationship between the share of trades which have quote changes around the time of the trade.

REGRESSION 1: *For each stock i on date t , we estimate:*

$$\begin{aligned} \text{ImprovementShare}_{it} = & \alpha_0 \text{Closing_Price}_{it} + \alpha_1 \text{Absolute_Intraday_Return}_{it} \\ & + \alpha_2 \text{Mean_Quoted_Spread}_{it} + \alpha_3 \text{Mean_Realized_Spread}_{it} \\ & + \alpha_4 \text{Off_Exchange_Share}_{it} + X + \epsilon_{it} \end{aligned}$$

Results are presented in Table 1. Improvement Share is the dollar volume share of trades receiving sub-penny price improvement. Closing Price is measured in dollars, Absolute Intraday Return is the percentage intraday return from open to close, mean quoted spread is the trade-weighted mean, realized spread is measured at the one second level, off-exchange share is the share of dollar volume executed off-exchange, and X is fixed effect estimated for the each stock (Table 1 Column 1) or date (Table 1 Column 2).

Large absolute returns are strongly associated with lower shares of trades receiving sub-penny price improvement. A 1% larger absolute return is associated with a 2.5% to 6.5% reduction in the volume share of trades receiving sub-penny price improvement, depending on whether date or stock fixed effects are used. More off-exchange trading is associated with fewer orders receiving sub-penny price improvement, perhaps suggesting a potential substitution between midquote and sub-penny venues. While sub-penny price improvement from the spread is substantial and appears to save investors substantial transaction costs, if these investors could receive execution at the midquote, this would be an even larger savings. As midquote facilities are by their very nature "dark" in

Table I: Price Improvement Share. This table estimates Regression 1. ImprovementShare measures the volume share of prices which receive sub-penny price improvement. Closing Price is measured in dollars, while Absolute Intraday Return and Off-Exchange Share are measured in percentages. The level of observations is the stock-day level. Column (1) has a fixed effect for each date, while column (2) has a fixed effect for each stock. Standard errors are clustered at the stock and day level.

	<i>Dependent variable:</i>	
	ImprovementShare	
	(1)	(2)
Closing Price	-0.004*** (0.001)	
Absolute Intraday Return	-9.005*** (1.439)	-2.946*** (0.648)
Mean Quoted Spread (BPS)	0.004*** (0.001)	0.001*** (0.0002)
Mean Realized Spread (BPS)	0.028*** (0.002)	0.021*** (0.002)
Off-Exchange Share	-0.413*** (0.003)	-0.279*** (0.003)
Date Fixed Effect	X	
Stock Fixed Effect		X
Observations	3,689,300	3,689,300
R ²	0.472	0.554
Adjusted R ²	0.470	0.552
Residual Std. Error	9.002 (df = 3688636)	8.269 (df = 3683531)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

the sense that they have no pre-trade transparency, we cannot directly test whether there is any potential midquote volume available at the time trades are given sub-penny price improvement.

For quoted spreads, larger quoted spreads and realized spreads are both associated with a larger share of orders receiving sub-penny price improvement. As the minimum quoted spread is one penny, larger quoted spreads reduce the value to investors of sub-penny price improvement, especially when compared to the half-spread reduction crossing at the midquote would provide. Larger realized spreads are strongly associated with a larger share of orders receiving improvement, with a 10 basis point increase realized spreads being associated with a 0.2% increase in the share of trades receiving improvement. With larger realized spreads, trading at the prevailing quotes becomes more profitable for market makers, and purchasing trade volume becomes more attractive. As Figure 3 shows, while the median sub-penny price improvement costs around 25% of the total realized spread, there is considerable variation across stocks.

To test how the profitability of internalization changes with market conditions, we test Regression 2. As defined in Equation 3, the realized ratio is the ratio between two different measures of realized spreads: one measured against the actual trade price, and one measured against the national best bid or offer. The measure of realized spreads using the NBBO could be thought of as the total potential revenue available to a market maker, thus the difference between the two realized spreads represents the cost to the market maker of offering the sub-penny price improvement. This ratio is defined only for sub-penny improved trades, and to reduce the variance of this ratio we exclude any stock-day observations with fewer than 50 sub-penny trades.

REGRESSION 2: *For each stock i on date t with at least 50 subpenny trades, we estimate:*

$$\begin{aligned} \text{Realized_Ratio}_{it} = & \alpha_0 \text{Closing_Price}_{it} + \alpha_1 \text{Absolute_Intraday_Return}_{it} \\ & + \alpha_2 \text{Mean_Quoted_Spread}_{it} + \alpha_3 \text{Mean_Realized_Spread}_{it} \\ & + \alpha_4 \text{Off_Exchange_Share}_{it} + X + \epsilon_{it} \end{aligned}$$

Results of this estimation are presented in Table II. The mean realized spread is measured in basis points and at the one second time interval. Larger realized spreads are associated with a smaller share of the realized spread being devoted to sub-penny price improvement. Mean quoted

spreads are also associated a smaller share of the spread being devoted to improvement, suggesting that the sub-penny price improvement is more lucrative for wholesalers when spreads are wider. At a one-tick bid-ask spread, the potential realized spreads are small, so the sub-penny improvement represents a larger share of market maker revenues. With stock fixed effects, the association between intraday returns and realized ratio is negative, suggesting that on days when an individual stock makes a large move, market makers devote a smaller share of realized spreads to subpenny improvement. With date fixed effects, the association is positive, suggesting that stocks which are more volatile than the average stock also see a larger share of realized spreads devoted to subpenny improvement.

To test whether market conditions have a similar relationship with retail trade timing as they do with non-retail trades, we estimate Regression 3. *Quote_Difference_Share* measures the percentage of trades for which the quotes matched at one time differ from the quotes matched at another time. We evaluate three time comparisons: quotes 3 milliseconds prior to execution against quotes at execution, quotes at the SIP time of a trade against quotes at the participant timestamp, and quotes 3 milliseconds after execution against quotes at execution. Figure 5 plots the distribution of differences for each of these timestamps.

REGRESSION 3: *For each stock i on date t , we estimate:*

$$\begin{aligned} \text{Quote_Difference_Share}_{it} = & \alpha_0 \text{Closing_Price}_{it} + \alpha_1 \text{Absolute_Intraday_Return}_{it} \\ & + \alpha_2 \text{Mean_Quoted_Spread}_{it} + \alpha_3 \text{Mean_Realized_Spread}_{it} \\ & + \alpha_4 \text{Off_Exchange_Share}_{it} + X + \epsilon_{it} \end{aligned}$$

Results of Regression 3 are presented in Table III. Larger returns are strongly associated with a larger quote difference share at all time horizons. An intraday return is a pre-requisite for price changes. The coefficient estimate is much larger for non-retail trades than it is for retail trades, but the mean level of quote differences, as well as the variance, are higher for non-retail trades.

Higher closing prices are also associated with a larger quote difference share, as stocks with a larger price typically have more frequent price changes, given the minimum one-penny bid-ask spread. Stocks with higher realized spreads have lower quote difference shares; one potential

Table II: Realized Spread Share. This table estimates Regression 2. Realized Ratio, defined in Equation 3, is the ratio on realized spreads for sub-penny improved orders, and compares the realized spread calculated with the trade price against the realized spread calculated with with no subpenny price improvement. A larger ratio indicates a larger share of market-maker revenue goes to offering sub-penny price improvement. Closing Price is measured in dollars, while Absolute Intraday Return and Off-Exchange Share are measured in percentages. The level of observations is the stock-day level; to reduce noise in the realized spread ratio, we exclude stock-day observations with less than 50 sub-penny trades. Odd columns have a fixed effect for each date, while even columns have a fixed effect for each stock. Standard errors are clustered at the stock and day level.

	<i>Dependent variable:</i>					
	Realized Ratio 3ms		Realized Ratio 1s		Realized Ratio 30s	
	(1)	(2)	(3)	(4)	(5)	(6)
Closing	0.002 (0.003)		0.003 (0.003)		0.005* (0.003)	
Absolute Intraday Return	-10.270*** (1.609)	-11.497*** (1.886)	-3.733*** (1.186)	-7.002*** (1.519)	14.634*** (2.687)	2.301 (1.618)
Mean Quoted Spread (BPS)	0.024*** (0.002)	0.008*** (0.001)	0.026*** (0.002)	0.010*** (0.001)	0.026*** (0.002)	0.009*** (0.001)
Mean Realized Spread (BPS)	-0.084*** (0.007)	-0.070*** (0.004)	-0.099*** (0.007)	-0.083*** (0.004)	-0.115*** (0.007)	-0.094*** (0.004)
Off-Exchange Share	-0.116*** (0.004)	0.009*** (0.003)	-0.108*** (0.004)	0.006** (0.003)	-0.088*** (0.005)	-0.011*** (0.003)
Date Fixed Effect	X		X		X	
Stock Fixed Effect		X		X		X
Observations	3,044,374	3,044,374	3,029,709	3,029,709	2,935,098	2,935,098
Adjusted R ²	0.068	0.238	0.059	0.205	0.042	0.146
Residual Std. Error	15.076	13.637	16.023	14.734	18.520	17.483
Degrees of Freedom	3043710	3038605	3029045	3023940	2934434	2929329

Note:

*p<0.1; **p<0.05; ***p<0.01

explanation is that quote difference shares are often reversals, which reduce realized spreads. The effect of off-exchange trades differs between the retail and non-retail trades.

Across all specifications, market conditions explain a large portion of the variance in quote difference shares for all trades, and a much smaller portion of the variance in quote difference shares for retail trades. The R^2 for the non-retail trades is around 35 to 40%, while the R^2 for the retail trades is below 10%. This suggests that retail traders do not time their trades at the millisecond level, and as a result, their trades are unlikely to benefit from executing a few milliseconds faster or slower.

Table III: Realized Spread Share. This table estimates Regression 3. Quote Difference Share measures the percentage of trades which have a quote change from one timestamp to another. Columns (1) and (2) measure how often the quote from 3 milliseconds before a trade differs from the quote at the time of trade. Columns (3) and (4) measure how often the quote matched to a trade's SIP timestamp differs from the quote matched to the trade's participant timestamp. Columns (5) and (6) measure how often the quote from 3 milliseconds after a trade differs from the quote at the time of trade. Closing Price is measured in dollars, while Absolute Intraday Return and Off-Exchange Share are measured in percentages. Odd columns estimate the effect for all trades, while even columns estimate the effect for retail trades only. Standard Errors clustered at the stock and day level.

	<i>Dependent variable: Quote Difference Share</i>					
	3 Milliseconds Prior		SIP vs. Participant		3 Milliseconds Posterior	
	All Trades	Subpenny	All Trades	Subpenny	All Trades	Subpenny
	(1)	(2)	(3)	(4)	(5)	(6)
Closing Price	0.053*** (0.009)	0.004*** (0.001)	0.026*** (0.005)	-0.0003*** (0.0001)	0.038*** (0.007)	0.002*** (0.0002)
Absolute Intraday Return	93.827*** (13.049)	4.616*** (0.668)	49.103*** (6.967)	1.115*** (0.174)	84.049*** (11.549)	2.608*** (0.356)
Median Quoted Spread (BPS)	0.006*** (0.002)	0.002*** (0.0002)	0.001 (0.001)	0.001*** (0.0001)	0.006*** (0.002)	0.001*** (0.0001)
Realized Spread (BPS)	-0.181*** (0.010)	-0.004*** (0.001)	-0.093*** (0.006)	-0.002*** (0.0003)	-0.143*** (0.009)	-0.002*** (0.0003)
Off-Exchange Share	0.539*** (0.006)	-0.035*** (0.001)	0.337*** (0.004)	-0.014*** (0.0003)	0.500*** (0.005)	-0.004*** (0.0002)
Date Fixed Effect	X	X	X	X	X	X
Observations	3,689,300	3,689,300	3,689,300	3,689,300	3,689,300	3,689,300
Adjusted R ²	0.424	0.105	0.359	0.050	0.448	0.061
Residual Std. Error	16.020	2.215	10.942	1.313	13.347	0.886

Note: (df = 3688636) *p<0.1; **p<0.05; ***p<0.01

IV. Internalization in Options Markets

Options trade in a significantly different regulatory framework than U.S. equities. Unlike equities, options carry risks of counter-party default. The Options Clearing Corporation oversees the clearing of all options trades in U.S. single name equities, and requires that these options be traded on an exchange. Thus unlike U.S. equities, all trades in options occur on an exchange. There is no off-exchange internalization or dark trading: all trades occur on lit exchanges.

Price improvement and payment for order flow are distinct payments, with price improvement accruing to the customer and payment for order flow accruing to the broker. Both in the case of internalization and payment for order flow the counterparty (e.g., market maker or broker) is obligated to respect the prevailing quotes (and possibly improve upon them). Nevertheless, both internalization and payment for order flow lead to potential conflicts of interest in order routing. In the equity markets payment for order flow or internalization frequently occurs away from the traditional exchanges (e.g., this is often referred to as off-exchange trading). As our paper notes, the scope for such actions is often limited in the equity market due to the prevailing penny tick size. In options markets, spreads are much wider, so per-trade profits (or potential room for price improvement or payment for order flow) from individualizing uninformed trades is potentially much larger in options markets.

There is substantial price improvement associated with internalization in options markets, but it must go through exchanges. Exchanges have adopted rules to facilitate internalization, and we highlight some of these mechanisms and evaluate their effectiveness in Section V. There are 16 competing options trading venues, and wholesalers looking to internalize a trade have a choice of exchange. This leads to potential competition among some exchanges to offer terms that are particularly favorable to a wholesaler looking to internalize, such as giving them a price-match option or a large discount on make-take pricing. Some brokers can effectively route or steer much of their order flow to an exchange where they can act through an affiliated market maker who can obtain a guaranteed allocation (e.g., see footnote 37 in “Staff Report on Equity and Options Market Structure Conditions in Early 2021”). In this way significant internalization in options trades can arise, and competition to provide the best price may be limited.

A. Data

We obtain all U.S. equity options trades reported by the Options Price Reporting Authority (OPRA) from November 4, 2019 to December 31, 2021 through SpiderRock⁹. Due to a limitation of the data provider, we have some missing data during January, 2021. From SpiderRock, we also obtain matching quotes for the option as well as the underlying asset, and the option Greek values.

B. Price Improvement

We focus our analysis on trades which take place in Price Improvement Mechanisms (PIM). In such a mechanism, an order is advertised, and market makers have 100 milliseconds in which to place bids. In the OPRA datafeed, these trades are formally defined as “Single Leg Auction Non ISO.” These trades are predominantly retail trades. In these single-leg auction trades, regular trade execution stops, and the proposed trade goes through a two-sided auction mechanism with an exposure period. Exchanges may refer to these trades as “Price Improvement Mechanism”, “Customer Best Execution (CUBE),” or an “Automated Improvement Mechanism.”

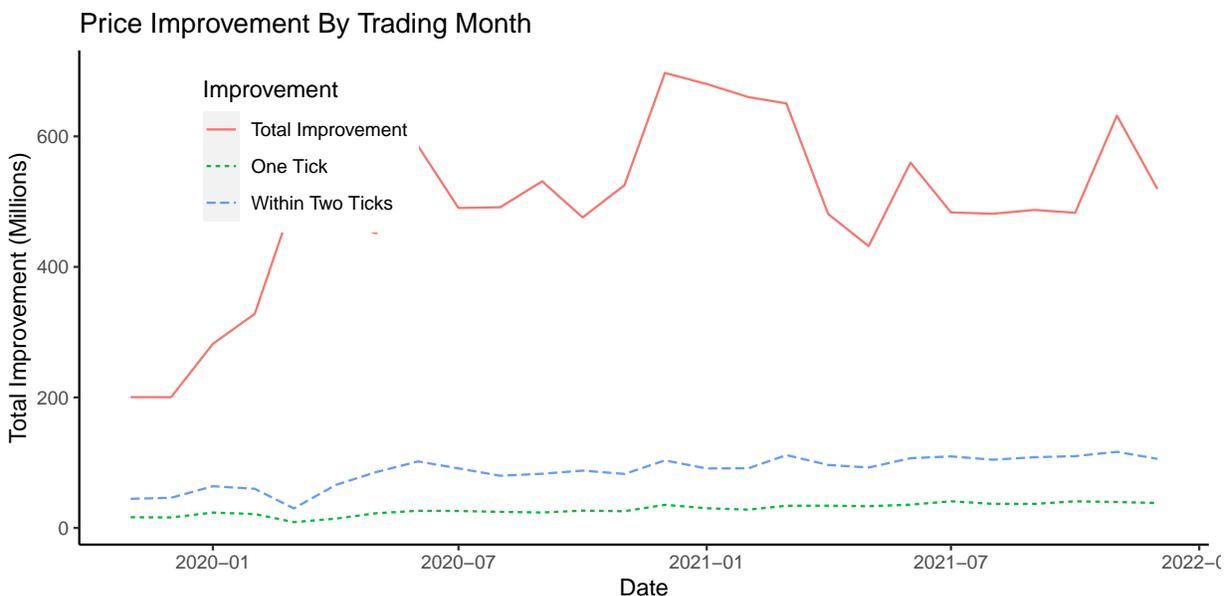
The Price Improvement Mechanisms involved facilitate internalization by market makers. While the execution of the trade happens on an exchange where anyone can ostensibly participate, the exchanges often adopt rules that discourage anyone other than the market maker internalizing the trade from participating. Such rules are an important component of the problem, though given these rules our analysis points out that that the routing decisions of (at least) some brokers are problematic in light of Best Execution standards. As an example, the NASDAQ PHLX exchange allows a market maker who proposes internalizing a trade in a Price Improvement Mechanism to selectively auto-match any competing bids in the auction. This gives the market maker a powerful first-mover advantage. When there are multiple bids at a price level, market makers also receive a guaranteed fill of one contract or 40% of the original size of the order.

The distribution of price improvement provided to orders is plotted in Figure 8. Most orders receive between 0 and 10 cents of price improvement, with the median order receiving 5 cents of improvement. An improvement of 5 cents means that a buy order fills at a price 5 cents lower than the best ask, while a sell order fills at a price 5 cents better than the best bid. Option trades

⁹SpiderRock Holdings, LLC is a Chicago-based market data vendor offers SpiderRock EXS, an agency broker-dealer.

have low average prices. If improvement is measured as a percentage of the trade price, the median trade receives 3% price improvement.

Figure 8. Option Price Improvement By Month. We plot price improvement across all option trades. Approximately 5 to 10% of option trades are traded in Price Improvement Mechanism (PIM) trades. We plot the total daily improvement with the solid red line. We plot total improvement when spreads are approximately one tick (5 cents) with the green dashed line, and improvement when spreads are two ticks (10 cents) with the blue dashed line. Total improvement is \$12.8 billion over our sample period.



Around 5 to 10% of trades in our sample go through an automated improvement mechanism. Figure 8 plots the total improvement by trading day, with a typical month receiving around \$100 million compared to the prevailing spreads. Across our entire sample period, PIM trades receive over \$2.4 billion in price improvement compared to the OPRA best bid or best ask.

C. Specialist / Designated Market Maker (DMM) Identification

To analyze how PFOF affects execution quality, we consider a simple question: does routing appear worse when it occurs at an exchange where a DMM pays PFOF? While we do not observe the individual brokers routing the trades, we observe which DMMs pay the most in PFOF. We rely on the fact that DMM assignments at each exchange are random, which gives us an exogenous way to measure how execution quality varies with whether the DMM does or does not provide PFOF.

From SEC 606 reports, we identify five key PFOF DMM's in the options space: Citadel, Wolver-

ine Execution Services, Susquehanna International Group, Morgan Stanley, and Dash IMC. Together, these DMM firms account for approximately 98% of total PFOF in options trades, as noted in Table VI. We compare these firms to the following DMM firms which pay nothing or very little for order flow: Belvedere, Two Sigma, GTS, XR Securities, Cutler, Simplex, Hudson River Trading, and Optiver.

V. Option Regression Analysis

A. Price Improvement Mechanism Trades

In this section, we examine how execution quality in price improvement mechanism trades varies with specialist identities. We use PFOF as an indicator which takes the value 1 if the exchange’s specialist assignment for the option is a specialist who is a major provider of PFOF (Citadel, Wolverine, Susquehanna, Morgan Stanley, and Dash IMC). This indicator takes the value zero for other securities. For this section, we restrict our analysis in this section to trades on exchanges which use a DMM, and we only analyze trades which OPRA reports as executing in “Single Leg Auction Non ISO” for the trade mechanism. Our hypothesis is that when DMMs pay PFOF, they can abuse their DMM position and offer less price improvement in auctions without losing future orders, due to the captive nature of their purchased order flow.

REGRESSION 4: *For each option trade i in security j on exchange k on date t :*

$$PriceImprovement_{ijkt} = \alpha_0 + \alpha_1 PFOF_{jk} + X_{ijkt} + \epsilon_{ijkt}$$

Our main regression is to test whether α_1 , the coefficient on the PFOF indicator, is negative. This PFOF indicator value is 1 whenever the designated market maker in security j on exchange k is one of the five major providers of PFOF payments. When the coefficient is negative, it implies that the execution in these cases is associated with less price improvement relative to the prevailing bid-ask spread.

We include several control variables. The option Greeks: delta, vega, gamma, and theta, as well as the option price and size are included as controls. We also include a fixed effect for each underlying symbol and for each exchange. We also cluster standard errors by exchange.

We present an estimation of Regression 4 in Table IV for the specific window beginning January 1, 2020, which is approximately the mid-point of our sample period. For this rolling 30 day window, we have 8,743,078 option trades which execute in a price-improvement mechanism on exchanges with a specialist. Within this sample, our estimate of α_1 is -54.0 ; that is, when a PIM trade occurs on an exchange where the DMM is a firm which provides PFOF, that trade will receive 54 basis points less price improvement than PIM trades where the DMM does not provide PFOF.

Given the sizeable quantity of data we have available, we construct a full estimate of Regression 4 in two ways. The first is to use rolling 30-trading-day windows, which allows us to check whether the patterns we observe are consistent across time. The second is to bootstrap estimates by drawing repeated subsamples of 30 days of data at random.

Estimates from the rolling window approach are presented in Figure 9. Across all subsamples, estimates of α_1 are negative: that is, price improvement auctions occurring on exchanges where the DMM provides PFOF on average receive less price improvement from the prevailing quotes. Our estimates across time range from -50 to -150 basis points. When we cluster standard errors by exchange, our estimates are statistically significant for over half of the dates in our sample. If we do not cluster standard errors by exchange, our results are always statistically significant.

Estimates from the bootstrap approach are presented in Figure 10. Similar to the rolling-window analysis, we find negative estimates of α_1 in all sub-samples. Across the 1,000 subsamples of 30 randomly selected trading days, we have a negative coefficient α_1 for every subsample. Estimates range from -80 to -120 basis points, and are centered around -100 basis points. When an exchange's DMM provides PFOF, trades which execute in price-improvement mechanisms will receive 100 basis points *less* price improvement. As price improvement is measured as the improvement against the bid-ask spread, this means investors receive worse prices in price improvement auctions when an exchanges' DMM provides PFOF.

Table IV: Price Improvement Based on Specialist Type. This table estimates Regression 4 for the 30 trading days starting on January 1, 2020. The dependent variable, Price Improvement, measures the amount of price improvement trades in price-improvement auctions provide relative to prevailing quotes. For example, if the price-improvement auction merely matches existing quotes, the improvement is zero. Our primary coefficient of interest, α_1 uses PFOF: an indicator for whether a DMM at a specific exchange is a major PFOF firm. We find trades in this case are associated with 50 basis points less improvement. We fit a fixed effect for each exchange and cluster standard errors by exchange.

	<i>Dependent variable:</i>
	Price Improvement (BPS)
PFOF (Coefficient α_1)	-53.939*** (9.785)
Delta	-256.165*** (28.905)
Vega	-368.575*** (33.348)
Gamma	269.056*** (71.572)
Theta	97.219*** (7.459)
Price	-3.969*** (0.593)
Size	0.002** (0.001)
Observations	8,741,549
R ²	0.174
Adjusted R ²	0.174
Residual Std. Error	1,024.373 (df = 8738087)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

Figure 9. Rolling Window Estimates of α_1 : PFOF-DMM coefficient. We estimate Regression 4 over rolling 30-trading-day windows. Along the x-axis, the date marks the beginning of the rolling sample. In black, we plot the point estimate of α_1 , the coefficient which measures how Price Improvement (measured as the distance from the trade price to the best bid or ask, in basis points) varies depending on whether the DMM in a stock-exchange pairing pays for order flow. We plot standard errors in light grey. Across all windows, we estimate a negative value of α_1 , that is, we estimate that trades receive *less* price improvement at exchanges where the DMM is a firm which pays PFOF.

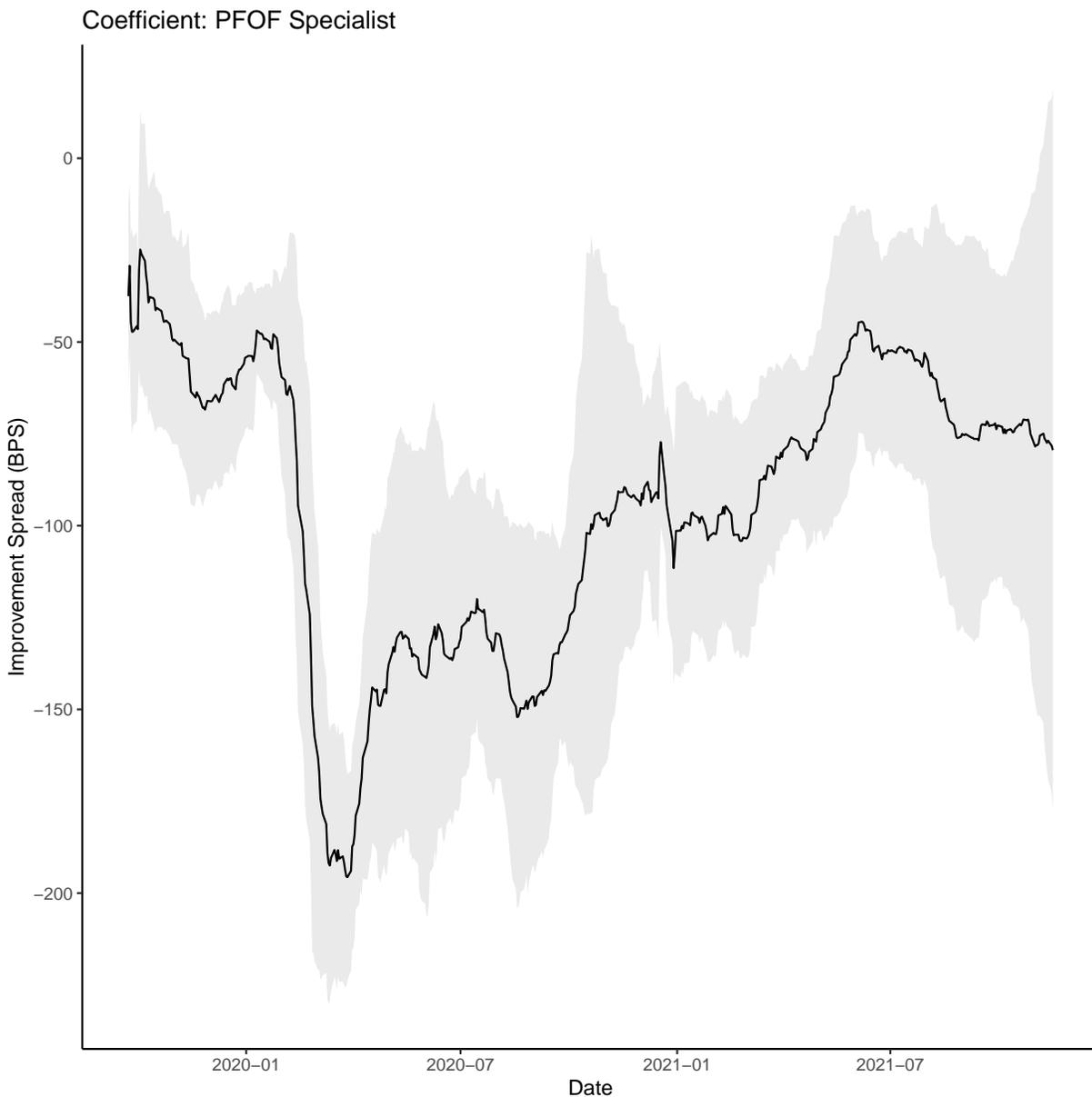
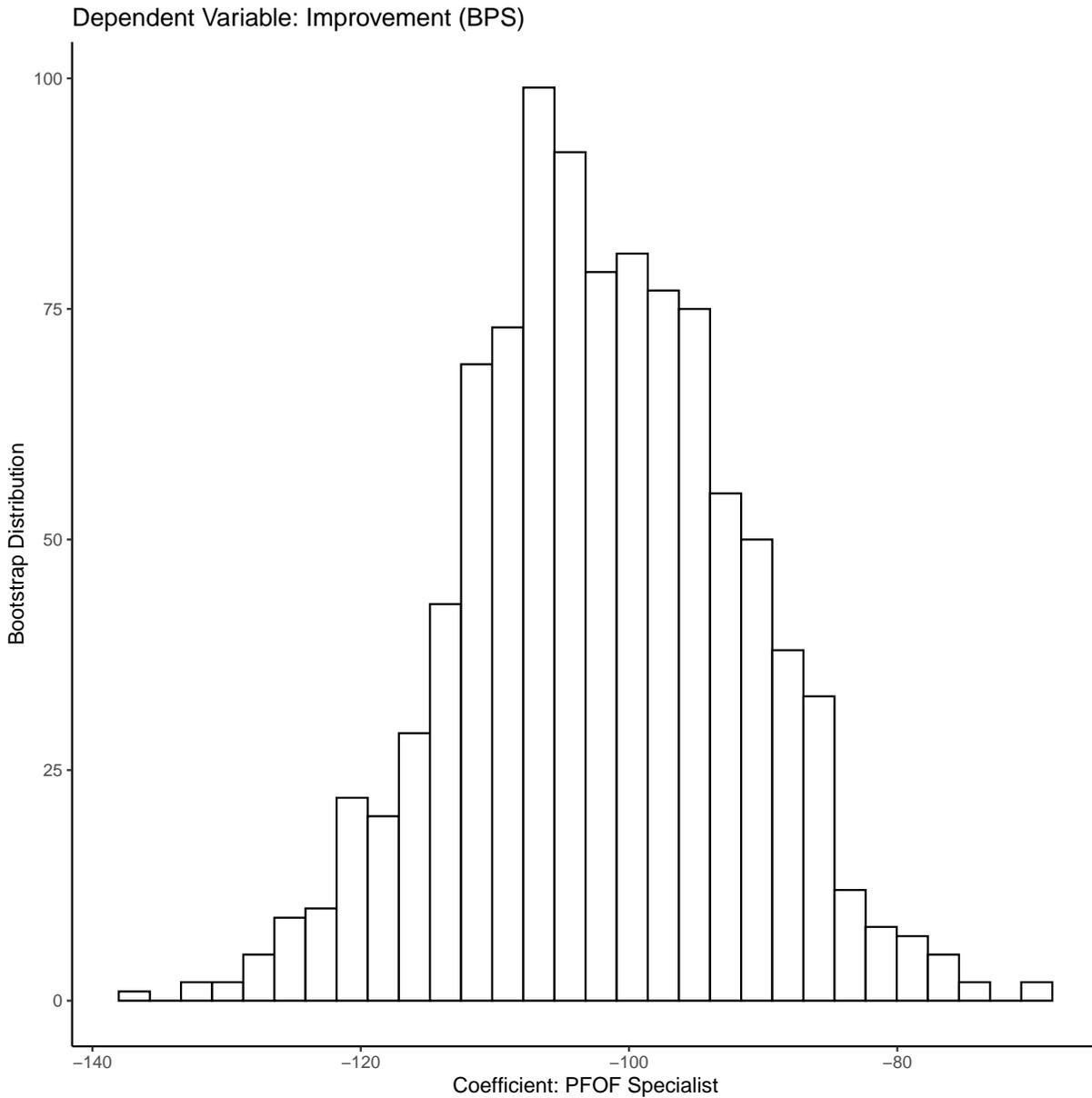


Figure 10. Bootstrapped Estimates of α_1 : PFOF-DMM coefficient. We estimate Regression 4 over subsamples of random draws of 30 individual trading days from our sample. We plot the distribution of point estimates of α_1 , the coefficient which measures how Price Improvement (measured as the distance from the trade price to the best bid or ask, in basis points) varies depending on whether the DMM in a stock-exchange pairing pays for order flow. Across all subsamples, we estimate a negative value of α_1 , that is, we estimate that trades receive *less* price improvement at exchanges where the DMM is a firm which pays PFOF.



B. Single DMM Stock Analysis

As an alternative test of the effect of PFOF on option transaction costs, we conduct a test using cases where, across all exchanges, there is at most a single firm assigned as a DMM. We then look at how quoted, effective, and realized spreads vary with the characteristic of this sole DMM, for all trades across all exchanges.

REGRESSION 5: *For each option trade i in security j on exchange k on date t :*

$$\text{Spread}_{ijkt} = \alpha_0 + \alpha_1 \text{PFOF}_j + X_{ijkt} + \epsilon_{ijkt}$$

In contrast with Regression 4, we now use PFOF_j to refer to whether trades in stock j have a DMM who is a primary PFOF provider. We are no longer restricting to price-improvement trades on exchanges with DMMs, but instead are examining all trades in our sample period. In addition to the controls previously used (delta, vega, gamma, theta, price, and size), we add the total dollar value traded each option during our sample period. Due to the small volume in some of the symbols, we also use a weighted-OLS, with the total dollar value traded in each option as the weight in the regression. We no longer have a fixed effect for each stock (to avoid overlapping effects with PFOF, since there is a single DMM per stock), but we continue to fit a fixed effect for each exchange and cluster standard errors by exchange.

Estimates of Regression 5 are presented in Table V. When the sole DMM is a PFOF-paying firm, we find that across all option trades, effective spreads are a statistically significant 5% higher, quoted spreads a statistically significant 10% higher, and realized spreads are 2% higher, though the effect on realized spreads is not statistically significant. These increases in effective and quoted spreads suggest that overall option trading costs are higher in stocks where the sole DMM pays PFOF compared to stocks where the sole DMM does not make PFOF payments.

Table V: Option Spreads With a Single DMM. This table estimates Regression 5. Dependent variables are the effective, quoted, or realized spread, all measured in basis points. We examine all trades, but restrict analysis to the subset of options which have a single DMM across all exchanges. PFOF is an indicator for whether the single DMM in that stock is one of the major PFOF-paying firms. Estimates are weighted-least-squares regression, using the total traded value of each security as the weight. There is a fixed effect for each exchange, and standard errors are clustered by exchange.

	<i>Dependent variable:</i>		
	Effective Spread (BPS)	Quoted Spread (BPS)	Realized Spread (BPS)
	(1)	(2)	(3)
PFOF	504.358*** (117.097)	1,009.512*** (179.184)	237.425 (174.844)
Delta	-370.394*** (50.089)	-420.103*** (41.469)	-5.839 (25.994)
Vega	-678.123** (278.564)	145.943 (378.227)	-42.844 (235.780)
Gamma	148.379 (467.440)	830.374 (579.462)	2,753.099*** (721.007)
Theta	-403.594*** (118.788)	-1,835.196*** (225.954)	559.002*** (127.576)
Price	-33.933*** (7.043)	-58.200*** (11.401)	-10.536*** (2.598)
Size	0.0001*** (0.00003)	0.0003* (0.0001)	-0.0002 (0.0002)
Option Volume Total	-0.00000 (0.00000)	0.00001** (0.00000)	0.00001*** (0.00000)
Observations	798,522	614,307	801,294
R ²	0.092	0.110	0.021
Adjusted R ²	0.092	0.110	0.021
Residual Std. Error	6,280,252	9,218,955	9,670,449
Degrees Freedom	798496	614281	801268

Note:

*p<0.1; **p<0.05; ***p<0.01

VI. Transaction Revenue and Payments

We obtain SEC 606 data on payment for order flow from five brokerages: TD Ameritrade, Robinhood, E*Trade, Charles Schwab, and Vanguard. The first four brokerages were the four largest recipients of payment for order flow in 2020, while Vanguard is a large brokerage which does not take payment for order flow for equity, though accepting payment for order flow for options. Total payments by each broker are plotted in Figure 11. Across our sample period, we document over \$3 billion in total payment for order flow.

Payments vary considerably by asset class. Figure 12 plots the payment by each asset type. Options are by far the largest share of PFOF, with around 65% of all PFOF. Non-S&P 500 stocks account for 30% of PFOF, and S&P 500 stocks account for just 5% of all PFOF. These percentages are based on the total value of the payments, but the payment rate per order is also unequal. Averaged across the main brokerages, options pay around 40 cents per 100 shares, while stocks pay around 20 cents per 100 shares. These per-share differences understate the nominal value difference. Among options trades receiving price improvement, the median price is \$5. Thus a \$1,000 investment in options generates a far larger share volume than an investment in equities, and the option investment also receives a larger payment per share than an investment in equities.

The total value of PFOF to brokers is smaller than the value of price improvement given to customer orders. In equity markets, we can accurately identify sub-penny retail improvement. As Figure 2 notes, this improvement can range between \$50 and \$150 million per month, which is more than the monthly equity PFOF of between \$40 and \$100 million (Figure 11).

Routing is concentrated among a small number of wholesalers. Table VI documents the routing behavior across asset classes. In each asset class, the top two firms receive 70% of all broker order routing. The top 4 firms receive over 90% of all broker routing in each asset class.

Figure 11. PFOF By Asset Class. Payment for order flow has increased over time. For our 606 data from January 1, 2020 to July 2021, we document \$3.2 billion in payment for order flow across the five brokerages. Note that Vanguard does not take payment for order flow for equity, but does take payments for options. Payment for order flow is relatively stable by brokerage, with the exception of Robinhood. Robinhood grew from \$20 million in January 2020 to \$67 million in July 2021, with a peak of \$120 million in February 2021.

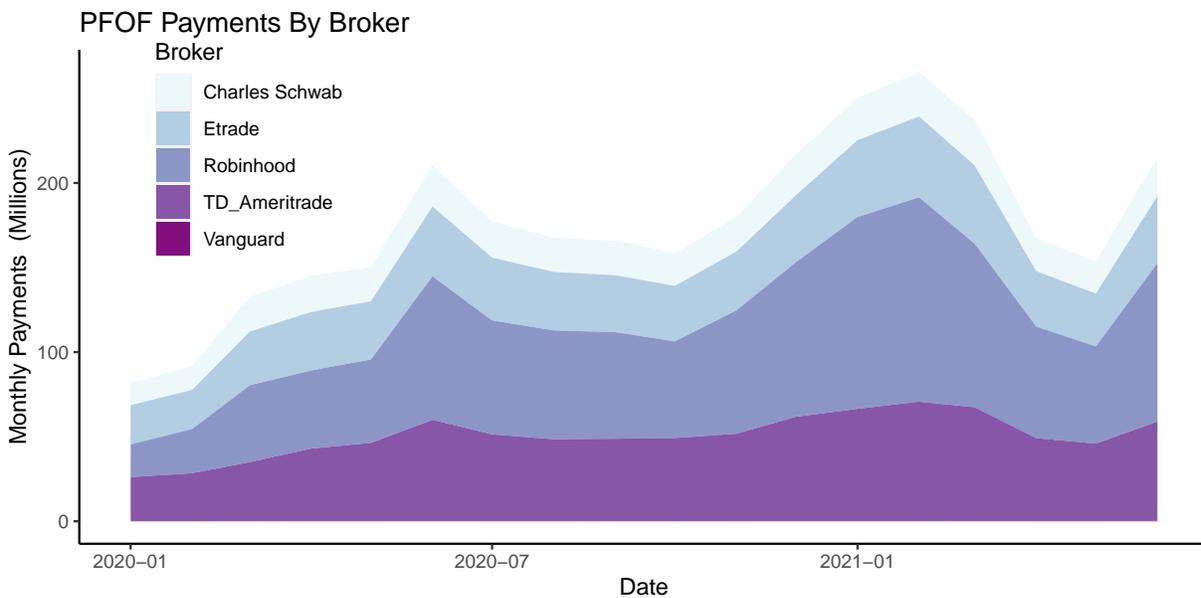
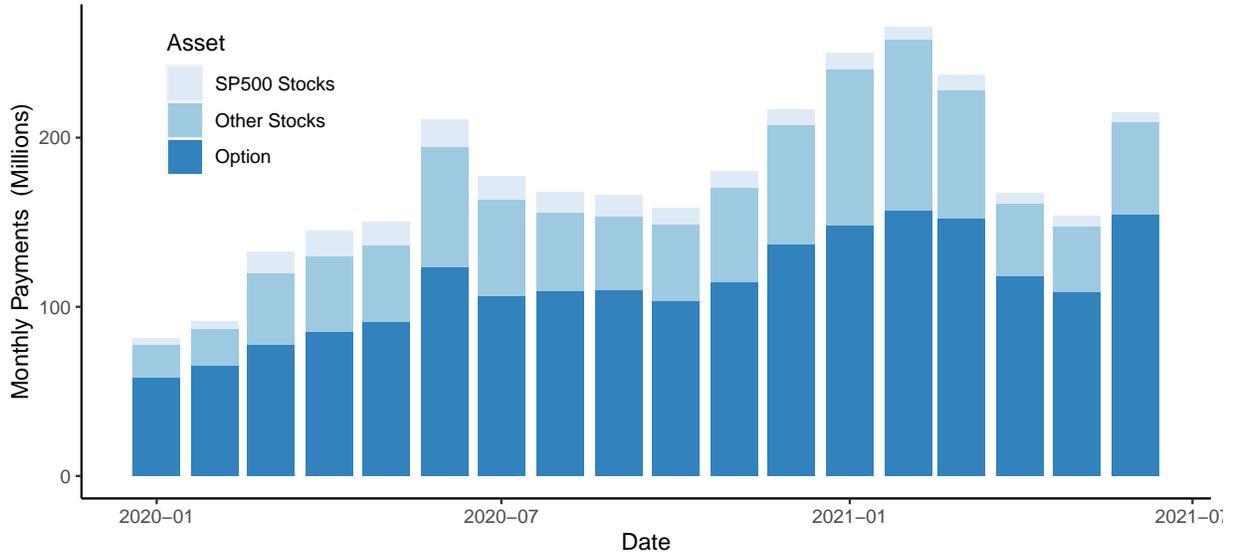


Figure 12. PFOF By Asset Class. There are large differences in payments across assets, both in total value and the payment per share. Panel A presents total payments. Most payment for order flow (65%) comes from options markets. The remainder comes from non-S&P 500 Stocks (30%) or S&P 500 stocks (5%). Panel B presents the payment rate per 100 shares traded. Options are consistently the highest in payments, averaging 40 cents per 100 shares traded.

Panel A: Total Payments



Panel B: Payment Per 100 Shares

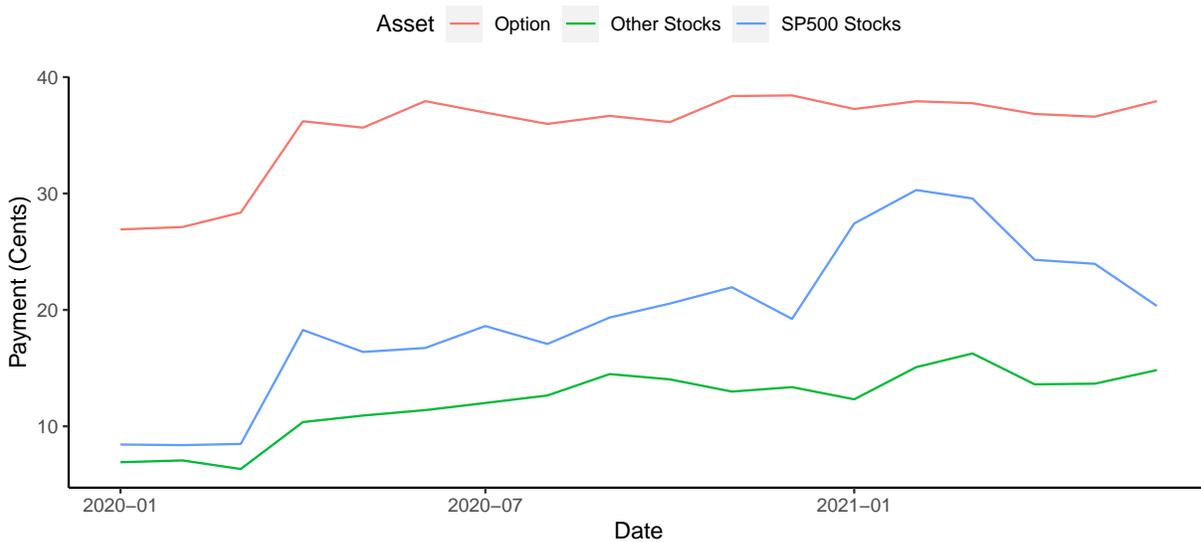


Table VI: Routing Destinations. A very small number of firms receive a very large share of order routing. Citadel and Virtu receive almost all equity routing, with G1X and Two Sigma receiving almost all of the remainder. Virtu is not active in options payment for order flow. In options, Citadel, Global Execution Brokers, Wolverine, Morgan Stanley, and Dash IMC receive almost all the order flow.

Options		
Firm	Total Orders (Millions)	Order Share
Citadel	852.18	42.20
Global Ex. Brokers	572.56	28.40
Wolverine	288.80	14.30
Morgan Stanley	156.88	7.80
Dash IMC	121.15	6.00
G1X	18.33	0.90
Two Sigma	5.13	0.30
Citigroup	3.58	0.20
Susquehanna	1.00	0.00

Other Stocks		
Firm	Total Orders (Millions)	Order Share
Citadel	395.42	40.70
VIRTU	292.01	30.10
G1X	125.61	12.90
Two Sigma	88.67	9.10
UBS	27.51	2.80
Wolverine	27.43	2.80
CBOE	8.78	0.90
Nasdaq	4.38	0.50
Jane Street Capital	0.62	0.10
Etrade	0.00	0.00
Susquehanna	0.00	0.00

SP500 Stocks		
Firm	Total Orders (Millions)	Order Share
Citadel	73.11	41.40
VIRTU	55.05	31.20
G1X	24.92	14.10
Two Sigma	11.11	6.30
UBS	6.67	3.80
CBOE	1.95	1.10
Nasdaq	1.91	1.10
Wolverine	1.84	1.00
Jane Street Capital	0.09	0.00
Susquehanna	0.00	0.00

VII. Asset Returns and Broker Conflict of Interest

Options have more volatile payoffs than stocks. Within options, there is extreme variation between the volatility of at-the-money options and far out-of-the money options. To provide a basic estimate of the effect of option trades on retail trades, we conduct a bootstrapped estimation from our dataset of all retail trades.

Our goal is to develop a reasonable estimate of how volatile the portfolios of retail traders are in practice. To do this from anonymous trade data, we make a set of assumptions, each with their own advantages and disadvantages:

1. Samples of 50 trades. For each date, we draw 1,000 samples of 50 trades each. The selection of 50 trades per portfolio creates a reasonably diverse portfolio.
2. Samples drawn from PIM trades. These trades are overwhelmingly retail trades. We note two limitations to our data: first, not all PIM trades are retail and second, not all retail trades go through PIM. We believe the latter issue is the more serious: some retail trades will not go through PIM, and the decision of a wholesaler not to internalize these trades may reflect that they may be more likely to earn profitable returns.
3. Samples of only call options. Retail traders will certainly buy both calls and puts, but buying a put leaves investors short the equity premium. By restricting to only calls, the option portfolios are long the equity premium, and we compare them against equivalent equity portfolios.
4. Samples with a three-month horizon. On any given day, observed retail option trades will have a variety of maturities. We restrict our analysis to only draw from trades with a maturity between 1 day and 3 months. To calculate 3 month returns, we calculate the option return at maturity, and then calculate the stock return between the maturity date and the end of the 3 month window. The geometric combination of these two returns gives an overall return to the sample window, and reflects the returns of an investor who held the option to maturity, and then held the stock to the ending period.
5. Samples are bench-marked against the same all-stock portfolio. One key concern with retail traders is that they may select stocks which deviate from the market portfolio. To account

for this, we compare the option portfolio return against the return of a portfolio comprised of the same underlying stock names.

6. Samples are assumed equally weighted. Out of the money options often have very low prices. When we draw a sample of 50 retail option trades, we combine trades across the portfolio in an equal-weighted average, rather than a value-weighted average.

As an example, on January 2, 2020, we construct 10,000 portfolios, each comprised of 50 option trades drawn from that day's PIM trades in call options. As an example option trade, a call option on APPL with a maturity date of February 2, 2021 and a strike price of 280 sold for \$22.42. On February 2, 2021, the closing price of Apple was \$313.03, giving a total return on the option of $\frac{(33.03-22.42)}{22.42} - 1 = 47.3\%$, while the closing price 3 months after January 2, 2020 was \$244.93, an 21.8% drop from the maturity date. The overall return for buying this option on January 2, 2020, and then holding the asset until April 2, 2020 was $(1 + 47\%)(1 - 21.8\%) - 1 = 15\%$. This 15% return is then equal-weighted with the other 49 returns on option trades from the portfolio.

We plot distributions of returns, combined across all dates, in Figure 14. The distribution of option returns has very high skew. Over 50% of all option portfolios lose 90% or more of their value, while 2.3% of option portfolios have a return greater than 500%. There is considerable time-series variation, however.

We plot the daily median returns of these portfolios in Figure 13. Across our sample, the median stock portfolio closely matches the return on the S&P 500 Index, as measured by the return of the S&P 500 ETF, SPY. The median option portfolio return varies considerably from the return of the S&P 500 Index, with a considerably higher return in some months, and considerably lower return in others.

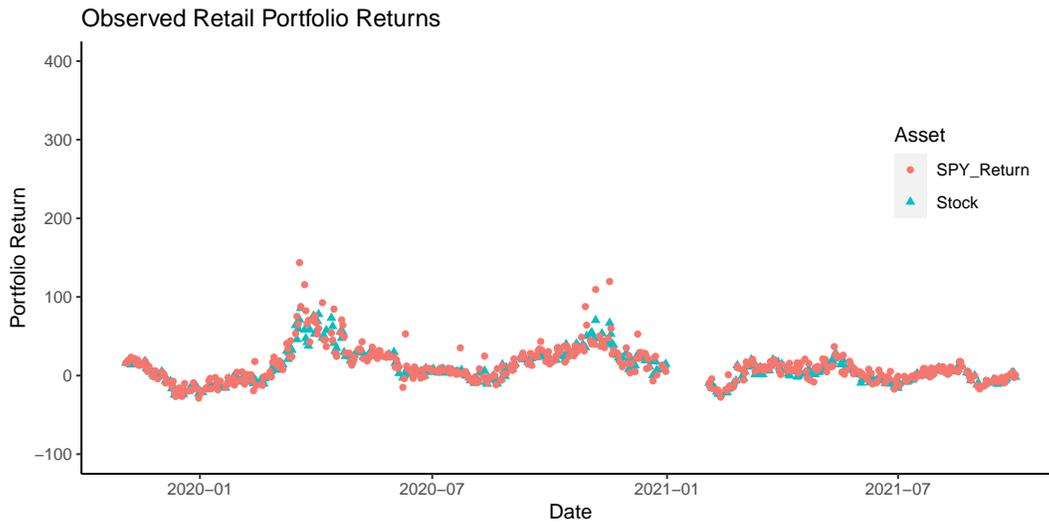
For brokers, the difference in returns is, in a way, no less stark. Options trades pay roughly double what equity trades pay, and these payments are guaranteed. Thus rather than a distribution of possible returns, as investors may obtain in Figure 13, the broker has a binary set of two possible payoffs. If investors are investing a fixed nominal amount, the low nominal price of options can further amplify this difference in payments. For example, an equally priced \$1,000 investment in a stock with a share price of \$100 would give 20 cents worth of payment for order flow. In contrast, an equally priced \$1,000 investment in an equity option with a price of \$10 would give approximately

\$4.00 worth of payment for order flow.

This conflict of interest between the broker and client is far larger in magnitude than the conflict of interest over routing choice. As we note in Section III, sub-penny improved trades are not sensitive to timing, as retail trades typically do not arrive at times when market prices are changing. Executing a millisecond faster or slower is important for trades on exchanges, but far less important for internalized trades. Moreover, these trades frequently occur at minimum one-tick spreads, meaning prevailing quotes are already at the minimum they could be. In options markets, spreads are wider and there is more potential room for price improvement. But even in options markets, spreads are measured in basis points, i.e. hundredths of one percent. Differences in portfolio returns between stocks and options, however, are measured in percentage points, and often exceed double-digit differences.

Figure 13. Comparison of Realized Returns Through Time. We simulate returns from an empirical distribution of option trades. We draw 1,000 portfolios of 50 option trades, and calculate returns assuming each option is held to maturity. Note that there are some missing dates in January 2021 due to missing data from SpiderRock, our data provider. Panel B plots the distribution of the daily median of portfolio returns, while Panel A plots the distribution of the daily median of portfolio returns for a portfolio which invests in stocks rather than options. The option portfolios have considerably higher volatility.

Panel A: Median Realized Returns for Retail Stock Trades



Panel B: Median Realized Returns for Retail Option Trades

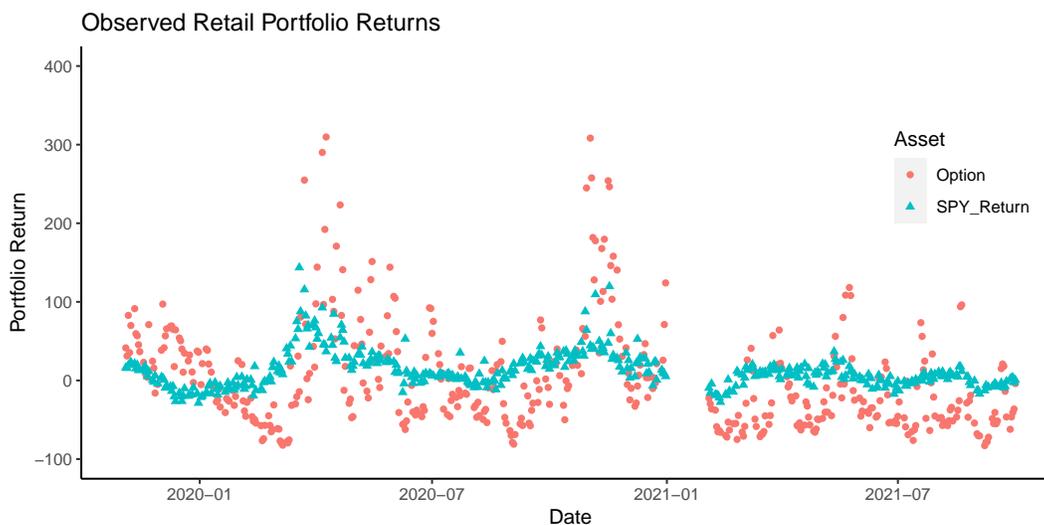
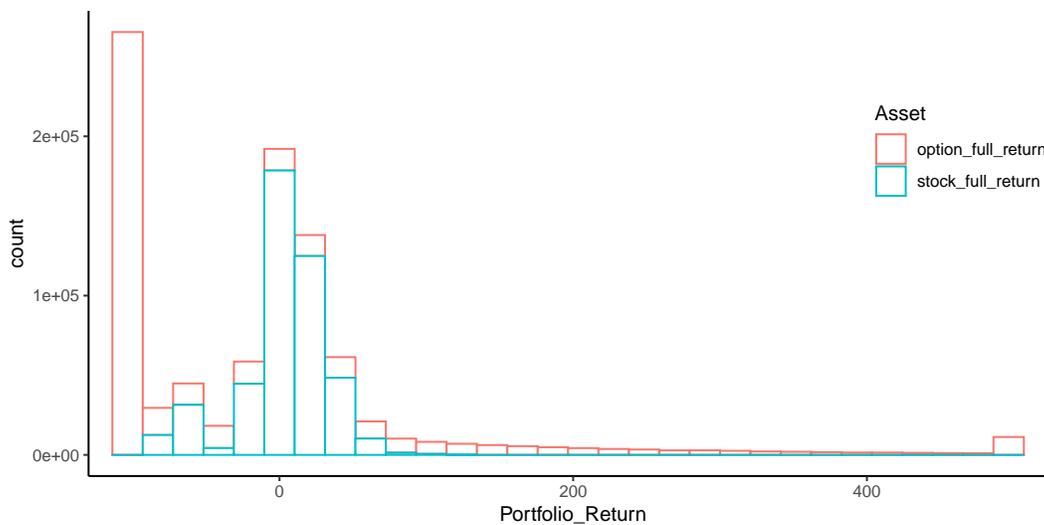


Figure 14. Comparison of Distribution of Realized Returns. We simulate returns from the empirical distribution of PIM option trades. For each day, we draw 1,000 portfolios of 50 option trades. We plot the distribution of returns assuming each option is held to maturity. Over 75% of option trades lose money; over half of the option portfolios lose more than 90% or more of their value. Portfolios have a very positive skew, with 2.3% of option portfolios having a return exceeding 500% (which we plot as a single point below).



REFERENCES

- Anand, Amber, Mehrdad Samadi, Jonathan Sokobin, and Kumar Venkataraman, 2021, Institutional Order Handling and Broker-Affiliated Trading Venues, *Review of Financial Studies* 34, 3364–3402.
- Barber, Brad M, Xing Huang, Terrance Odean, and Christopher Schwarz, 2021, Attention Induced Trading and Returns: Evidence from Robinhood Users, *Journal of Finance*, *Forthcoming* .
- Barber, Brad M, and Terrance Odean, 2000, Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *Journal of Finance* 55, 773–806.
- Bartlett, Robert P, and Justin McCrary, 2019, How Rigged are Stock Markets? Evidence from Microsecond Timestamps, *Journal of Financial Markets* 45, 37–60.
- Bartlett, Robert P, Justin McCrary, and Maureen O’Hara, 2022, The Market Inside the Market: Odd-Lot Quotes, *Available at SSRN 4027099* .
- Battalio, Robert, Shane A Corwin, and Robert Jennings, 2016a, Can Brokers Have it All? On the Relation Between Make-take Fees and Limit Order Execution Quality, *Journal of Finance* 71, 2193–2238.
- Battalio, Robert, Todd Griffith, and Robert Van Ness, 2021, Do (Should) Brokers Route Limit Orders to Options Exchanges that Purchase Order Flow?, *Journal of Financial and Quantitative Analysis* 56, 183–211.
- Battalio, Robert, Robert Jennings, Jamie Selway, and LLC Archipelago, 1998, Payment for Order Flow, Trading Costs, and Dealer Revenue for Market Orders at Knight Securities, *P* .
- Battalio, Robert, and Paul Schultz, 2011, Regulatory Uncertainty and Market Liquidity: The 2008 Short Sale Ban’s Impact on Equity Option Markets, *Journal of Finance* 66, 2013–2053.
- Battalio, Robert, Andriy Shkilko, and Robert Van Ness, 2016b, To Pay or be Paid? The Impact of Taker Fees and Order Flow Inducements on Trading Costs in US Options Markets, *Journal of Financial and Quantitative Analysis* 51, 1637–1662.

- Bernhardt, Dan, Yashar Barardehi, Zhi Da, and Mitch Warachka, 2022, Institutional Liquidity Demand and the Internalization of Retail Order Flow: The Tail Does Not Wag the Dog .
- Boehmer, Ekkehart, Charles M Jones, Xiaoyan Zhang, and Xinran Zhang, 2021, Tracking Retail Investor Activity, *Journal of Finance* 76, 2249–2305.
- Chordia, Tarun, and Avanidhar Subrahmanyam, 1995, Market Making, the Tick Size, and Payment-for-order Flow: Theory and Evidence, *Journal of Business* 543–575.
- Easley, David, Nicholas M Kiefer, and Maureen O’Hara, 1996, Cream-skimming or Profit-Sharing? The Curious Role of Purchased Order Flow, *Journal of Finance* 51, 811–833.
- Ernst, Thomas, Jonathan Sokobin, and Chester Spatt, 2021, The Value of Off-Exchange Data .
- Glosten, Lawrence R, and Paul R Milgrom, 1985, Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders, *Journal of Financial Economics* 14, 71–100.
- Hasbrouck, Joel, 2018, Price Discovery in High Resolution, *Journal of Financial Econometrics* .
- Holden, Craig W, and Stacey Jacobsen, 2014, Liquidity Measurement Problems in Fast, Competitive Markets: Expensive and Cheap Solutions, *Journal of Finance* 69, 1747–1785.
- Jain, Pankaj K, Suchi Mishra, Shawn O’Donoghue, and Le Zhao, 2020, Trading Volume Shares and Market Quality in a Zero Commission World, *Available at SSRN 3741470* .
- Jensen, Michael C, 1968, The Performance of Mutual Funds in the Period 1945-1964, *Journal of Finance* 23, 389–416.
- Li, Sida, Xin Wang, and Mao Ye, 2021, Who Provides Liquidity, and When?, *Journal of financial economics* 141, 968–980.
- Li, Sida, and Mao Ye, 2022, The Optimal Price of a Stock: A Tale of Two Discretenesses, *Available at SSRN 3763516* .
- Muravyev, Dmitriy, and Neil D Pearson, 2020, Options Trading Costs Are Lower Than You Think, *Review of Financial Studies* 33, 4973–5014.

Parlour, Christine A, and Uday Rajan, 2003, Payment for Order Flow, *Journal of Financial Economics* 68, 379–411.

Appendix A. Total Improvement Based on NBBO

We measure price improvement for sub-penny trades as only the sub-penny portion of the order. We could alternatively measure sub-penny improvement against the prevailing NBBO, matched via either the SIP or participant timestamp.

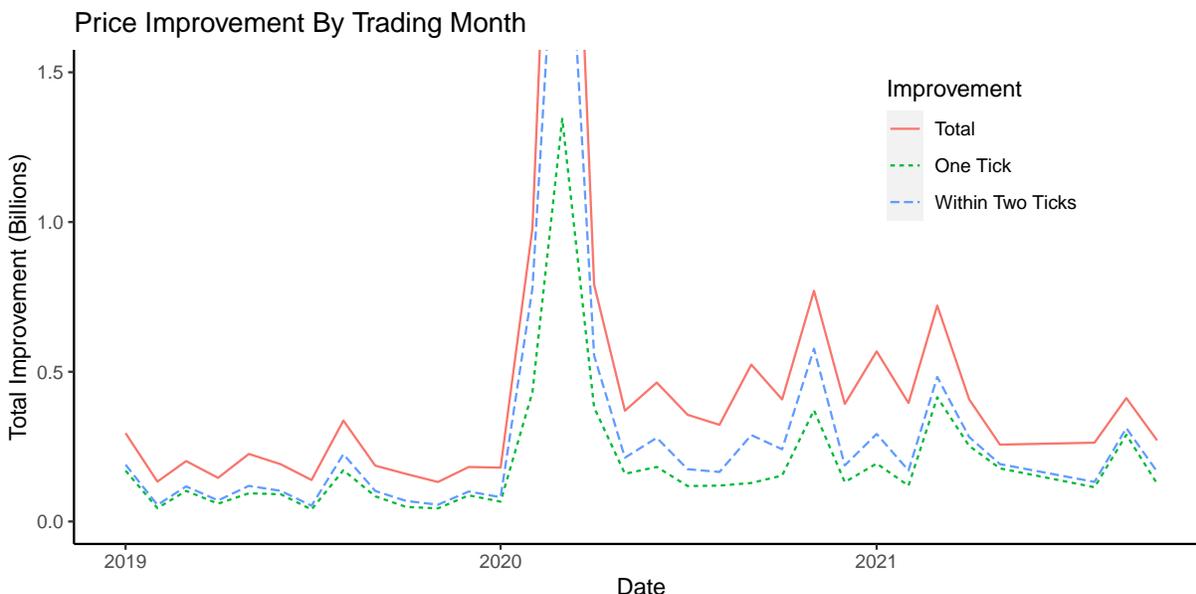
This alternative measure of improvement yields significantly larger estimates, but is open to errors in timestamps of trades. For example, participant timestamps for off-exchange trades are only accurate to the nearest millisecond. Matching quotes, therefore, may be off by as much as a millisecond, meaning trades with large improvement are also possibly trades in a volatile market. Note that during the highest volatility of the COVID-19 pandemic, estimated price improvement under the NBBO-based measure substantially increases (Figure 15).

On the other hand, if wholesalers do provide more than a sub-penny improvement, this alternative measure captures such improvement. When spreads are wider than one penny, providing more than one penny improvement, but less than a full half-spread of improvement, is possible. We re-conduct any analysis we have on the sub-penny improvement using this alternative NBBO-based measure in this Appendix.

While these volumes are substantial in part due to the tremendous volume of U.S. equities trades, they also represent a meaningful portion of transaction costs. With monthly transaction volumes of sub-penny trades ranging between \$300 billion and \$1 trillion, the sub-penny price improvements amount to an average of a 5 basis point improvement. This is a substantial value of price improvement. As Figure 2 shows, around half of the total sub-penny price improvement occurs when stocks are at the minimum one-tick spread, i.e. a single penny bid-ask spread.

To further capture the value of these price improvements, we consider how market-making profits would be impacted were there to be no sub-penny price improvements. We use realized spreads as a measure of market-making profits, as a realized spread compares the signed trade price against the midquote some time interval after the trade. For each sub-penny price-improved trade, we also consider the national best bid or offer, *NBBO*, at the time of the trade. We compare two different measures of realized spreads: one measured against the actual trade price, and one measured against the national best bid or offer. The measure of realized spreads using the NBBO could be thought of as the total potential revenue available to a market maker, while the measure

Figure 15. Price Improvement By Month. Total price improvement for sub-penny trades, by month. Following Boehmer et al. (2021), sub-penny trades are defined as trades in which the price has a sub-penny component between (0, 40) and (60, 100). For these trades, we calculate improvement as the difference between the price and the prevailing NBBO. For example, for a buy order at \$10.2575 with a best offer of \$10.27, the improvement would be \$0.125. We separately calculate the total value of price improvements which occur when the quoted spread is at one tick (red solid line) or at two ticks (blue dashed line). Note that March 2020, with \$3.3 billion in total improvement, is a substantial outlier and is not captured by the axis of this chart.



of realized spreads using the actual trade price is the total profit. If sub-penny price improvement is viewed as an expense, the ratio of the two realized spread measures captures the share of total revenue devoted to sub-penny price improvement.

Formally, for a trade price P_T , national best bid or offer NBBO, trade sign Y , and midquote m which occurs X seconds after the trade, we define the two possible definitions of a realized spread:

$$\text{Realized_With_Improvement}_t = Y(P_t - m_{t+X}) \tag{A1}$$

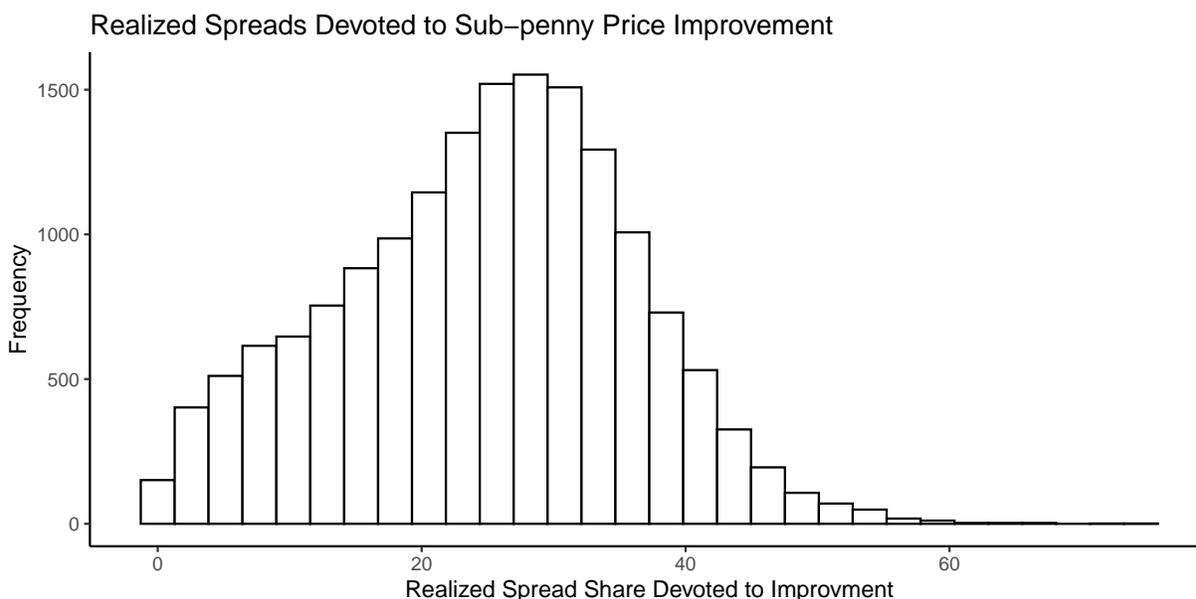
$$\text{Realized_No_Improvement}_t = Y(NBBO_t - m_{t+X}) \tag{A2}$$

$$\text{Alt_Expense_Ratio} = 1 - \frac{\sum \text{Realized_With_Improvement}}{\sum \text{Realized_No_Improvement}} \tag{A3}$$

For each stock, we calculate the value of this expense ratio, and plot the distribution of this ratio across stocks in Figure 3. The average stock has a 25% difference the two measures. If we consider the total revenue from retail trades to be the realized spread on these trades calculated using the

NBBO, around 25% of this total revenue goes to offering sub-penny price improvements.

Figure 16. Price Improvement As Fraction of Realized Spreads. Realized spreads for sub-penny price-improved trades are 20 to 40% lower than a realized spread measured against the contemporaneous national best bid or offer. For all sub-penny trades, we calculate the realized spreads using both the trade price and the NBBO (Equation A3). The realized spread using the trade price reflects market maker profits, while the realized spread using the NBBO reflects market maker revenue. In the average stock, total realized spreads in sub-penny stocks are around 25% lower than the total realized spreads on those same trades using the NBBO rather than the trade price. This suggests around 25% of the total revenue market makers make from retail trades is allocated to sub-penny price improvement.



To test how the profitability of internalization changes with market conditions, we test Regression 2. As defined in Equation 3, realized ratio is the ratio between two different measures of realized spreads: one measured against the actual trade price, and one measured against the national best bid or offer. The measure of realized spreads using the NBBO could be thought of as the total potential revenue available to a market maker, thus the difference between the two realized spreads represents the cost to the market maker of offering the sub-penny price improvement. This ratio is defined only for sub-penny improved trades, and to reduce the variance of this ratio we exclude any stock-day observations with fewer than 50 sub-penny trades.

REGRESSION 6: For each stock i on date t with at least 50 subpenny trades, we estimate:

$$\begin{aligned} \text{Realized_Ratio}_{it} = & \alpha_0 \text{Closing_Price}_{it} + \alpha_1 \text{Absolute_Intraday_Return}_{it} \\ & + \alpha_2 \text{Mean_Quoted_Spread}_{it} + \alpha_3 \text{Mean_Realized_Spread}_{it} \\ & + \alpha_4 \text{Off_Exchange_Share}_{it} + X + \epsilon_{it} \end{aligned}$$

Results of this estimation are presented in Table VII. Results are generally consistent with Table VII, with the exception that the closing price here is not significant, and here the relationship between Realized Ratios and intraday returns is unambiguously negative.

Table VII: Realized Spread Share. This table estimates Regression 6. Realized Ratio, defined in Equation A3, is the ratio on realized spreads for sub-penny improved orders, and compares the realized spread calculated with the trade price against the realized spread calculated with the prevailing best bid or offer. A larger ratio indicates a larger share of market-maker revenue goes to offering sub-penny price improvement. Closing Price is measured in dollars, while Absolute Intraday Return and Off-Exchange Share are measured in percentages. The level of observations is the stock-day level; to reduce noise in the realized spread ratio, we exclude stock-day observations with less than 50 sub-penny trades. Odd columns have a fixed effect for each date, while even columns have a fixed effect for each stock. Standard errors are clustered at the stock and day level.

	<i>Dependent variable:</i>					
	Realized Ratio 3ms		Realized Ratio 1s		Realized Ratio 30s	
	(1)	(2)	(3)	(4)	(5)	(6)
Closing	0.002 (0.003)		0.004 (0.003)		0.006** (0.003)	
Absolute Intraday Return	-13.724*** (1.715)	-9.291*** (1.498)	-7.640*** (1.250)	-5.032*** (1.288)	10.405*** (1.845)	4.537*** (1.608)
Mean Quoted Spread (BPS)	0.021*** (0.002)	0.009*** (0.001)	0.023*** (0.002)	0.010*** (0.001)	0.024*** (0.002)	0.010*** (0.001)
Mean Realized Spread (BPS)	-0.084*** (0.006)	-0.064*** (0.004)	-0.097*** (0.006)	-0.076*** (0.004)	-0.113*** (0.006)	-0.088*** (0.004)
Off-Exchange Share	-0.107*** (0.004)	0.012*** (0.003)	-0.100*** (0.004)	0.009*** (0.003)	-0.080*** (0.004)	-0.008*** (0.003)
Date Fixed Effect	X		X		X	
Stock Fixed Effect		X		X		X
Observations	3,132,771	3,132,771	3,117,756	3,117,756	3,021,496	3,021,496
R ²	0.067	0.240	0.059	0.207	0.042	0.148
Adjusted R ²	0.067	0.239	0.058	0.206	0.042	0.147
Residual Std. Error	15.055	13.596	16.003	14.698	18.484	17.441
Degrees of Freedom	3132107	3126697	3117092	3111682	3020832	3015422

Note:

*p<0.1; **p<0.05; ***p<0.01