# Payment for Order Flow And Asset Choice*

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**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. 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.

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# 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 has 22.8 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 quasi-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. 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 spreads[2] with and without subpenny price improvement. We find that around 10% of market maker revenue on retail trades goes to providing subpenny price im-

[1] Boehmer 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 and trades crossed on public equity markets are clearly not subject to internalization.

[2] A 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 initial option spreads are considerably wider. Due to clearing considerations, options markets do not have off-exchange internalization. Instead, all trading happens on-exchange, with exchange-provided methods for internalizing trades. Exchanges appoint designated market makers, or DMMs, who can route incoming orders to their own quotes, regardless of position in the price-time or price–pro-rata queue. Market makers can also use price improvement mechanisms, whereby 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 a reduced take fee or gain a price-match option against any competitor in the auction. These rules diminish 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 Walgreens. At the Miami Options Exchange, Global Trading Systems is the DMM in Walgreens, while Citadel is the DMM in Coca-Cola. Comparing option trades in Coca-Cola at CBOE vs. Miami against option trades in Walgreens at CBOE vs. Miami allows us to fit fixed effects for both assets and exchanges, and isolate the role of PFOF. We present evidence that PFOF-paying market making firms use the specialist system to internalize trades: when a PFOF-paying DMM is present, there are more single-participant trades and these trades earn larger realized spreads.

Market makers also internalize trades via price-improvement mechanism (PIM) trades, but these trades do not use the DMM-allocation rule. In these PIM trades, the initiator of the trade has certain advantages which facilitate internalization, like a price-match auto-bid where the initiator can choose to automatically match any competing bid. To analyze execution quality in these auctions, we exploit changes in tick size for a subset of stocks in the Penny Pilot Program which have a one-penny tick size for options priced below $3.00, and a five-penny tick size above $3.00. Compared to trades just below the cutoff, trades just above receive much higher price improvement, but also have higher realized spreads, consistent with market makers internalizing profitable trades and retaining significant profit for themselves.

Finally, we compare the performance of retail equity and option portfolios to highlight the dangers of over-trading different assets. From observed retail call option trades of not more than

[3]For 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.

three months maturity, 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 wider spreads. While the price improvement offered in PIM trades is larger when quoted spreads are wider, the average realized spread of these trades is larger, too. 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.

Compared to equity, option trades have larger discrepancies between the prices obtained and the best quotes reported publicly; this generates potential profit opportunities for market makers, and market makers in options provide higher payments 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

[4]It 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.

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.

## 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] 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 been studied over time in various contexts ranging 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

[5] In questioning by House Committee on Financial Services member Jim Himes (D-CT) suggesting that 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.)

[6] Easley, Kiefer, and O'Hara (1996) present evidence of cream-skimming with payment for order flow, while Battalio and Holden (2001) provide a theoretical basis for order segregation of retail orders, regardless of tick size. Battalio, Jennings, and Selway (2001) find brokers can reduce commissions, while Parlour and Rajan (2003) model social welfare effects.

[7] Typical 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.

trading, as documented in Barber, Huang, Odean, and Schwarz (2021), and among stocks, retail traders like low-priced, high-volatility stocks Greenwood, Laarits, and Wurgler (2022). 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 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 small individual trades that 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 Ni, Pearson, Potesh-

man, and White (2021) show that gamma-hedging by option market makers can impact equity pricing. While option spreads are wide, investors can time their trades (Muravyev and Pearson (2020)) or route to exchanges with particular make-take pricing models (Battalio, Shkilko, and Van Ness (2016b)). Battalio, Griffith, and Van Ness (2021) examine the switch of the PHLX options exchange from make-take to payment pricing mode.

Two working papers analyze options trade-level data. Bryzgalova, Pavlova, and Sikorskaya (2022) use price improvement auctions to identify retail trades, and show retail traders fail to optimally exercise calls before dividends. Hendershott, Khan, and Riordan (2022) examine price improvement auctions theoretically and empirically, and argue option auctions are consistent with cream-skimming, having lower price impact than limit order book trades. The model also provides tests of competitiveness and their evidence suggests that neither auctions nor the limit order book are perfectly competitive. We focus on the execution quality in these auctions, utilize the Penny Pilot tick-size cutoff as an exogenous source of variation in the decision to internalize trades. We also introduce the importance of DMM assignments for the analysis of option-internalization, with trades being internalized through both the DMM allocation and the PIM process.

## 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 hundreths 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 hundreths 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.

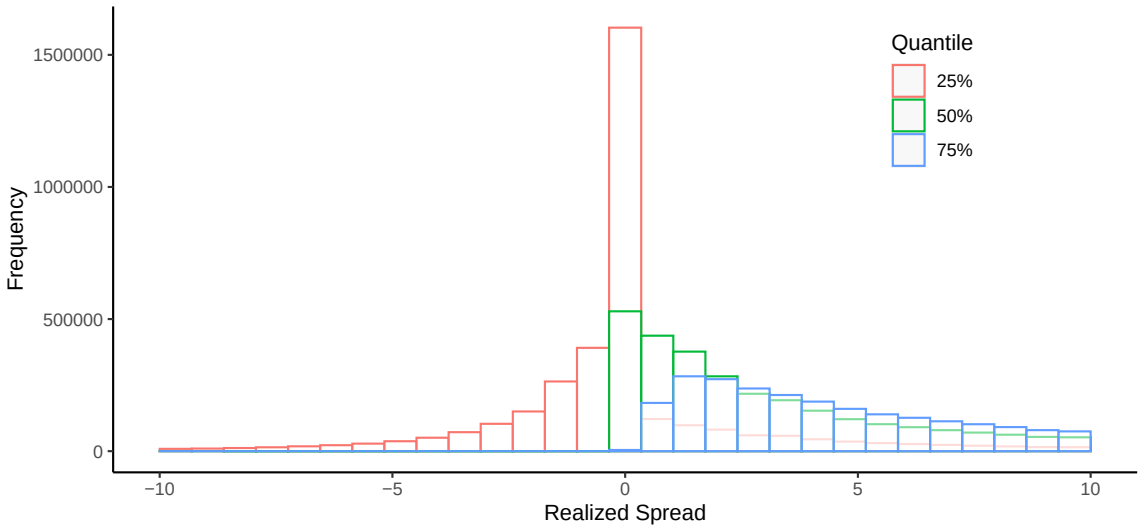
Market makers offer sub-penny price improvement to attract retail flow. Under a Glosten and Milgrom (1985) model, bid-ask spreads depend on the ratio of informed to uninformed traders. If retail traders are less informed than the general population of traders, market makers could charge a smaller bid-ask 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 loose 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 (most, but not all, stock-days have a negative observation for the 25% quantile), suggesting market makers loose money on a portion of all 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 $20 and $30 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.

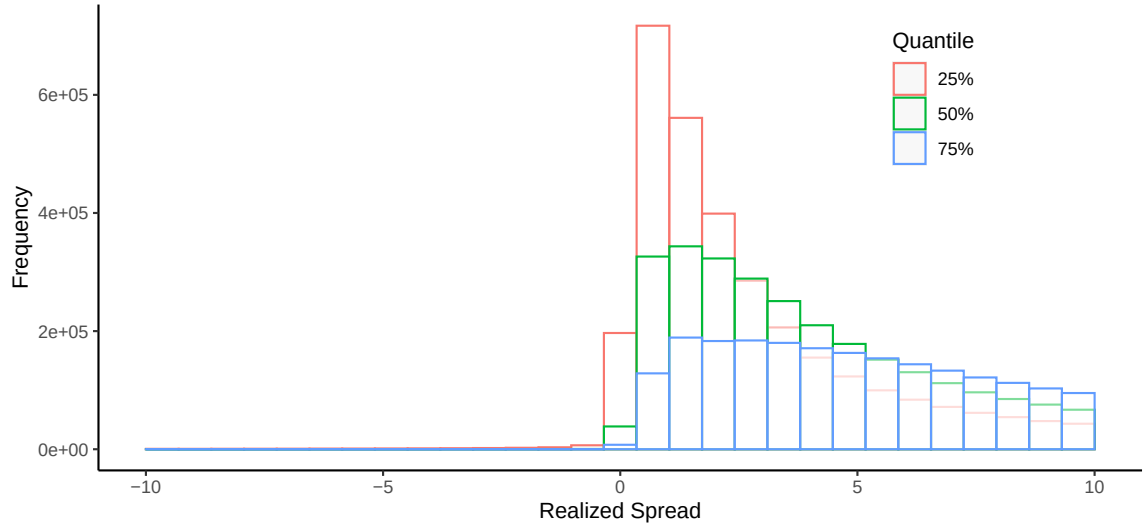
While these volumes are substantial in part due to the tremendous volume of U.S. equities trades, they also represent a meaningful portion of transaction costs. With monthly transaction volumes of sub-penny trades ranging between $300 billion and $1 trillion, the average sub-penny

**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

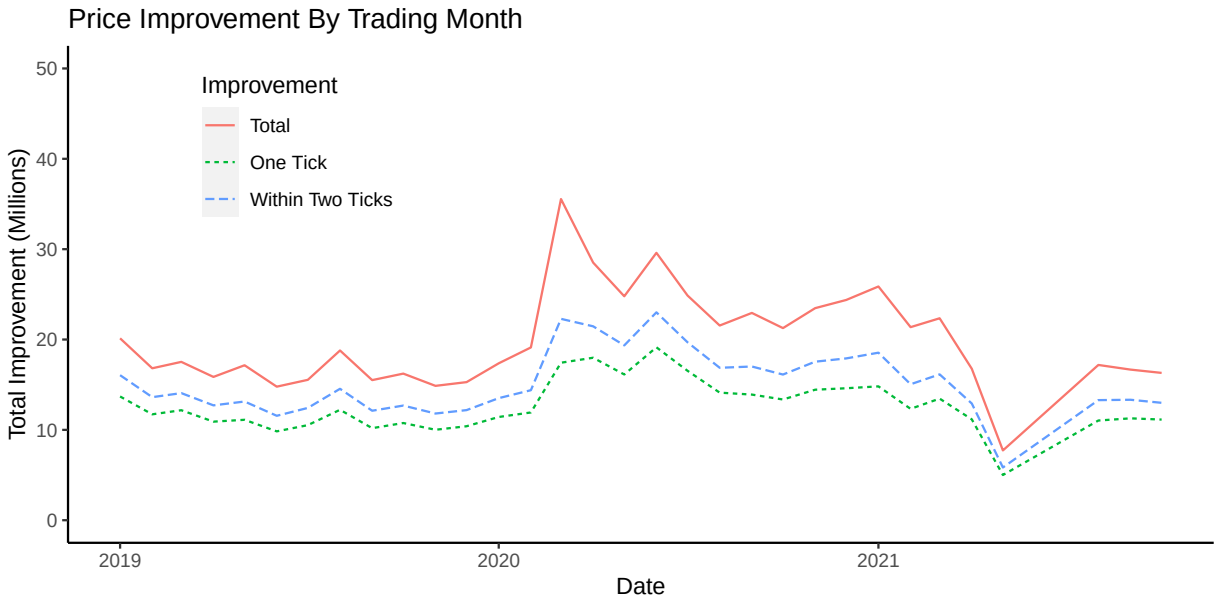



**Panel B:** Realized Spreads for Sub-penny Trades




price 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

**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 hundreths 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).




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 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, $NBBO$,

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:

$$\text{Realized\_With\_Improvement}_t = Y(P_t - m_{t+X}) \tag{1}$$

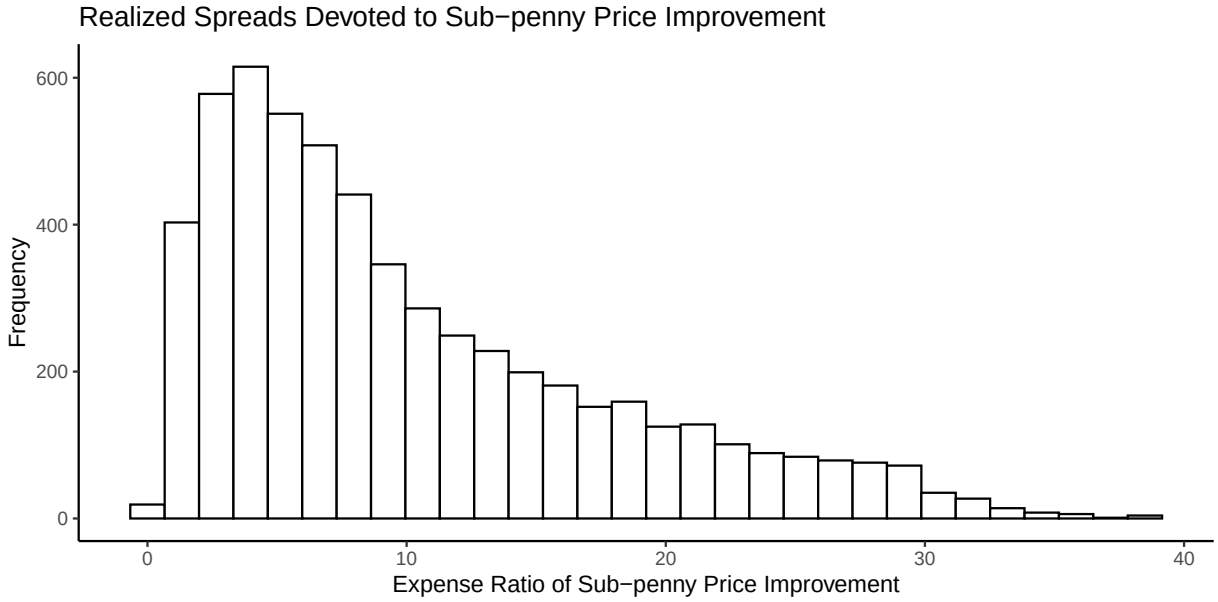
$$\text{Realized\_No\_Improvement}_t = Y(P_t - m_{t+X}) + Sub_t \tag{2}$$

$$\text{Expense\_Ratio} = 1 - \frac{\sum \text{Realized\_With\_Improvement}}{\sum \text{Realized\_No\_Improvement}} \tag{3}$$

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 10% 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 10% of this total revenue goes to offering sub-penny price improvements.

These calculations of market maker profits do not take into account how the NBBO itself depends on market maker behavior. Ernst, Sokobin, and Spatt (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.

**Figure 3. Price Improvement As Fraction of Realized Spreads.** Realized spreads for sub-penny price-improved trades are as much as 40% 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.



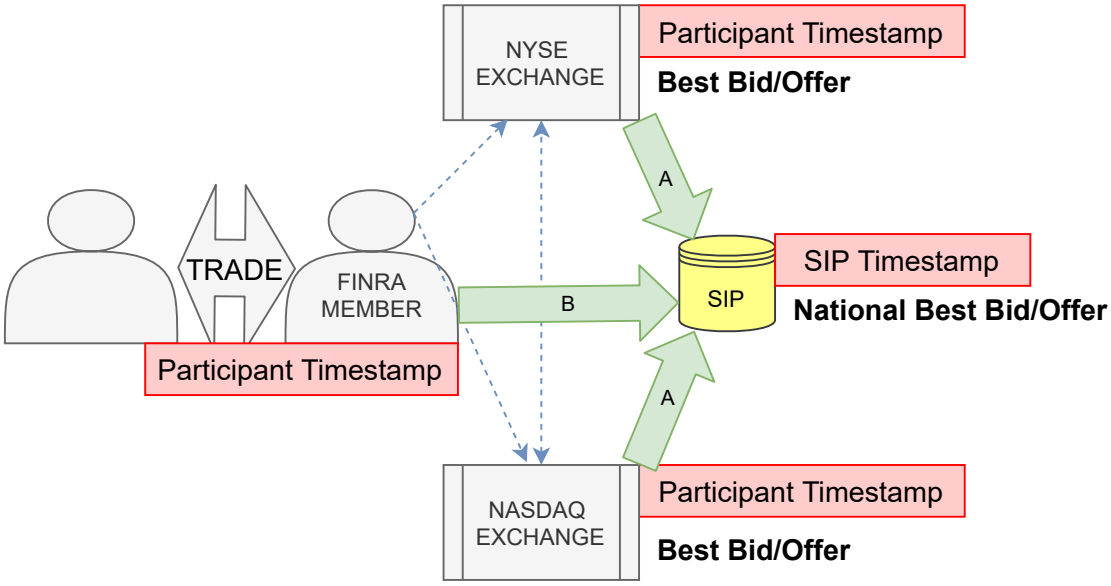

### *C. Time Sensitivity of Trades*

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, doing 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 the SIP, where the SIP timestamp is assigned according to the SIP's clock.

**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).




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

The multiplicity of timestamps and SIPs, depicted in Figure 4, 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

[8]There 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).

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 account 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 35% of the time (see Figure 5). 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 milliseconds 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 milliseconds after the SIP-matched quote averaging 35% 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.

**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.

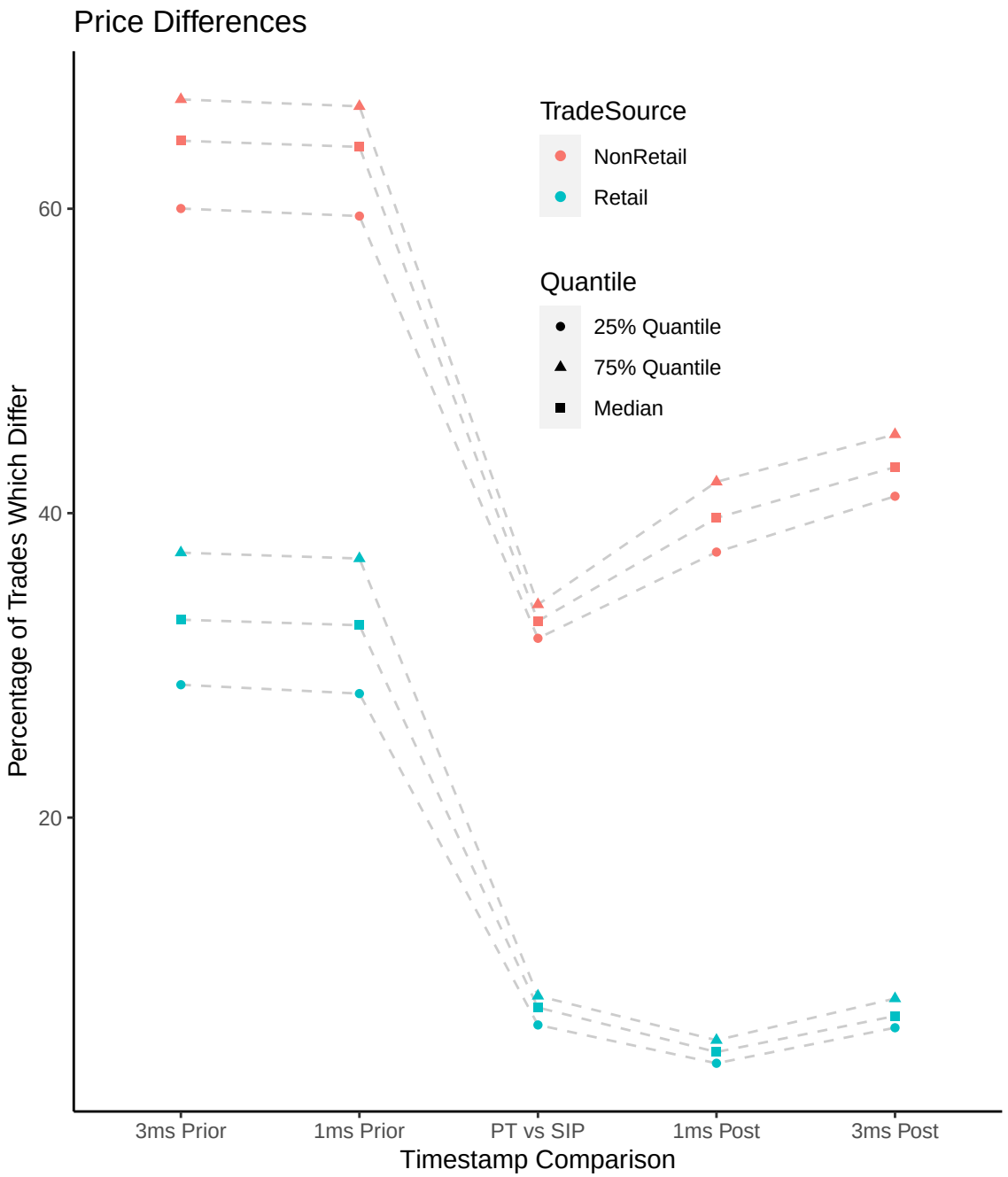


**Figure 6. Midquote Differences By Stock Characteristics.**. We plot the percentage of trades for which the SIP-timestamp-matched quotes differ from the participant-timestamp-matched quotes across stock-day observations. Stocks with a share price greater than $100 (dashed purple) have far more days 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.

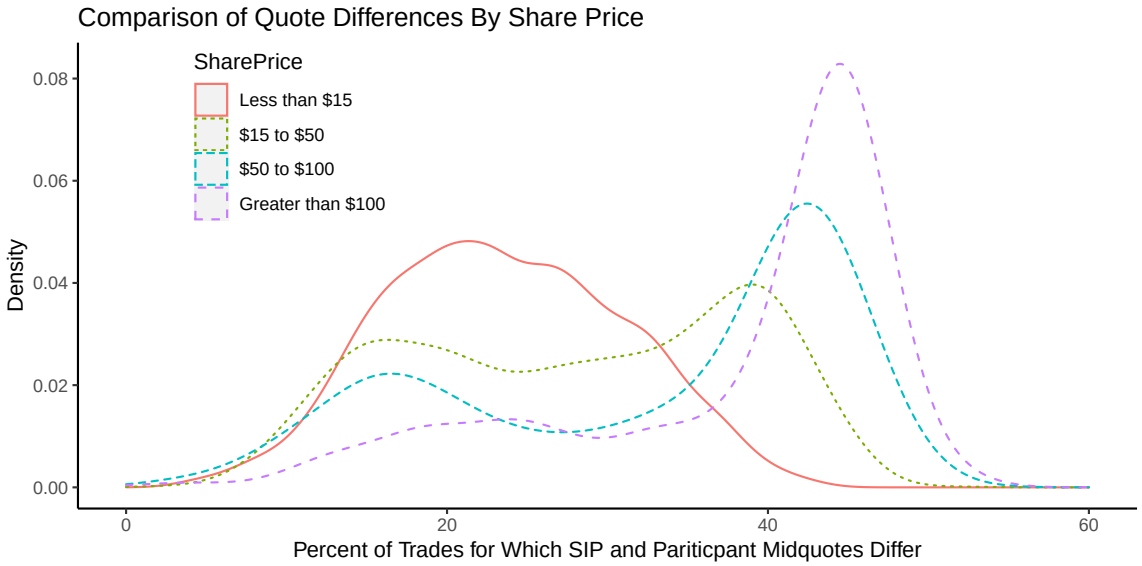
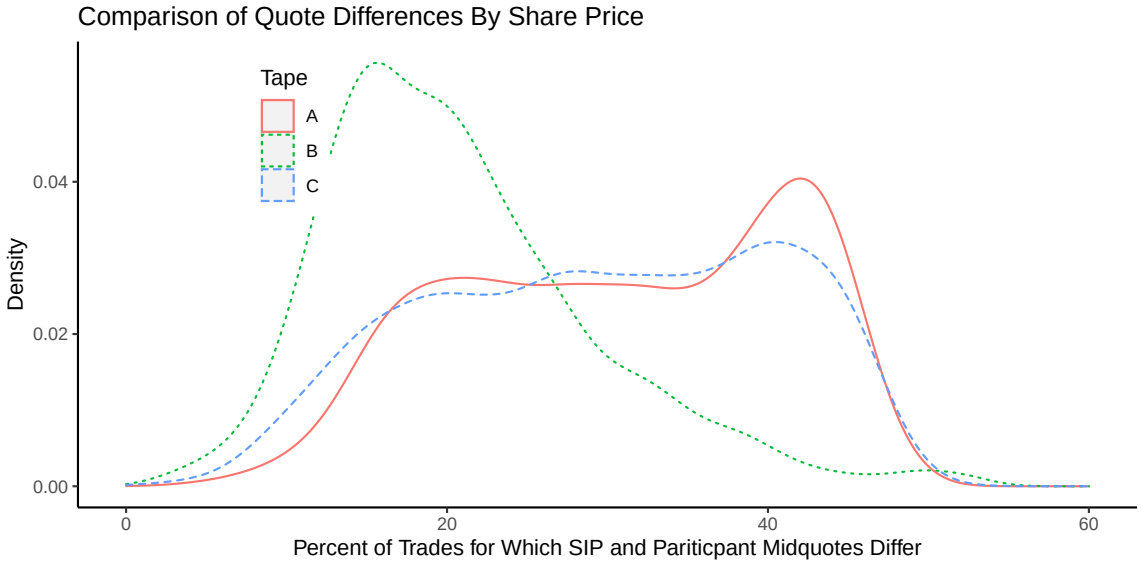



**Figure 7. Midquote Differences By Tape**. We plot the percentage of trades for which the SIP-timestamp-matched quotes differ from the participant-timestamp-matched quotes across stock-day observations. Stocks listed on Tapes A and C (solid red and dashed blue lines) are far more likely to have differences 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.



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 out 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 (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:*

$$\begin{aligned} ImprovementShare_{it} = \quad & \alpha_0 Closing\_Price_{it} + \alpha_1 Absolute\_Intraday\_Return_{it} \\ & + \alpha_2 Mean\_Quoted\_Spread_{it} + \alpha_3 Mean\_Realized\_Spread_{it} \\ & + \alpha_4 Off\_Exchange\_Share_{it} + X + \epsilon_{it} \end{aligned}$$

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).

**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.

| | *Dependent variable:* | |
|---|---|---|
| | ImprovementShare | |
| | (1) | (2) |
| Closing Price | $-0.004^{***}$ | |
| | (0.001) | |
| Absolute Intraday Return | $-9.005^{***}$ | $-2.946^{***}$ |
| | (1.439) | (0.648) |
| Mean Quoted Spread (BPS) | $0.004^{***}$ | $0.001^{***}$ |
| | (0.001) | (0.0002) |
| Mean Realized Spread (BPS) | $0.028^{***}$ | $0.021^{***}$ |
| | (0.002) | (0.002) |
| Off-Exchange Share | $-0.413^{***}$ | $-0.279^{***}$ |
| | (0.003) | (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) |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

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 3% to 9% 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 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 in 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 10% 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:*

$$\begin{aligned} Realized\_Ratio_{it} = \quad & \alpha_0 Closing\_Price_{it} + \alpha_1 Absolute\_Intraday\_Return_{it} \\ & + \alpha_2 Mean\_Quoted\_Spread_{it} + \alpha_3 Mean\_Realized\_Spread_{it} \\ & + \alpha_4 Off\_Exchange\_Share_{it} + X + \epsilon_{it} \end{aligned}$$

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:*

$$\begin{aligned} Quote\_Difference\_Share_{it} = \quad & \alpha_0 Closing\_Price_{it} + \alpha_1 Absolute\_Intraday\_Return_{it} \\ & + \alpha_2 Mean\_Quoted\_Spread_{it} + \alpha_3 Mean\_Realized\_Spread_{it} \\ & + \alpha_4 Off\_Exchange\_Share_{it} + X + \epsilon_{it} \end{aligned}$$

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.

**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.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Realized Ratio 3ms | | Realized Ratio 1s | | Realized Ratio 30s | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Closing | 0.002 | | 0.003 | | 0.005* | |
| | (0.003) | | (0.003) | | (0.003) | |
| Absolute Intraday | −10.270*** | −11.497*** | −3.733*** | −7.002*** | 14.634*** | 2.301 |
| Return | (1.609) | (1.886) | (1.186) | (1.519) | (2.687) | (1.618) |
| Mean Quoted | 0.024*** | 0.008*** | 0.026*** | 0.010*** | 0.026*** | 0.009*** |
| Spread (BPS) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) |
| Mean Realized | −0.084*** | −0.070*** | −0.099*** | −0.083*** | −0.115*** | −0.094*** |
| Spread (BPS) | (0.007) | (0.004) | (0.007) | (0.004) | (0.007) | (0.004) |
| Off-Exchange Share | −0.116*** | 0.009*** | −0.108*** | 0.006** | −0.088*** | −0.011*** |
| | (0.004) | (0.003) | (0.004) | (0.003) | (0.005) | (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 |

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 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 are clustered at the stock and day level.

| | *Dependent variable: Quote Difference Share* | | | | | |
|---|---|---|---|---|---|---|
| | 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*** | 0.004*** | 0.026*** | −0.0003*** | 0.038*** | 0.002*** |
| | (0.009) | (0.001) | (0.005) | (0.0001) | (0.007) | (0.0002) |
| Absolute Intraday Return | 93.827*** | 4.616*** | 49.103*** | 1.115*** | 84.049*** | 2.608*** |
| | (13.049) | (0.668) | (6.967) | (0.174) | (11.549) | (0.356) |
| Median Quoted Spread (BPS) | 0.006*** | 0.002*** | 0.001 | 0.001*** | 0.006*** | 0.001*** |
| | (0.002) | (0.0002) | (0.001) | (0.0001) | (0.002) | (0.0001) |
| Realized Spread (BPS) | −0.181*** | −0.004*** | −0.093*** | −0.002*** | −0.143*** | −0.002*** |
| | (0.010) | (0.001) | (0.006) | (0.0003) | (0.009) | (0.0003) |
| Off-Exchange Share | 0.539*** | −0.035*** | 0.337*** | −0.014*** | 0.500*** | −0.004*** |
| | (0.006) | (0.001) | (0.004) | (0.0003) | (0.005) | (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 individual 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 SpiderRock[9]. 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. *Options Internalization*

There are several methods for internalizing a trade on option markets. We highlight two mechanisms: designated market maker (DMM) assignments and price improvement mechanisms (PIM).

For the first method, exchanges appoint DMMs, or specialists, at the stock-specific level. Each exchange independently assigns DMMs to stocks, creating stock-exchange level variation in DMM assignments. If the DMM at an exchange has a limit order at the NBBO, the DMM has a special advantage, that they can route any order not exceeding five hundred shares to execute entirely against their own quote (or route at least five hundred shares against their own quote for larger orders). This is a serious advantage, as they will gain the entire order, regardless of the position in the time-queue at exchanges employing price-time priority, and regardless of their percentage of displayed depth at exchanges employing pro-rata distribution.

For the second method, trades take place in a Price Improvement Mechanisms (PIM) auction. 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. If the market maker does not have a quote at the NBBO, they cannot route to their own quote, but they can start a price improvement auction. In this price improvement auction, they can propose internalizing the trade at the NBBO or a better price. Offering price improvement also

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

matters for broker execution quality metrics. When option spreads are particularly wide, offering price improvement on the trade has the potential to greatly improve a wholesaler's average execution quality. The extent to which this is meaningful improvement, however, hinges on the competitiveness of the quotes.

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 initiating 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 at least one contract or 40% of the original size of the order, whichever is larger.

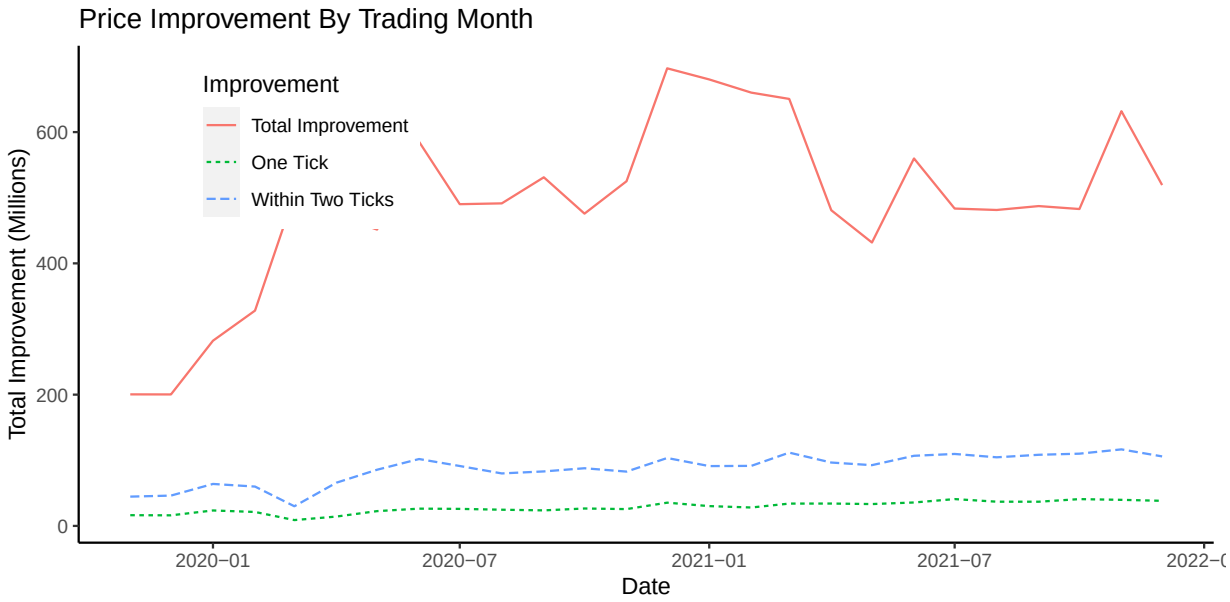
The distribution of price improvement provided to orders is plotted in Figure 8. Most orders receive between 0 and 10 cents of price improvement, with the median order receiving 5 cents of improvement. An improvement of 5 cents means that a buy order fills at a price 5 cents lower than the best ask, while a sell order fills at a price 5 cents better than the best bid. Option trades have low average prices. If improvement is measured as a percentage of the trade price, the median trade receives 3% price improvement.

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 quasi-random, which gives us an exogenous way to measure how execution quality varies with whether the DMM does or does not

**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.




provide PFOF.

From SEC 606 reports, we identify five key PFOF DMM's in the options space: Citadel, Wolverine 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 IX. 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.

As a second exogenous source of variation, we exploit the 500 share cutoff for DMM internalization. Trades at or below 500 shares can be entirely internalized by the DMM, while shares above 500 shares will not be fully internalized by the DMM; to capture the full order, the DMM would have to use a PIM trade. We note that, in contrast to equities, option trades always occur in even 100 share increments, and we compare option executions of trades of exactly 500 shares against trades of exactly 600 shares.

# V. Option Regression Analysis

## *A. Designated Market Maker (DMM) Effects*

In this section, we examine how execution in option markets 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 "(Auto) Electronic" for the trade mechanism. These are regular electronic trades on the exchange, for which the DMM receives some advantage.

One advantage of the DMM is the ability to internalize any trade of 5 shares or less, provided they have a quote at the NBBO. As an example, Citadel is the DMM in Walgreens options at the CBOE exchange. CBOE uses a pro-rata model, so if multiple market makers have a quote at the NBBO, each market maker is allocated a piece of incoming market orders, in proportion to their share of the depth at the NBBO at CBOE. As the DMM, however, Citadel can route a customer order to CBOE and will be allocated 500 shares, even if the pro-rata share is lower. For a market-maker seeking to internalize an order, the DMM seat offers a powerful advantage.

To test whether market-makers use their DMM seats to internalize orders, we examine the share of orders which involve multiple participants. OPRA data utilizes "printing on the passive side": that is, if an incoming market order executes against multiple quotes, there is a separate print for each quote, with the same price and timestamp, but potentially different quantities. We define the variable $MultipleParticipant$ as taking the value 1 if a trade involves multiple participants on the liquidity-supplying side, and 0 otherwise. We then estimate Regression 4 using a probit model. $PFOF$ takes the value 1 if the DMM at exchange $j$ for asset $k$ pays PFOF. Controls $X$ include the option Greeks, a fixed effect for each exchange, and a fixed effect for each symbol.

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

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

Results of Regression 4 are presented in Table IV. When the DMM at an exchange pays payment

for order flow, trades are 6% less likely to have multiple participants, consistent with DMMs using their 5-lot advantage to internalize entire trades for themselves.

We then consider what effect this internalization may have on market quality. In Section C, we consider the special case where only one DMM is assigned to a stock across all exchanges. While this has identification advantages, it restricts analysis to a set of stocks with only one DMM, which tend to be small stocks.

To analyze the effect of the DMM-internalization decision, we estimate Regression 5, which examines changes in outcomes around the 500-share cutoff. We define $BelowCutoff$ as 1 when an order is for 400 or 500 shares, and 0 when an order is for 600 or 700 shares. Of interest is the interaction term $\alpha_3$ between PFOF and $BelowCutoff$. Shares of 500 or less can be fully internalized by the specialist, while shares of 600 or more cannot be fully internalized.

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

$$\begin{aligned} RealizedSpreadBPS_{ijkt} = \quad & \alpha_0 + \alpha_1 PFOF_{jk} + \alpha_2 BelowCutoff_{ijkt} \\ & + \alpha_3 PFOF_{jk} * BelowCuttoff_{ijkt} + X_{ijkt} + \epsilon_{ijkt} \end{aligned}$$

Results of Regression 5 are presented in Table V. Quoted spreads for orders of 400 or 500 shares are slightly narrower when the DMM pays PFOF. We suspect this may be a strategic choice by market makers related to execution quality metrics. When quoted spreads are wide, internalizing via the specialist mechanism is less attractive than a price improvement mechanism trade, which offers the potential to offer price improvement. When quoted spreads are narrow, offering price improvement is less attractive, and market makers can prioritize the guaranteed allocation from their DMM assignment.

Realized spreads for the 400 to 500 share orders, which can be fully internalized via the DMM allocation, are 3 basis points higher when the DMM at an exchange pays PFOF compared to when the DMM does not pay PFOF. This is consistent with these DMMs utilizing the 500-share DMM allocation to internalize trades. Our measure relies on the stock-exchange based DMM assignments. We do not see whether any individual trade involves the DMM; as a result, our 3 basis point estimate is a potentially large underestimate, as this 3 basis points is average across all trades in stocks which have a PFOF-paying DMM, and not just those for which the DMM participated.

**Table IV: Probability of Multiple Participants.** This table estimates Regression 4 for auto electronic trades occurring in the 30 trading days starting on July 1, 2020. The dependent variable, MultipleParticipant, takes the value 1 if a trade involves multiple individuals on the quoting side, and zero otherwise. Our primary coefficient of interest, $\alpha_1$ uses PFOF: an indicator for whether a DMM at a specific exchange is a major PFOF firm. We restrict to trades between 200 and 500 shares, and estimate a probit model with a fixed effect for each stock and exchange.

| | *Dependent Variable:* Multiple Participants |
|---|---|
| PFOF | $-0.08^{***}$ |
| | (0.00) |
| Absolute Value Delta | $-0.03^{***}$ |
| | (0.01) |
| Vega | $0.05^{***}$ |
| | (0.00) |
| Gamma | $0.05^{***}$ |
| | (0.01) |
| Theta | $-0.01^{***}$ |
| | (0.00) |
| Price | $-0.00$ |
| | (0.00) |
| Size | $-0.02^{***}$ |
| | (0.00) |
| Deviance | 1203442.13 |
| Num. obs. | 10398327 |
| Num. groups: Stocks | 1873 |
| Num. groups: Exchanges | 9 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

**Table V: Spreads and DMM Allocations.** This table estimates Regression 4 for auto electronic trades occurring in the 30 trading days starting on July 1, 2020. PFOF takes the value 1 if the stock-exchange DMM pays PFOF, and 0 otherwise. Belowcutoff takes the value 1 for orders of 400 to 500 shares, and 0 for orders of 600 to 700 shares. We include the option Greek values, a fixed effect for each stock, and a fixed effect for each exchange.

| | *Dependent variable:* | |
|---|---|---|
| | QuotedSpread | Realized_1m_BPS |
| | (1) | (2) |
| PFOF | $-0.026^{***}$ | $-2.780^{***}$ |
| | (0.001) | (0.458) |
| BelowCutoff | $0.007^{***}$ | $-6.783^{***}$ |
| | (0.003) | (1.038) |
| Absolute Delta | $0.662^{***}$ | $-265.716^{***}$ |
| | (0.002) | (0.709) |
| Vega | $0.923^{***}$ | $-18.085^{***}$ |
| | (0.001) | (0.406) |
| Gamma | $-0.585^{***}$ | $170.586^{***}$ |
| | (0.004) | (1.784) |
| Theta | $-0.022^{***}$ | $1.367^{***}$ |
| | (0.0002) | (0.090) |
| PFOF$*BelowCutoff$ | $-0.008^{***}$ | $3.366^{***}$ |
| | (0.003) | (1.169) |
| Observations | 35,219,202 | 35,219,202 |
| $R^2$ | 0.135 | 0.085 |
| Adjusted $R^2$ | 0.135 | 0.085 |
| Residual Std. Error (df = 35215305) | 2.027 | 839.374 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | |

### *B. Price Improvement Mechanism Trades*

Upon purchasing order flow, market makers may also attempt to internalize trades via a price-improvement mechanism trade. These price-improvement mechanisms offer several advantages, as noted in Section IV: C. While PIM trades are overwhelmingly retail, the decision to internalize a trade is endogenous, and while the DMM assignments may influence the decision to internalize, they do not play a direct role in the PIM allocations. Instead, it is the initiator of the PIM auction who receives an outsized allocation.

As before, we consider how execution quality changes around the 500-share cutoff. Orders of 400 or 500 shares can be internalized via the DMM allocation rule, while orders of 600 or 700 shares cannot be fully internalized. We estimate Regression 6 using PIM-mechanism trades.

REGRESSION 6: *For each option trade $i$ in security $j$ on exchange $k$ on date $t$:*

$$RealizedSpreadBPS_{ijkt} = \quad \alpha_0 + \alpha_1 BelowCutoff_{ijkt} + X_{ijkt} + \epsilon_{ijkt}$$

Results of Regression 6 are presented in Table VI. For trades below the cutoff, we find that they receive, if anything, an extra tenth of a basis point of price improvement compared to stocks above the cutoff. Wider quoted spreads are also associated with larger price improvement. Customers, however, do not appear to benefit, as realized spreads for the stocks below at or just below the 500-share cutoff are 2 basis points higher than realized spreads of 600 to 700 share orders.

As an alternative way to evaluate execution quality, we consider stocks on the Penny Pilot Program. We focus on the set of stocks which have a sharp-cutoff in tick-size around \$3. Below \$3, these stocks trade with a one-penny bid-ask spread, while above \$3, these stocks trade with a five-penny bid-ask spread.[10] We examine how price-improvement mechanism trades vary in execution quality around this sharp cutoff with Regression 7. We define WideTick as taking the value 1 for stocks on the penny list priced above \$3, and 0 when they are priced below \$3. We restrict our analysis to trades priced between \$2.75 and \$3.25.

[10]In other words, limit orders may be priced in penny increments, like \$2.98, \$2.99, \$3.00, but then jump to \$3.05, \$3.10, and \$3.15.

**Table VI: Price-Improvement and Share Cutoff.** This table estimates Regression 6 for PIM trades occurring in the 30 trading days starting on July 1, 2020. $BelowCutoff$ takes the value 1 for orders of 400 to 500 shares, and 0 for orders of 600 to 700 shares. We include the option Greek values, a fixed effect for each stock, and a fixed effect for each exchange.

| | *Dependent variable:* | |
|---|---|---|
| | Price Improvement (BPS) | Realized Spread (BPS) |
| | (1) | (2) |
| BelowCutoff | $0.141^{***}$ | $2.031^{***}$ |
| | (0.030) | (0.398) |
| Absolute Delta | $-23.608^{***}$ | $-285.488^{***}$ |
| | (0.067) | (0.802) |
| Vega | $-1.757^{***}$ | $-59.618^{***}$ |
| | (0.034) | (0.697) |
| Gamma | $207.098^{***}$ | $91.016^{***}$ |
| | (0.430) | (1.833) |
| Theta | $0.144^{***}$ | $3.381^{***}$ |
| | (0.005) | (0.100) |
| Price | $0.027^{***}$ | $0.779^{***}$ |
| | (0.0004) | (0.011) |
| Quoted Spread | $0.179^{***}$ | $1.845^{***}$ |
| | (0.006) | (0.083) |
| Observations | 4,285,753 | 20,047,230 |
| $R^2$ | 0.176 | 0.072 |
| Adjusted $R^2$ | 0.175 | 0.072 |
| Residual Std. Error | 22.196 (df = 4285179) | 674.241 (df = 20046656) |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

REGRESSION 7: *For each option trade $i$ in security $j$ on exchange $k$ on date $t$:*

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

Results of Regression 7 are presented in Table VII. Trades with a wide tick size receive substantially more price improvement, of 13 basis points. Despite this larger improvement, however, trades with a wide tick are associated with larger realized spreads, suggesting the larger tick size leads to higher profits to market makers, in spite of the potential competition in the price improvement mechanism.

**Table VII: Price-Improvement and Tick Size.** This table estimates Regression 7 for PIM trades in securities participating in the Penny Pilot Program, priced between \$2.75 and \$3.25 occurring in the 30 trading days starting on July 1, 2020. WideTick takes the value 1 for orders priced above \$3, and 0 for orders priced below \$3. We include the option Greek values, a fixed effect for each stock, and a fixed effect for each exchange.

| | *Dependent variable:* | |
|---|---|---|
| | Price Improvement (BPS) | Realized Spread (BPS) |
| | (1) | (2) |
| WideTick | 13.515*** | 1.099** |
| | (0.560) | (0.508) |
| Absolute Delta | −68.735*** | 118.350*** |
| | (5.326) | (4.827) |
| Vega | 209.980*** | 31.859*** |
| | (10.470) | (9.488) |
| Gamma | 257.509*** | −571.608*** |
| | (40.071) | (36.311) |
| Theta | 26.552*** | 14.939*** |
| | (0.845) | (0.766) |
| Size | −0.004** | 0.005*** |
| | (0.002) | (0.002) |
| Observations | 558,493 | 558,493 |
| $R^2$ | 0.247 | 0.012 |
| Adjusted $R^2$ | 0.246 | 0.012 |
| Residual Std. Error (df = 558182) | 202.447 | 183.454 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

### *C. 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 8: *For each option trade $i$ in security $j$ on exchange $k$ on date $t$:*

$$Spread_{ijkt} = \quad \alpha_0 + \alpha_1 PFOF_j + X_{ijkt} + \epsilon_{ijkt}$$

In contrast with Regression 4, we now use $\text{PFOF}_j$ to refer to whether trades in stock $j$ have a DMM who is a primary PFOF provider. We are no longer restricting to either only auto-electronic or only PIM trades, 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 8 are presented in Table VIII. 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 VIII: Option Spreads With a Single DMM.** This table estimates Regression 8. 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.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Effective Spread (BPS) | Quoted Spread (BPS) | Realized Spread (BPS) |
| | (1) | (2) | (3) |
| PFOF | 504.358*** | 1,009.512*** | 237.425 |
| | (117.097) | (179.184) | (174.844) |
| Delta | −370.394*** | −420.103*** | −5.839 |
| | (50.089) | (41.469) | (25.994) |
| Vega | −678.123** | 145.943 | −42.844 |
| | (278.564) | (378.227) | (235.780) |
| Gamma | 148.379 | 830.374 | 2,753.099*** |
| | (467.440) | (579.462) | (721.007) |
| Theta | −403.594*** | −1,835.196*** | 559.002*** |
| | (118.788) | (225.954) | (127.576) |
| Price | −33.933*** | −58.200*** | −10.536*** |
| | (7.043) | (11.401) | (2.598) |
| Size | 0.0001*** | 0.0003* | −0.0002 |
| | (0.00003) | (0.0001) | (0.0002) |
| Option Volume Total | −0.00000 | 0.00001** | 0.00001*** |
| | (0.00000) | (0.00000) | (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 Fredom | 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 9. Across our sample period, we document over $3 billion in total payment for order flow.

Payments vary considerably by asset class. Figure 10 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 (note that ETFs, even those focused on S&P stocks, will be categorized as non-S&P), and individual 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 9).

Routing is concentrated among a small number of wholesalers. Table IX 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 9. PFOF By Broker.** 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 equity PFOF, and its total PFOF is small enough that it is not visible relative to the other firms. 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.

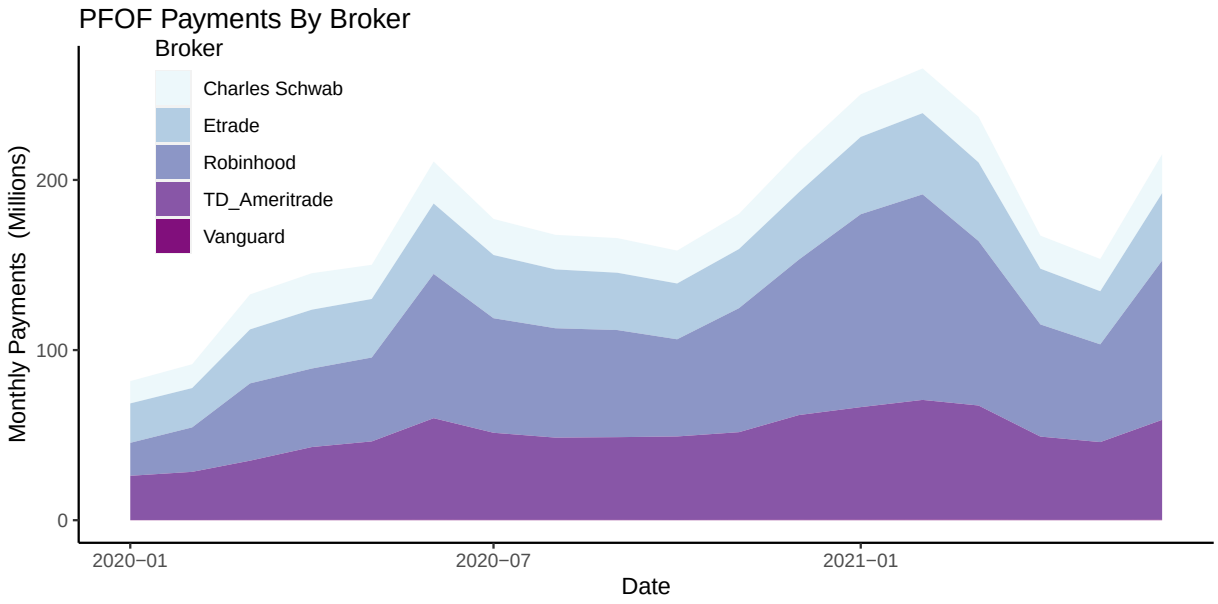
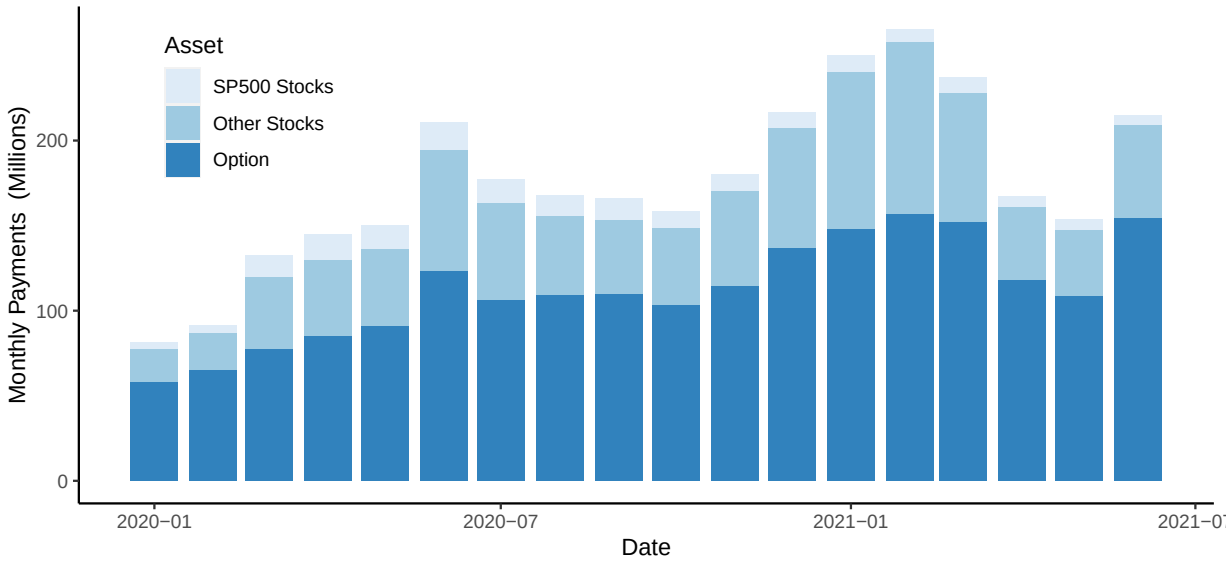


**Figure 10. PFOF By Asset Class**. There are large differences in payments across assets, both in total value and the payment per share. Panel A presents total payments. Most payment for order flow (65%) comes from options markets. The remainder comes from non-S&P 500 Stocks (30%) or S&P 500 stocks (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

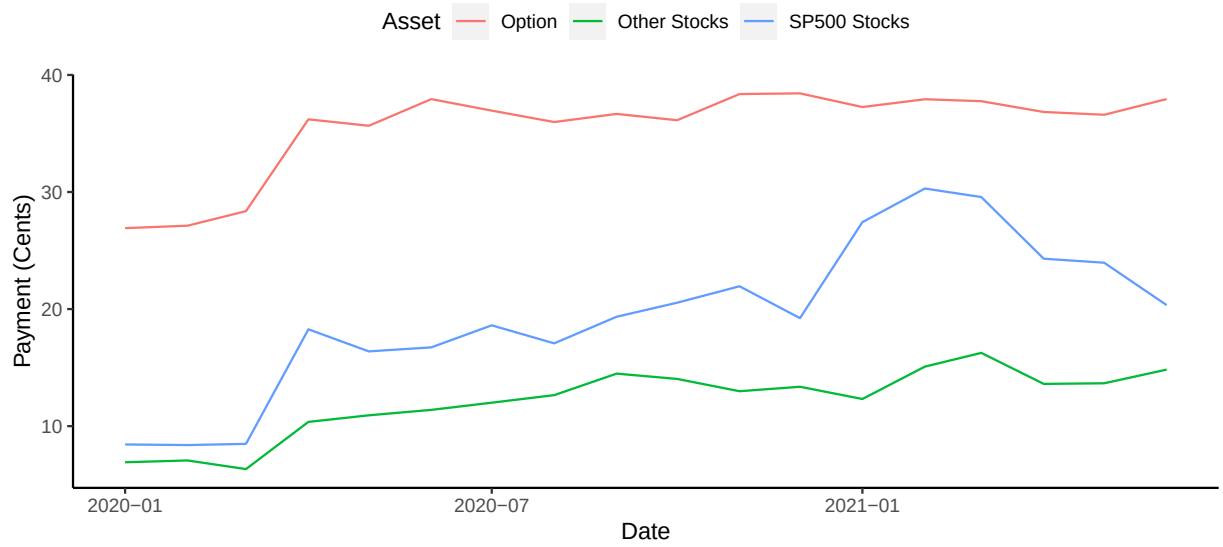


**Table IX: Routing Destinations**. A very small number of firms receive a very large share of order routing. Citadel and Virtu receive almost all equity routing, with G1X and Two Sigma receiving almost all of the remainder. Virtu is not active in options payment for order flow. In options, Citadel, 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 (SIG) | 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 |

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 benchmarked 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 11. 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 12. 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 12, 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 11. 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).

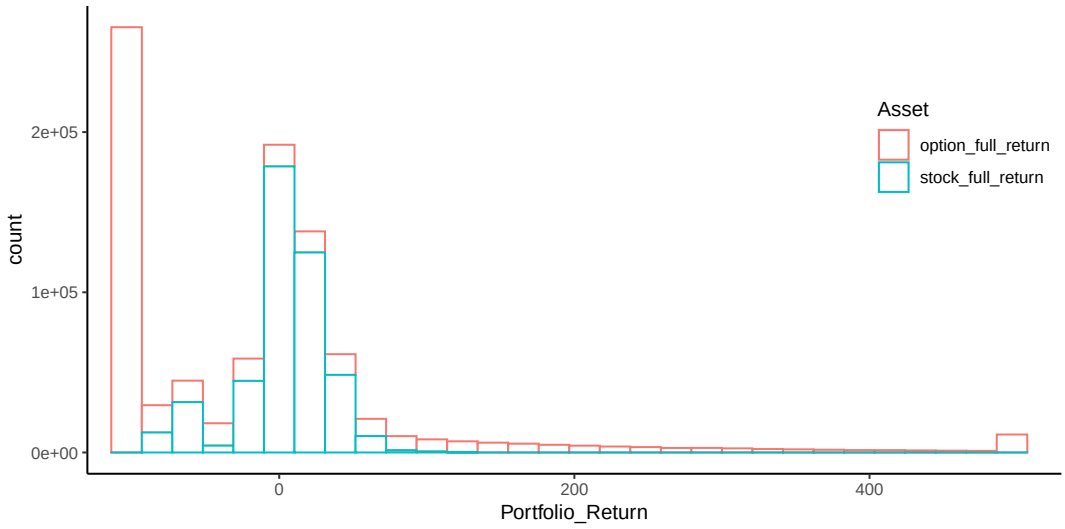
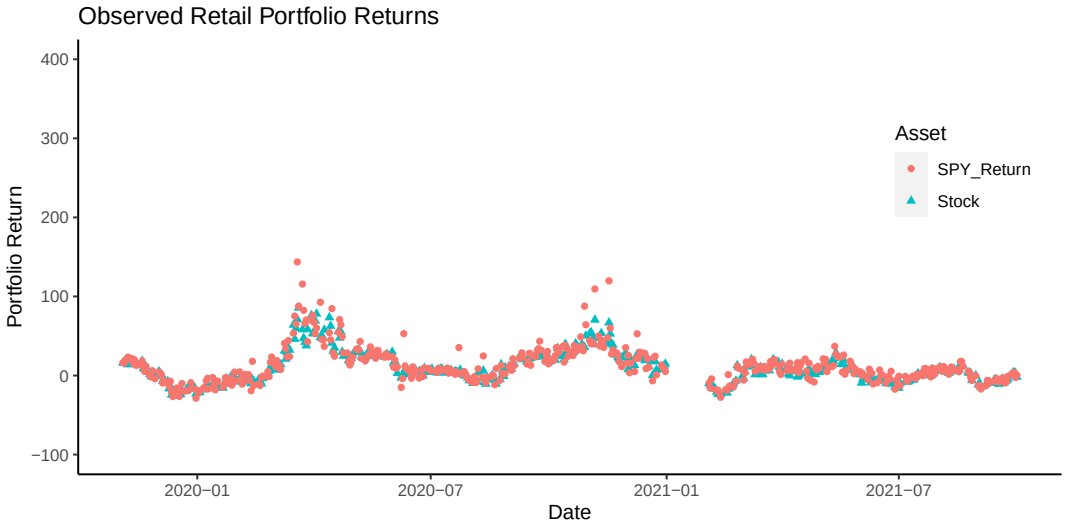
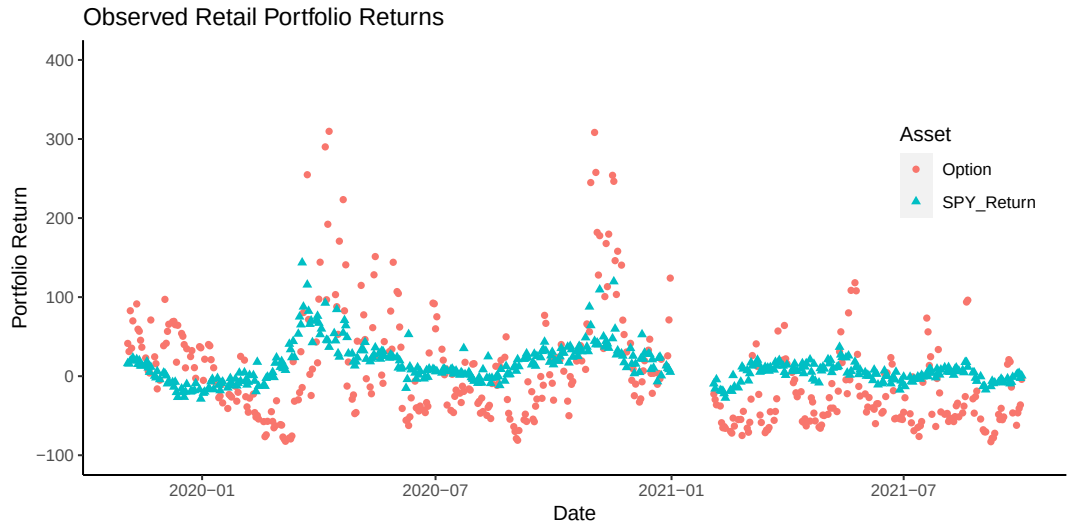


**Figure 12. Comparison of Realized Returns Through Time**. We simulate returns from an empirical distribution of option trades. We draw 1,000 portfolios of 50 option trades, and calculate returns assuming each option is held to maturity. Note that there are some missing dates in January 2021 due to 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



# VIII. Conclusion

We explore the underlying differences in execution quality in equity and option markets, as well as the associated PFOF in these respective markets. Relative to equity markets, option markets have much wider bid-ask spreads, more price improvement relative to spreads, and larger payments for order flow. We examine the underlying competitiveness of the rules around internalizing within the respective markets, and how some option trading rules protect profits from internalization. In turn, these profits from internalizing motivate high payments to brokers to secure order flow, with options orders consistently obtaining higher PFOF than equity orders. The resulting cross-asset variation in payments gives rise to substantially different financial rewards to brokers based on the types of assets their clients trade.

The traditional concern around payment for order flow focuses on best-execution of an individual trade. While the SEC can easily confirm whether trade prices are at least as good as posted quotes, market makers may be willing to improve on quotes. This unpublished potential improvement is difficult to measure, and the segregation of retail order flow has the potential to make on-exchange posted quotes worse. As a result, measuring execution quality is not just about comparing prices with the best displayed quotes, but about the possible price obtainable off-exchange, and regulators must further consider the equilibrium impact of segregating order flow.

In equity markets, we show that around half of all trades occur when bid-ask spreads are constrained at a one-penny bid-ask spread. When stocks are tick constrained, routing internalized trades to the exchange would do nothing to the width of the bid-ask spread, unless the minimum tick size on exchanges were also changed. By comparison to equity markets, option markets are far less likely to be tick-constrained, particularly in the contracts traded by retail investors. While all trades must be done on-exchange, we document two limits to competition: designated market-maker assignments and PIM auctions. With DMM assignments, market makers at the NBBO can internalize trades for 5 contracts or less regardless of their price-time or pro-rata position. Within the subset of stocks with a single DMM, we show that PFOF-paying DMMs are associated with wider bid-ask spreads. Within PIM trades, an initiating market maker has the ability to auto-match competing bids and receives a larger allocation in the event of a tie. We exploit variation in the tick size pilot to show that while larger minimum tick sizes lead to more price improvement,

the realized spreads are also larger. In other words, the large discount given in the PIM auction says more about the wideness of the quotes than the competitiveness of the auction.

The impact of asset choice on broker PFOF revenue is, to the best of our knowledge, a previously unstudied aspect of payment for order flow. While PFOF has ushered in zero-commission trading, the PFOF-only business model pays brokers far more when their clients trade options than when their clients trade stocks. Differences in execution quality are measured in basis points, but the difference between an equity or option investment return is typically measured in double-digit percentages. Brokers do have suitability standards around the assets they can offer clients. Distinguishing between a broker who pushes high-variance securities to gain higher PFOF, and a broker who merely satisfies client demands for high-variance securities, however, is a difficult task. In comparison, measuring execution quality against posted spreads is far easier. Developing more competitive price improvement mechanisms in the auction market, with different participants on even footing in the auction, has the potential to reduce the profitability, and the associated PFOF, surrounding internalizing option trades, and potentially turn broker incentives to a more equal level between equity and options.

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# 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.

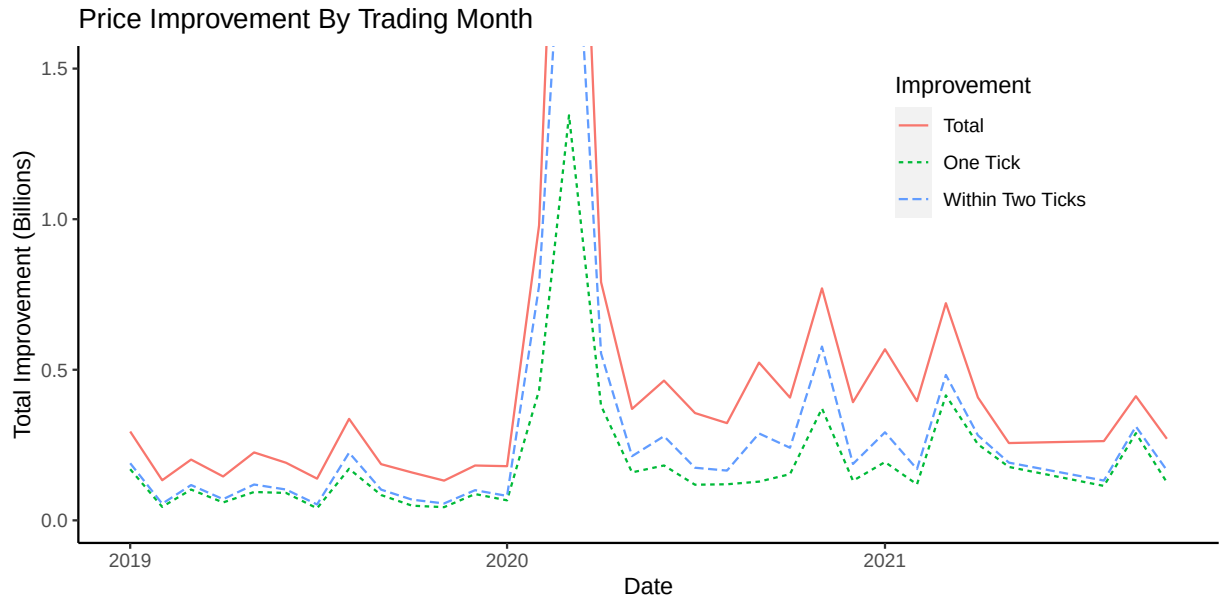
This alternative measure of improvement yields significantly larger estimates, but is open to errors in timestamps of trades. For example, participant timestamps for off-exchange trades are only accurate to the nearest millisecond. Matching quotes, therefore, may be off by as much as a millisecond, meaning 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 13).

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 redo our analysis 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 13. 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:

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

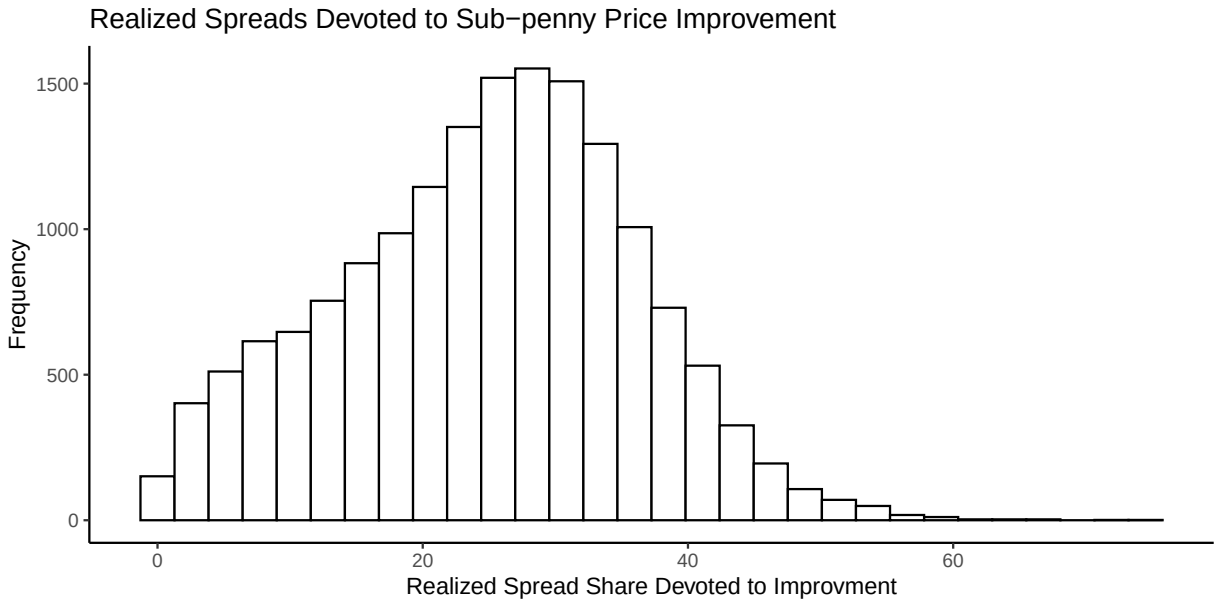
$$\text{Realized\_No\_Improvement}_t = Y(NBBO_t - m_{t+X}) \tag{A2}$$

$$\text{Alt\_Expense\_Ratio} = 1 - \frac{\sum \text{Realized\_With\_Improvement}}{\sum \text{Realized\_No\_Improvement}} \tag{A3}$$

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 14. 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 9: *For each stock $i$ on date $t$ with at least 50 subpenny trades, we estimate:*

$$\begin{aligned} Realized\_Ratio_{it} = \quad & \alpha_0 Closing\_Price_{it} + \alpha_1 Absolute\_Intraday\_Return_{it} \\ & + \alpha_2 Mean\_Quoted\_Spread_{it} + \alpha_3 Mean\_Realized\_Spread_{it} \\ & + \alpha_4 Off\_Exchange\_Share_{it} + X + \epsilon_{it} \end{aligned}$$

Results of this estimation are presented in Table X. Results are generally consistent with Table X, 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 X: Realized Spread Share**. This table estimates Regression 9. 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.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Realized Ratio 3ms | | Realized Ratio 1s | | Realized Ratio 30s | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Closing | 0.002 | | 0.004 | | 0.006** | |
| | (0.003) | | (0.003) | | (0.003) | |
| Absolute Intraday Return | −13.724*** | −9.291*** | −7.640*** | −5.032*** | 10.405*** | 4.537*** |
| | (1.715) | (1.498) | (1.250) | (1.288) | (1.845) | (1.608) |
| Mean Quoted Spread (BPS) | 0.021*** | 0.009*** | 0.023*** | 0.010*** | 0.024*** | 0.010*** |
| | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) |
| Mean Realized Spread (BPS) | −0.084*** | −0.064*** | −0.097*** | −0.076*** | −0.113*** | −0.088*** |
| | (0.006) | (0.004) | (0.006) | (0.004) | (0.006) | (0.004) |
| Off-Exchange Share | −0.107*** | 0.012*** | −0.100*** | 0.009*** | −0.080*** | −0.008*** |
| | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) | (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 |