Essay 1: Price Improvement, Auctions and Order Imbalance in the Options Market

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Abstract

We investigate the impact of inventory pressures on market makers' decisions in the equity options market, particularly concerning price improvements and participation in price improvement auctions. We also examine the cross-market effects of inventory pressures from other venues and their impact on local exchange dynamics. Our findings show that higher order imbalances lead to reduced price improvements, as market makers are concerned about rising inventory risks. However, when competition is characterized by uniform order flows across multiple venues in an auction setting, market makers with higher inventory imbalances tend to provide higher price improvements in auctions. The probability of auctions increases during periods of less correlated orders, which contribute minimally to inventory risks. Furthermore, market makers significantly reduce price improvements for short-maturity, deep out-of-the-money options due to the higher adverse selection risks they pose. This study highlights the role of inventory management in market makers’ strategic decision-making and the importance of cross-market interactions in fragmented markets.

Price Improvement, Auctions and Order Imbalance in the Options Market

1.0 Introduction

In intermediated markets like the options market, the concept of order imbalance among intermediaries over specific intervals is relevant (Chordia and Subrahmanyam, 2004). Options market makers (MMs) intermediate both retail and institutional order flow, using their capital to provide liquidity, facilitate price discovery, and accommodate trading imbalances. In doing so, they sometimes bear unwanted inventories to maintain a fair and orderly options market. Despite MMs' affirmative obligations to quote two-sided markets, they are not obligated to sell or buy an unlimited number of contracts in a specific option series (Bollen and Whaley, 2004). And in a fragmented and competitive options market, MMs can selectively execute trades that positively impact their inventory positions, leading to a more efficient risk allocation (Daures and Moinas, 2022). As a result, MMs continuously monitor their portfolio positions, and assess the inventory and adverse selection risk that might be associated with incoming orders to decide how to interact with them. For instance, designated market makers (DMMs) can internalize customer orders through price improvement auctions (PIA) or internalize orders for five or fewer contracts through the simple limit order book.[1] [2] They can also offer price improvements using hidden

[1]DMMs are specialized market makers with stricter obligations and special privileges in a randomly exchange-assigned options security. According to Ernst and Spatt (2024), most US options exchange have them.

[2]Some exchange trading and priority rules provide two methods for DMMs to internalize retail orders: price improvement auctions and limit orders for five contracts or less if the DMM is quoting at the National Best Bid and Offer (NBBO). Also, institutional broker-dealers can utilize price improvement auctions to pursue better pricing for their institutional clients' orders. Certain exchanges have designed auctions specifically for large orders, incorporating an "all-or-none" feature.

orders in the limit order book or route incoming orders to other markets for execution.[3] According to Jameson and Wilhelm (1992), the primary challenges MMs face in managing inventory risk include the need for continuous rebalancing of option positions and the unpredictability of the return volatility of the underlying stock.

This study investigates how supply and demand dynamics in equity options influence price improvements and auction trades through changes in MMs' inventory positions. We explore several hypotheses to assess whether the endogenous decision of MMs to internalize retail orders in PIAs and the level of price improvement are influenced by inventory pressures or order imbalances. Muravyev (2016) suggests that large order imbalances lead to significant price movements, with the inventory component of price impact being larger than the informational component. Daures and Moinas (2022) suggest that MMs adjust their quoting strategies based on the extent of order imbalances they face across different venues. The inventory model proposed by Bauldauf et al. (2024) suggests that inventory pressures can influence MMs' decisions to siphon and execute retails orders off-exchange. Bollen and Whaley (2004) argue that MMs respond to temporary inventory pressures by adjusting option prices. We investigate how MMs' order imbalances affect option price improvements both broadly and within PIAs. We also assess how these imbalances influence MMs' decisions to participate in option auctions.

Our study is relevant given the recent growth in retail options trading, which raises important questions for regulators and academics, particularly concerning the welfare of public customers. A key consideration in this context is the role of MMs and/or DMMs (formerly

[3] Exchanges also have price improvement orders. Price improvement orders are hidden limit orders within the limit order book, placed inside the NBBO spread. They can increase in 1-cent increments, regardless of the option series tick size. <u>See</u> https://www.sec.gov/files/rules/proposed/2022/34-96496.pdf

specialists). Given the often one-sided nature of retail order flows, growth in options retail trading—particularly those demanding liquidity—can lead to higher inventory costs and imbalances for MMs. Some studies suggest that the inventory risk faced by MMs in the options market has a "*first order effect*" on option spreads and prices, as MMs find it challenging to manage inventory risk by promptly liquidating their inventories (Battalio et al. (2016); Muravyev (2016)). This emphasizes the importance of MMs' ability to quickly adjust orders based on updated market valuations and adequately manage their inventories, as this is essential for price discovery and reducing transaction costs**.**

Since retail customer orders are often smaller, less correlated, and generate less adverse selection (i.e., they are less informed), their execution quality is usually enhanced through execution at narrower spreads (Easley et al. (1996); Battalio and Holden (2001); Bauldauf et al. (2024)). The options PIA mechanism provided by some exchanges offers better execution prices for customer orders by allowing MMs to internalize these orders at narrower spreads than the National Best Bid and Offer (NBBO) spread, or at worst, at the NBBO spread. And given that wholesalers handle *almost all* retail options order flows and tend to route more orders to their affiliated MMs, PIA might be part of a portfolio-based inventory management strategy for these MMs.[4] The model by Bauldauf et al. (2024) suggest that the inventory hedging benefits provided by retail orders should contribute to MMs' endogenous decisions to offer price improvements.

[4]Hendershott et al. (2023) argues that wholesalers tend to route more orders to their affiliated DMMs. According to the Rule 606 filings for the top 15 retail brokers for listed options, on average, non-directed orders made up around 99.13% of all retail orders in Q1 of 2022.
See https://www.sec.gov/files/rules/proposed/2022/34-96496.pdf

This means that asymmetric information alone cannot fully explain the endogenous decision by options MMs to provide price improvement to retail orders in auctions or limit order books.

Bryzgalova et al. (2023) and Ernst and Spatt (2024) argue that the *vast majority* of retail order flow in listed options is internalized on exchanges through *single-leg* PIA mechanisms. However, leveraging Cboe options trade data related to retail platform trading, Han (2024) finds a significant presence of retail trading in the multi-leg complex options market. Han's findings suggest that focusing on single-leg auction trades as a proxy for retail trading or assuming that retail investors only participate in single-leg trading is misleading. This narrow focus can result in inaccurate conclusions about retail trading in the options market, as it fails to capture the multifaceted retail options trading landscape. Therefore, in our investigation to understand the effects of MMs' inventory pressures on the dynamics of price improvements and PIAs, we use both single-leg and multi-leg equity options trades.[5] We then estimate the implied trade directions using the Lee and Ready (1991) tick-test (LRTT) algorithm. In addition to the LRTT algorithm, we utilize a procedure described in Section 3.2 of this paper to slightly improve classification accuracy of single-leg PIA trades. We also compute various measures of options risk exposure, such as vega and gamma.

The main independent variable in our empirical investigation is individual net order imbalance, which reflects inventory pressures on a specific exchange within a fixed interval. Following Bollen and Whaley (2004), we define individual net order imbalance as the aggregate

[5]A multi-leg or complex order is a single order for two or more different options series (referred to as "legs") simultaneously, ensuring execution within a specified net price and ratio if filled. The net prices achieved are typically better than those obtained by trading the component legs separately. In contrast, single-leg or simple orders involve only one series, such as buying or selling calls or puts

signed volume of option contract trades within a fixed time interval, but we adjust this measure to dollar terms to reflect the financial exposure of MMs. While Bollen and Whaley use aggregate daily data, our research focuses on intraday data. Consistent with previous empirical works on intraday options trading volume (see Easley et al. (1998) and Stephan and Whaley (1990)), we use 5-minute intervals. Given the interconnected liquidity and competition across options exchanges, we also investigate cross-market effects of order imbalance on price improvements. We estimate two additional measures: "other-venues-order-imbalance", which captures inventory pressures on other venues, and SAME, which indicates whether the direction of order flow on one venue is the same as the net direction of order flow across other venues within the same 5-minute interval. These additional measures are necessary as Daures and Moinas (2022) argue that the market-making behaviors of MMs in one venue is influenced by activities on other venues. They emphasize that the interaction between direction of order flows—whether identical or divergent across venues— and MM's order imbalance influences their liquidity supply across multiple venues. Higher inventory imbalance typically leads to tighter spreads in the presence of uniform directional shocks, as MMs consider their actions in one venue in relation to their costs in other venues. When the direction of order flows across venues is uniform, competition intensifies, leading MMs to narrow their spreads to avoid being undercut. Conversely, when the direction of order flow is not uniform, competition is less intense, allowing MMs to selectively manage their inventory by focusing on venues where liquidity provision is most beneficial. Using data from Euronext, Daures and Moinas (2022) find that the direction of order flows across venues and the inventory divergence of MMs significantly influence local liquidity and MMs' market-making strategies. They suggest that when competition is high, indicated by uniform order flows across multiple venues, MMs with higher inventory imbalance tend to be more aggressive in their liquidity supply to manage inventory risks. Their findings underscore the importance of considering cross-market interactions when examining price improvement in fragmented markets.

Our empirical results show that MMs' order imbalances significantly reduce the level of price improvement in the options market. This occurs because MMs, concerned about rising inventory risks due to higher imbalances, tend to execute trades at effective spreads closer to the quoted spreads, offering less price improvement as compensation for the increased inventory risk or as a deterrent to order flow. Additionally, our findings on cross-market effects suggest that inventory pressures from other venues influence the dynamics of the local exchange. When there is inventory pressure on other exchanges and order flows are uniform across multiple venues, MMs with higher inventory imbalances might offer lower price improvements to minimize their exposure to adverse selection. However, when competition intensifies, as indicated by uniform order flows across multiple venues and a competitive PIA environment, MMs with higher inventory imbalances are more likely to provide higher price improvements to better manage inventory risks. Our findings also indicate that the probability of auctions increases during periods of less correlated orders, as these contribute minimally to inventory risks, a finding consistent with Bauldauf et al. (2024).

If order imbalances could predict price improvement and MMs' participation in PIAs, it would be interesting to investigate the role of information proxies like leverage using a moneyness measure. The view that out-the-money contracts are leveraged contracts has been entertained by many studies that include Hu (2014) and Pan and Poteshman (2006). If informed traders seek leverage through options, they are likely to prefer those that provide the highest leverage. The multi-market sequential trade model of Easley et al. (1998) suggests that the amount of information in the options market is related to the leverage provided by the stock and options markets, as well as the liquidity of both markets. Furthermore, Chakravarty et al. (2004) argue that leverage effects are of primary importance relative to liquidity effects in determining the information content of option trades. Deep out-of-the-money (DOTM) options with short maturities offer the highest leverage, as their prices primarily reflect the attributes of the risk-neutral jump process rather than the level of diffusive volatility (Andersen et al., 2017). In other words, DOTM with short maturities have very low time-value and benefit the most from sudden and favorable large price movements. Conversely, long-dated deep in-the-money (DITM) options offer the least leverage.

As anticipated, we find that MMs provide lower price improvements for short-maturity, DOTM options compared to long-dated, DITM options due to the higher adverse selection risk associated with DOTM with short tenors. OTM options with short maturities tend to attract more informed traders seeking high leverage, which may cause MMs to adjust their pricing behavior accordingly by offering lesser price improvement due to higher adverse selection risks.

The remainder of the paper is organized as follows. Section 2 discusses the hypotheses development from related literature. Section 3 describes the data and variables. Section 4 describes the empirical methodology and discusses the main empirical results and Section 5 reports the conclusions of the study.

2. Hypothesis Development

Retail orders are mostly non-directed orders, meaning that retail brokers/broker-dealers decide how these orders are handled or where they are routed for best execution. Some options exchanges primarily compete for this order flow by offering liquidity discounts, rebates, quoting the best bid/ask prices, and providing depth at these prices. Other exchanges, in addition to these methods, also purchase order flows from retail-oriented options firms.[6] In contrast, wholesalers mainly compete for options retail order flows through payment for order flow (PFOF) agreements.[7]

Battalio et al. (2021) examine how the pricing models of options exchanges influence retail brokers' order routing behavior and the execution quality of nonmarketable orders. They find that some retail brokers maximize the value of their order flow by selling marketable orders through PFOF agreements and routing nonmarketable orders to exchanges offering substantial liquidity rebates. Since wholesalers handle *almost all* retail options order flow and often route more orders to their affiliated DMMs, who may internalize them, Battalio et al. (2021) findings suggest that PFOF exchanges can attract more order flow by selectively diverting less informed marketable trades away from primary markets. This selective routing may create an environment with less competition, leading to potentially lower overall execution quality for nonmarketable orders. While Battalio et al. (2021) finds that PFOF is associated with higher execution quality, Hendershott et al. (2023) finds that the non-random routing behaviors of PFOF DMMs is

[6] A pricing model where exchanges pay for order flow is found only in the options market. Stock exchanges do not have such pricing model.

[7] Since not all retail order flow providers accept PFOF, wholesalers also compete by offering relatively low-cost market access and execution services. See https://www.sec.gov/files/rules/proposed/2022/34-96496.pdf

associated with larger effective spreads in trade executions. Notably, all PFOF exchanges use preferencing systems that grant special privileges to DMMs in trade executions, albeit with stricter quoting obligations.

As retail order flows are typically concentrated on one side of the market, an increase in retail order flow can lead to higher inventory costs and imbalances for MMs. For instance, Barber et al. (2022) finds that retail equity order flows from Robinhood tend to be more concentrated than those from other retail brokerages, contributing to momentum-oriented herding that is often followed by market reversals. Using brokerage outages as an exogenous shock, Eaton et al. (2022) find that Robinhood traders, compared to more sophisticated equity traders on traditional brokerages, create order imbalances and inventory risks that worsens market liquidity and volatility in equities with high retail interest. In contrast, studies like Han (2024) and Baldauf et al. (2024) suggest that increase in retail participation can mitigate MMs' inventory imbalance. Leveraging Cboe options trade data related to retail platform trading, Han (2024) finds that despite increased retail participation in SPX options in recent years, "*the monthly MM order imbalance has decreased from -14% in December 2016 to -12% in May 2023*."

The findings from Barber et al. (2022), Eaton et al. (2022), Baldauf et al. (2024) and Han (20204) highlight the heterogeneity in intermediation costs of retail order flow through inventory imbalances**.** However, when retail order flow creates inventory imbalance for MMs, the increased inventory risks may affect the price improvement of orders. Schwarz et al. (2023) experimentally compares execution quality of equity trades across five brokers and finds that Robinhood equity order flows received, on average, price improvements of 2.10 cents and 3.40 cents per share less than those from Fidelity and TD Ameritrade, respectively.

Furthermore, the significance of inventory considerations in determining price improvement for orders is also underscored in the models by Baldauf et al. (2024) and Daures and Moinas (2022). Bauldauf et al. (2024) show that in a PFOF environment, MMs are more likely to siphon retail equity orders off-exchange and execute them at smaller spreads when these orders are less correlated than institutional orders. However, when institutional orders pose lower inventory risks compared to retail orders, both types of orders are executed on lit exchanges. Unlike the stock market, where internalization occurs off-exchange, all trading in the options market happens on exchanges, with internalization mostly executed through PIA mechanisms (Bryzgalova et al. (2023); Ernst and Spatt (2024)). Applying this to the options market where MMs manage inventory risk at the portfolio level, the Bauldauf et al. (2024) model suggests that MMs on PFOF exchanges might initiate more PIAs to manage inventory risks arising from their broader portfolio of trades. During periods of higher market volatility and lower liquidity, MMs may initiate more PIAs to attract order flow for risk management purposes. If retail orders are less correlated than institutional orders, MMs are more likely to offer price improvement by segmenting them through PIAs. Less correlated orders generally contribute to lower order imbalances because their flow directions are not uniformly buys or sells. This implies that price improvement might be lower when the order imbalance is higher.

Muravyev (2016) finds that higher order imbalances lead to higher option returns due to MMs increased inventory risks. MMs require higher expected returns as compensation for taking on more inventory risk. This suggests that MMs are less likely to offer higher price improvement during periods of higher order imbalance, as such imbalances increase inventory risks.

Ernst and Spatt (2024) find that execution quality of options trade is lower when a PFOF-paying DMM is involved as customer orders receive less price improvement and worse prices. In contrast, Hendershott et al. (2023) suggest that competition in a PFOF environment can result in a positive relationship between price improvement and MMs' order imbalance. Their findings suggest that MMs on PFOF-DMMP exchanges may improve their price improvement in auctions to maintain or enhance their order flow from retail brokers, particularly when their execution quality has previously been poor relative to competitors. This suggests that, even during periods of relatively high order imbalance, the need to remain competitive in terms of execution quality can lead to higher price improvements in PFOF auctions.

Daures and Moinas (2022) explore how MMs often implement strategies across several exchanges simultaneously to predict how liquidity provision by MMs in one trading venue is influenced by trade conditions on other venues. They emphasize that the interaction between direction of order flows—whether identical or divergent across venues— and MM's order imbalance influences their liquidity supply across multiple venues. Using data from Euronext, Daures and Moinas (2022) suggest that when competition is high, indicated by uniform order flows across multiple venues, MMs with higher inventory imbalance tend to be more aggressive in their liquidity supply to manage inventory risks. That is, contrary to adverse selection hypothesis, the presence of same-sign order flows across venues does not negatively impact liquidity. Adverse selection hypothesis suggests that the presence of same-sign order flows across multiple venues would influence MMs to reduce their liquidity provision across all venues and offer less price improvement.

The studies discussed above motivate the following hypotheses:

Hypothesis 1: MMs will provide lower price improvement during periods of higher order imbalance, as higher order imbalances increase inventory risks. This effect is likely more pronounced on PFOF-DMMP exchanges. Muravyev (2016) finds that higher order imbalances lead to higher option returns due to MMs increased inventory risks. MMs require higher expected returns as compensation for taking on more inventory risk. Ernst and Spatt (2024) find that execution quality of options trade is lower when a PFOF-paying DMM is involved, as customer orders receive less price improvement and worse prices. Higher order imbalance will likely worsen this effect, as MMs facing increased inventory pressures may further reduce the level of price improvement they provide to mitigate potential losses.

Hypothesis 2: In a PFOF setting, MMs will initiate more PIAs and provide higher levels of price improvement when orders are smaller and less correlated. Modeling retail orders as smaller and less correlated, Bauldauf et al. (2024) suggests that price improvement for retail orders might be higher when the order imbalance is lower, i.e., when they are less correlated. This implies that a negative relationship exists between likelihood of auctions and order imbalance. When orders contribute less to inventory risks, Bauldauf et al. (2024) suggests that MMs on PFOF exchanges might initiate more PIAs to manage inventory risks arising from their broader portfolio of trades.

Hypothesis 3: In auctions, PFOF-DMMs will provide higher levels of price improvement, even during periods of higher order imbalance, due to the competitive pressure to maintain or enhance execution quality. Hendershott et al. (2024) finds that PFOF-DMMP exchanges provide higher price improvement in auction trades compared to non-PFOF-DMMP.

Hypothesis 4: When competition is intense, as indicated by uniform order flows across multiple venues, MMs with higher inventory imbalances will provide higher price improvement to manage inventory risks. Daures and Moinas (2022) suggest that when order flows are uniform across venues, the cross-market cost linkage can lead to increased marginal costs of liquidity provision. Consequently, the interaction between a MM's inventory imbalance and same-sign order flows across venues may drive more competitive pricing.

The multi-market sequential trade model of Easley et al. (1998) suggests that the amount of information in the options market is related to the leverage provided by the stock and options markets, as well as the liquidity of both markets. Chakravarty et al. (2004) argue that leverage effects are of primary importance relative to liquidity effects in determining the information content of option trades. This is particularly evident in short-maturity options, as Andersen et al. (2017) demonstrates in their study on S&P 500 index options. Andersen et al. (2017) finds that the pricing of short-maturity ("weeklies") options can identify periods of higher concerns about negative tail events, which are not always reflected by standard volatility measures. DOTM options with short maturities are less sensitive to broader economic shifts and offer the highest leverage, as their prices primarily reflect the attributes of the risk-neutral jump process rather than the level of diffusive volatility (Andersen et al., 2017). In other words, DOTM with short tenors have low time-value and benefit the most from sudden, significant and favorable price movements. Conversely, long-dated DITM options offer the least leverage and are less sensitive to sudden market changes. Therefore:

Hypothesis 5: MMs will provide lower price improvements for short-maturity, DOTM options compared to long-dated, DITM options due to the higher adverse selection risk associated with DOTM with short tenors. The significant leverage and sensitivity to immediate market risks associated with DOTM options with short maturities make them more likely to be informed trades, potentially signaling jump risks or other sudden market movements.

3. Data and Empirical Methodology

3.1 Data Sample

We obtain options series quote and trade data on U.S. listed stocks, ETFs and Indices for the month of October 2022 from OPRA LiveVol provided by CBOE. The data include the exchange where the trade was executed, trade quantity, execution price, trade mechanism, prevailing quoted spread for the options series and underlying asset, implied volatility and option delta at the time of trade, and the date and timestamp of the trade. Our analysis focuses on trade mechanism flags of "*SingLegAuctNonISO*", "*MultLegAuct*", "*AutoExecution*", and "*MultLegAutoEx*" on common-stock options with the underlying stock incorporated in the United States.[8] For the rest of the paper, we refer to *SingLegAuctNonISO* trades as *SLAN*, "*MultLegAuct*" trades as *MLAN*, "*AutoExecution*" trades as AutoEx and "*MultLegAutoEx*" trades as MLAutoEx.[9] We eliminate trades with locked or crossed quotes, trades with zero implied volatility, and trades within five minutes of market open and close (i.e., only including trades from 9:35 a.m. to 3:55

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[8] We use CRSP to eliminate trades in ETF options, index options, and options on American Depositary Receipts (ADRs), Real Estate Investment Trusts (REITs), closed-end funds and foreign firms.

[9]The "AutoExecution" and "MultLegAutoEx" flags represents single-leg and multi-leg electronic trade executions, respectively. The "SingLegAuctNonISO" ("MultLegAuct") flag indicates the execution of single-leg-non-ISO (multi-leg) electronic orders traded in a two-sided auction mechanism that goes through an exposure period within a simple (complex) options market

p.m.).[10] Data on the daily trading volume of the underlying stock and the market capitalization of the underlying stock are from CRSP.[11] Furthermore, to be included in the sample, the option series must have a daily trading volume of 10 or more contracts. The initial sample contains over 115 million trades and 900 million contracts. After applying the filters, we are left with approximately 37 million trades. Table 1 presents the summary of the filtered data.

[INSERT TABLE 1]

The average trade size is 5.27. Most trades have a small size and low price, with median values of 1 contract and $2.38, respectively. The data also show that most options traded have low implied volatility and short days to expiry, with a median of 10 days. Price improvement is generally small, indicating a small difference between quoted and effective spreads.

Table 2 provides an overview of the pricing models, auction types, and contract volumes across various U.S. options exchanges for the sample period of October 2022. It categorizes exchanges by whether they use PFOF, maker-taker (MT), or taker-maker (TM) pricing models. The table also indicates which exchanges offer single-leg or multi-leg auction mechanisms and whether they use DMM preferencing. The data show a wide variation in trading volumes and the prevalence of different auction mechanisms, with some exchanges, like Nasdaq PHLX, handling a significant portion of trades through their auction mechanisms.

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[10] We eliminate observations where the best bid in the option series at the time of trade (NBB) is greater than or equal to the best offer at the time of trade (NBO). According to CBOE LiveVol specifications, "*implied volatility (IV) will be zero in cases where the calculation model did not have sufficient input data (i.e. no quoted markets), the option price was below intrinsic value, or the implied volatility exceeded the acceptable upper limit*." Thus, we eliminated trades with IV equal to zero.

[11] Market capitalization is the product of the outstanding shares of the stock and the closing price. The closing price and shares outstanding data are from CRSP.

[INSERT TABLE 2]

Table 3 compares price improvement and EQ ratios across different trade mechanisms—SLAN, MLAN, AutoEx, and MLAutoEx. The table highlights how different exchanges and trade mechanisms impact execution quality, with auction trades generally showing better execution quality compared to non-auction mechanisms.

[INSERT TABLE 3]

Table 4 presents a difference-in-means analysis of price improvement across binary regressors. This table analyzes how various factors, such as auction participation and DMM preferencing, affect execution quality. The results indicate that trades involving auction mechanisms, particularly multi-leg auctions, generally receive higher price improvements, while trades on exchanges with PFOF and DMM preferencing systems receive lower price improvements. This suggests that while auctions can enhance price improvement, the structure of market-making and preferencing systems on some exchanges might dilute these benefits.

[INSERT TABLE 4]

3.2 Improving Lee and Ready Tick Test Classification Scheme for SLAN Trades.

The LRTT procedure has been widely used in many empirical studies (Chan et al. (2002); Chordia and Subrahmanyam (2004); Easley et al. (1998); Hendershott et al. (2023); Pan and Poteshman

(2006); Hu (2014) and much more) to infer the direction of stock and option trades. The procedure first classifies trades based on the position of the trade price relative to the midpoint of the prevailing bid-ask spread. Trades above (below) the midpoint are classified as buys (sells). For trades at the quote midpoint, the tick-test procedure compares the price of the current trade to that of the last trade at a different price, classifying trades on an uptick or zero-uptick (downtick or zero-downtick) as buys (sells). However, with SLAN trades, the LRTT procedure can sometimes inconsistently classify trades within the same auction session. Table 5 illustrates this. The table shows that some trades within the same electronic auction session are classified differently – as buys, sells and mid – by the LRTT procedure. In electronic auction mechanisms, public customer orders are submitted with a contra-side agency or principal order. Since only one auction session can be active at a time in a particular option series, it is unlikely for both buyer-initiated and seller-initiated trades to exist within the same single-leg electronic auction session. Additionally, each executed quote in OPRA data has a separate print regardless of trade mechanism. Consequently, in a PIA with multiple participants (or executed quotes), there will be multiple trade observations in the option series with the same timestamp. This occurs even if the quotes are submitted at different points within the typical 100-millisecond duration of the auction session. These trades may have the same or different prices and potentially the same or different sizes.

[INSERT TABLE 5]

Combining this knowledge in our classification sequence for SLAN trades, we implement the following approach, assuming that trades with the best price in an exchange's auction session has the *lowest sequence number* in OPRA data. In our dataset, we do not observe any instances where prices both higher and lower than the first recorded trade price occur within the same auction session.

- We use LRTT procedure for SLAN trades with only one participant.
- For SLAN trades with multiple participants, if any other trades within the same auction session occur at a price higher than the first recorded trade in OPRA data, we classify all trades in that particular auction as "buy." Conversely, if any other trades within the same auction session occur at a price lower than the first recorded trade in OPRA data, we classify all trades in that particular auction as "sell."
- When executed quotes within the same auction session occur at the same price, we use the LRTT classification of the first recorded trade of the bunch (i.e., lowest sequence number) for all trades executed in that session. Therefore, all trades within the same auction session have the same implied trade direction.

A snapshot of the results of our procedure is shown in Table 5 as "OurTD". We use PHLX October 2022 SLAN data to test the effectiveness of our classification procedure. Trades in the PHLX data are identified by trade type (either buy or sell), so we do not need to infer the direction. We are able to increase the correct classification of PHLX SLAN trades by about eight thousand observations. For an auction session where all trades have the same price, the accuracy of our classification depends on the accuracy of LRTT's classification of the first recorded trade of the session. In the overall dataset that spans multiple exchanges, we believe our SLAN classification method enhances the results beyond the eight thousand observations of PHLX SLAN trades. However, to test the effectiveness, we only use PHLX SLAN trades data here.

3.3 Main Independent Variables

3.3.1 Order Imbalances

Following standard practice, we estimate implied trade directions using the LRTT. In addition to the LRTT algorithm, we also utilize a procedure, described in Section 3.2 to slightly improve the classification accuracy of SLAN trades. When neither our procedure nor the LRTT algorithm can determine whether the trade is a buy or sell, the trade is classified as "mid" and excluded from our analyses, similar to the approach taken by Bryzgalova et al. (2023).

We assume that when trades occur in the options market, MMs are the counterparties, profiting from the bid-ask spread when they sell option contracts at higher prices than they buy. As the primary liquidity providers in the options market, MMs are concerned about inventory risk. Thus, following Bollen and Whaley (2004), we define a measure of net *order imbalance* as the aggregate signed dollar volume of option contract trades over a 5-minute interval, but we adjust this measure to dollar terms to reflect the financial exposure of MMs. While Bollen and Whaley use aggregate daily data, our research focuses on intraday data. Our second measure is a market-wide order imbalance that excludes the local exchange’s order imbalance. We compute the order imbalance (*OI*) for option series *i* on exchange *A* at time *t* (in 5-minutes intervals), and other-venues’ order imbalance (*OVOI*) for option series *i* on other exchanges different from *A* within the same time interval as follows:

$$\mathrm{OI}_{\mathrm{i,A,t}} = \frac{\sum_{\mathrm{i}}\left(\mathrm{BuyDollarVolContracts}_{\mathrm{i,A,t}} - \mathrm{SellDollarVolContracts}_{\mathrm{i,A,t}}\right)}{\sum_{\mathrm{i}}\left(\mathrm{BuyDollarVolContracts}_{\mathrm{i,A,t}} + \mathrm{SellDollarVolContracts}_{\mathrm{i,A,t}}\right)}$$

$$\mathrm{OVOI}_{\mathrm{i,J,t}} = \sum_{\mathrm{J} \neq \mathrm{A}}^{\mathrm{N}} \left(\mathrm{OI}_{\mathrm{i,J,t}}\right)$$

A positive *OI* value indicates that MMs on a specific exchange sold more contracts than they bought and a positive *OVOI* value indicates that MMs are net sellers on a market-wide level that excludes the local exchange.

3.3.2 Leverage

To evaluate the effect of leverage on PIA dynamics, we compute a moneyness measure to proxy leverage. The view that DOTM are highly leveraged options has been entertained by many studies that include Hu(2014) and Pan and Poteshman (2006). We estimate a moneyness measure as the natural logarithm of the ratio of the strike price to the current stock price. To ensure consistent comparisons across options with varying time to expiration, we standardize this measure by dividing it by the square root of the *calendar* years to expiration. This is expressed as:

$$\mathrm{Moneyness} = \left[\ln\left(\frac{\mathrm{StrikePrice}}{\mathrm{Stockprice}}\right) \Big/ \sqrt{\mathrm{CalendarDTE}} \right] \qquad \text{where CalendarDTE} > 0$$

For analyses involving our moneyness measure, we exclude trade observations on their expiration date. Moneyness variable tends to be positive and higher for OTM call options with short maturities, while it is negative and lower for ITM call options with longer maturities. For put options, moneyness tends to be negative (positive) and lower (higher) for OTM (ITM) options with short (longer) maturities. We expect the partial effects of moneyness on the level price improvement provided to be positive for puts and negative for calls.

3.4 Dependent Variables

The main dependent variables in our analyses include *price improvement* and *Auction*. *Auction* is a binary variable, where a value of one indicates that there was at least one simple or complex PIA in the 5-minute interval, and zero otherwise. To measure the level of price improvement provided, we first estimate quoted half spread, effective half spread and effective spread to quoted spread ratio (EQ). Following Hendershott et al. (2023), we compute quoted half spread as the difference between the national best offer (NBO) and bid (NBB) prices at the time of trade, and effective half spread as the difference between transaction price and the spread midpoint multiplied by 1 (-1) if the implied direction of the transaction is a buy (sell).

$$\text{QuotedHalfSpread (QHS)} = \frac{\text{NBO} - \text{NBB}}{2}$$

$$\text{EffectiveHalfSpread (EHS)} = \text{Dir.} \times \left(\text{TradePrice} - \left(\frac{\text{NBO} + \text{NBB}}{2}\right)\right)$$

Where *Dir.* is 1 for buys and -1 for sells. EQ is the ratio of the effective half spread to the quoted half spread with a lower value indicating lower transaction cost relative to the quoted spread.

$$\text{EQ} = \frac{\text{EHS}}{\text{QHS}}$$

Price improvement is the difference between QHS and EHS, in cents. This is expressed in cents as: [12]

$$\text{Price Improvement (PI)} = 100 \times (\text{QHS} - \text{EHS})$$

Thus, simplified for buy trades, price improvement is expressed as:

$$\text{PI} = 100 \times (\text{NBO} - \text{trade price})$$

[12] By design, price improvement (PI) measure in the options market auction mechanism (SLAN or MLAN) should not be negative. However, we found a few instances where trades were executed at prices outside of the prevailing bid-ask spread. Further investigation shows that for a lot of these trades, execution occurred at or within the bid/ask prices of the most recently executed preceding trade that was often within a fraction of a second.

and for sell trades as:

$$\mathrm{PI} = 100 \times (\text{trade price} \ - \ \mathrm{NBB})$$

4 Empirical Strategy and Results

4.1 Individual and Cross Market Imbalance Effects

4.1.1 Individual Imbalance Effects

In this section, we examine how short-term inventory pressures, particularly within a PFOF environment, affect the price improvement provided for orders. Baldauf et al. (2024) argue that MMs might initiate PIAs and execute retail orders at narrower spreads not primarily due to lower information asymmetry, but because they reduce inventory risk. The analysis in this section also considers the presence of a DMM preferencing system, since DMMs pay the most in PFOF and DMM exchanges handled a greater share of trade executions (Ernst and Spatt, 2024). In our dataset, exchanges with DMM preferencing systems handled approximately 62% of listed equity options trades. This is consistent with broader industry trends, as reported by SIFMA Insights (2023), which indicates that 63.9% of all trades in the fiscal year 2022 occurred on exchanges with such systems.[13] The first unrestricted regression model is specified as follows:

Regression 1: For each option series *i*, at time *t*, on exchange *j*, on day *k*:

$$\mathrm{PI_{ijkt}} = \alpha_0 + \ \alpha_1 \mathrm{OI_{ijkt}} + \alpha_2\left(\mathrm{OI_{ijkt}} \times \mathrm{PFOF\_DMMP_j}\right) + \alpha_3\left(\mathrm{OI_{ijkt}} \times \mathrm{PFOF\_DMMP_j} \times \mathrm{Auction_{ijkt}}\right) + \alpha_4 \mathrm{Auction_{ijkt}} + \mathrm{StockFE} + \mathrm{ExchangeFE} + \mathrm{DateFE} + \mathrm{X_{ijkt}} \ + \ \gamma_{\mathrm{ijkt}}$$

[13] SIFMA Insights (2023) reports that a group of exchanges, including AMEX, ARCA, CBOE, GEMX, ISE, MIAX, MRX, PHLX and NasdaqBX, collectively executed 63.9% of all options trades. See: https://www.sifma.org/wp-content/uploads/2023/04/SIFMA-Insights-The-ABCs-of-Equity-Market-Structure.pdf

We also estimate and report restricted forms of this regression model. In the models, the key variables include:

- **PI**: The price improvement provided.
- **OI**: The individual order imbalance.
- **Auction**: A binary variable that equals 1 if a SLAN or MLAN trade occurs within the interval, and 0 otherwise.
- **PFOF-DMMP**: A binary variable equal to 1 if the exchange uses a payment for order flow pricing schedule and DMM preferencing, and 0 otherwise.[14]

The control variables X include the average size of trades within the interval, the average bid-ask spread of the underlying stock, the square root of the calendar days to maturity, a binary indicator "Call" (1 for call options and 0 for puts), the average of absolute trade delta within the interval, the average implied volatility, gamma and vega within the interval, the natural logarithm of the market capitalization of the underlying stock, the natural logarithm of the daily traded volume of the underlying stock, the inverse of the average option and underlying stock quote midpoint, and a binary variable "Tick" that equals 1 if the average trade price of the option series within the interval is $3.00 or greater.

Table 6 presents the regression results, highlighting key findings on auction activity and order imbalance. The coefficient on the auction variable is statistically significant and positive across all models, demonstrating that price improvements are higher in PIA mechanisms. The finding underscores the importance of PIA mechanisms in enhancing the execution quality of orders. In contrast, OI exhibits a statistically significant negative impact on price improvement across all models. In Models 1 and 2, the coefficients are significant at the 1% significance level,

[14] We obtained information about exchanges that have Payment for Order Flow (PFOF) fee model and DMM preferencing from Hendershott et al. (2023)

suggesting that greater order imbalance reduces price improvement for option orders. This suggests that MMs are generally concerned about increasing inventory risks due to higher inventory pressures. To mitigate these risks, they execute trades at higher relative effective spreads, thus providing less price improvement as a compensation for the higher inventory risk.

[INSERT TABLE 6]

In Models 3 and 4, the inclusion of interaction terms diminishes both the magnitude and significance of OI. The interaction between OI and PFOF-DMMP in Model 3 is statistically significant and negative, suggesting that in PFOF-DMMP environments, orders that are more correlated with market trading trends receive less price improvement. Ernst and Spatt (2024) find that execution quality of options trade is lower when a PFOF-paying DMM is involved as customer orders receive less price improvement and worse prices. We find that inventory pressures worsen execution quality on DMMP exchanges that purchase order flow. The coefficient on the interactions “OI x PFOF-DMMP x Auction” is statistically significant and positive and offers additional insights. The positive coefficient on “OI x PFOF-DMMP x Auction” indicates that execution quality tends to be better in PFOF auctions where MM have special privileges. This improvement is likely driven by the need for PFOF exchanges to remain competitive in terms of execution quality to attract order flow from retail brokers.

Additionally, the statistically significant positive coefficients on variables related to stock liquidity suggest that higher stock prices and wider spreads may signal increased risk associated with the underlying stock. In response, MMs may provide higher price improvements as a tradeoff between managing inventory risk and generating spread income. Lower inventory risk and higher liquidity allows for more efficient risk hedging, as MMs can offset positions quickly and with lower execution costs.

4.1.2 Cross Market Imbalance Effects

Daures and Moinas (2022) argue that the quoting behavior of MMs on one trading venue is influenced by trade conditions on other venues, suggesting interconnected liquidity and competition across venues. Their model suggests that price improvements may be provided to orders on one venue in response to inventory-related quote adjustments by others resulting from trades in other venues. To explore this hypothesis, we investigate the impact of order imbalances and trading activities in other venues on the price improvement of orders on the local exchange in the following regression model:

Regression 2: For each option series *i*, at time *t*, on exchange *j or* other exchanges *m*, on day *k*:

$$\begin{aligned}\mathrm{PI_{ijkt}} = \alpha_0 + \alpha_1\mathrm{OI_{ijkt}} + \alpha_2\mathrm{SAME_{ikt}} + \alpha_3\left(\mathrm{OI_{ijkt}} \times \mathrm{SAME_{ikt}}\right) + \alpha_4\mathrm{OVOI_{imkt}} \\ + \alpha_5\left(\mathrm{OI_{ijkt}} \times \mathrm{OVOI_{imkt}} \times \mathrm{SAME_{ikt}}\right) + \alpha_6\left(\mathrm{OI_{ijkt}} \times \mathrm{PFOF\_DMMP_j}\right) + \alpha_7\mathrm{Auction_{ijkt}} \\ + \mathrm{StockFE} + \mathrm{ExchangeFE} + \mathrm{DateFE} + \mathrm{X_{ijkt}} + \gamma_{\mathrm{ijkt}}\end{aligned}$$

We also estimate and report restricted forms of this regression model. The control variables X remains consistent with the previous regression models. SAME is a binary variable set to one if the net order flow across other venues is in the same direction as the order flow on the local exchange in the time interval. OVOI represents the order imbalance on other exchanges, and $\mathrm{OI} \times \mathrm{OVOI} \times \mathrm{SAME}$ captures the combined effects of trading activities on the both the local exchange and other venues.

Table 7 and Table 8 present the results. Table 7 focuses on the full sample of trades, while Table 8 examines a subsample restricted to intervals where there is at least one auction trade. The coefficient on the interaction term 'SAME x OI x OVOI' is statistically significant and negative in Table 7, suggesting that when buying pressure exists across all venues, and the direction of order flow is uniform between the local exchange and other trading venues, it signals increased inventory risk. As a result, MMs are likely to provide lesser price improvement to orders under these conditions to mitigate further inventory imbalances and reduce their exposure to potential losses. This suggest that when marginal costs are non-constant, MMs may provide lower price improvement to mitigate their risk exposure. In contrast, this coefficient is statistically significant and positive in the auction subsample analysis in Table 8, indicating that in the context of auction trades, MMs might adjust their strategies to remain competitive, potentially offering slightly higher price improvements to attract order flow despite the inventory pressure. Exchange trading and execution rules discourage broader participation in PIAs by anyone other than the initiating MM. Using Nasdaq PHLX as an example, Ernst and Spatt (2024) noted that MMs initiating PIAs on Nasdaq PHLX have the significant advantage to "selectively auto-match any competing bids in the auction."

[INSERT TABLE 7]

[INSERT TABLE 8]

Additionally, the initiating order is “guaranteed a minimum of 40% allocation” if it is at the best price provided in the auction, and “50% allocation if the initiating order is matching only one other participant at the execution price.”[15] These preferential rules likely incentivize MMs to participate actively in auctions and offer competitive price improvements, as they can secure a larger share of the trade, thus justifying the slightly higher price improvements observed in auction settings. This analysis highlights how exchange-specific rules and competitive pressures in auction environments can lead to different price improvement strategies by MMs, depending on the broader market conditions and their inventory risk profiles. The results of this section support our fourth hypothesis, albeit only when competition is indicated by both uniform order flows across venues and a competitive PIA environment.

4.2 Price Improvements, Moneyness and Order Imbalance

Chakravarty et al. (2004) suggests that leverage effects are of primary importance relative to liquidity effects in determining the information content of option trades. This is particularly evident in short-maturity options, as Andersen et al. (2017) demonstrates in their study on S&P 500 index options. Andersen et al. (2017) finds that the pricing of short-maturity ("weeklies") options can identify periods of higher concerns about negative tail events, which are not always reflected by standard volatility measures. DOTM options with short maturities are less sensitive to broader economic shifts and offer the highest leverage, as their prices primarily reflect the attributes of the risk-neutral jump process rather than the level of diffusive volatility (Andersen et al., 2017). Given this, informed traders seeking leverage through options are likely to gravitate

[15] See: https://nasdaqtrader.com/content/phlx/PIXLfaqs.pdf

toward those that offer the greatest leverage. We investigate the effects of moneyness on the price improvement of orders using the following regression:

Regression 3: For each option series *i*, at time *t*, on exchange *j or* other exchanges *m*, on day k ≠ expiration date:

$$\begin{aligned} \mathrm{PI_{ijkt}} = {} & \alpha_0 + \alpha_1 \mathrm{Moneyness_{ijkt}} + \alpha_2 \mathrm{OI_{ijkt}} + \alpha_3 \mathrm{SAME_{ikt}} + \alpha_4 \mathrm{OVOI_{imkt}} \\ & + \alpha_5 (\mathrm{OI_{ijkt}} \times \mathrm{OVOI_{imkt}} \times \mathrm{SAME_{ikt}}) + \alpha_6 (\mathrm{OI_{ijkt}} \times \mathrm{PFOF\_DMMP_j}) + \alpha_7 \mathrm{Auction_{ijkt}} \\ & + \mathrm{StockFE} + \mathrm{ExchangeFE} + \mathrm{DateFE} + \mathrm{X_{ijkt}} + \gamma_{\mathrm{ijkt}} \end{aligned}$$

The results are reported in Table 9 and 10. As expected, the moneyness variable is significant in both tables, reflecting the influence of leverage on price improvement. In Table 9, which focuses option trades excluding expiration days, the coefficient for moneyness is negative (positive) for calls (puts), indicating that as call (put) options move further OTM and the days to expiration shorten, price improvements tend to be lower. However, the coefficient is not statistically significant for calls.

Table 10 examines option auction trades excluding expiration days and shows similar patterns. Here, the coefficient on moneyness is statistically significant for both calls and puts. The findings in Table 9 and 10 suggest that OTM options, particularly those that are DOTM with short tenors, tend to attract more informed traders seeking high leverage. As a result, MMs may adjust their pricing behavior by providing lesser price improvement due to increased adverse selection risks. Overall, the results in this section support our fifth hypothesis that MMs provide lower price improvements for short-maturity, DOTM options compared to long-dated, DITM options due to the higher adverse selection risk associated with DOTM with short tenors.

[INSERT TABLE 9]

[INSERT TABLE 10]

4.3 Auctions and Order Imbalance

In the preceding section, we show that order imbalance significantly influences the level of price improvement in the options market and document cross-market effects of Daures and Moinas (2022) model. In this section, we investigate whether order imbalance plays a significant role in MMs' decisions to initiate PIAs. Bauldauf et al. (2024) demonstrates that in a PFOF environment, MMs may be driven by portfolio management concerns to cream-skim retail orders, executing them off-exchange at smaller spreads. Their model implies that in the options market, the inventory hedging benefits derived from retail orders could drive MMs' endogenous decisions to initiate PIAs. They argue that retail orders are less correlated, smaller and contribute less to inventory risk. To test this hypothesis, we use trade data of exchanges that have PIA mechanisms. We estimate the following linear probability model on trades on exchanges with PIA mechanisms:

Regression 4: For each option series *i*, at time *t*, on exchange *j*, on day *k*:

$$\begin{aligned} Auction_{\mathrm{ijtk}} = {} & \alpha_0 + \alpha_1 \mathrm{OI}_{\mathrm{ijkt}} + \alpha_2 \mathrm{SAME}_{\mathrm{ikt}} + \alpha_4 \mathrm{OVOI}_{\mathrm{imkt}} + \alpha_5 \left(\mathrm{OI}_{\mathrm{ijkt}} \times \mathrm{OVOI}_{\mathrm{imkt}} \times \mathrm{SAME}_{\mathrm{ikt}}\right) \\ & + \alpha_6 \left(\mathrm{OI}_{\mathrm{ijkt}} \times \mathrm{PFOF\_DMMP}_{\mathrm{j}}\right) + \mathrm{StockFE} + \mathrm{ExchangeFE} + \mathrm{DateFE} + \mathrm{X}_{\mathrm{ijkt}} + \gamma_{\mathrm{ijkt}} \end{aligned}$$

Tables 11 and 12 present the results of this regression and its restricted forms.

[INSERT TABLE 11]

[INSERT TABLE 12]

Table 11 reports regression results of the probability of auctions in exchanges with PIA mechanisms. The coefficients of *OI* and average size are negative and statistically significant across all model specifications. This suggests that the probability of an auction decreases as order imbalance and average trade size increase. Bauldauf et al. (2024) show that in a PFOF environment, MMs are more likely to execute retail equity orders off-exchange at smaller spreads, particularly when these orders are less correlated than institutional orders. In their model, retail orders are smaller and less correlated. The negative coefficients on *OI* and *AvgSize* in our analysis suggest that PIAs are more likely to occur during periods of non-uniform order flow and for smaller trades. In PFOF environments, higher order imbalances further decrease the probability of PIA. This implies that MMs internalize smaller and less correlated trades through PIA mechanisms, where they can offer price improvements while managing their inventories. MMs, particularly in PFOF-DMMP settings, are likely concerned about inventory risks and are less likely to participate in PIAs when they face significant order imbalances. This behavior aligns with the idea that MMs strategically use PIAs to manage broader portfolio risks.

Moreover, the coefficient for the lagged *Auction* variable is statistically significant and positive, suggesting that the occurrence of an auction in the previous interval increases the probability of another auction in the current interval. Hendershott et al. (2024) argue that PFOF-paying DMMs compete more on the number of auctions rather than on price improvements, using the frequency of auctions as a signal to encourage others to improve prices.

Table 12 provides additional insights by focusing on a subsample of exchanges that utilize a PFOF-DMMP pricing model. The results are consistent with Table 11, further highlighting the negative impact of OI and the cross-market effects of order imbalance on auction probability.

While the coefficient for option spreads is insignificant in Table 11, it is significant and positive in Table 12. This suggests that PFOF-paying DMMs are more likely to initiate auctions when spreads are wider, a finding consistent with Hendershott et al. (2024).

In summary, the findings from Tables 11 and 12 support our second hypothesis: MMs are more likely to initiate PIAs when they face lower order imbalances, typically associated with less correlated order flows. This behavior highlights the importance of inventory management in MMs' decision-making processes, particularly in the context of PFOF-DMMP exchanges.

5.0 Conclusions

We investigate the impact of inventory pressures on the probability of auctions in equity options and the level of price improvement these options receive, both within single- and multi-leg limit order books and auction environments. Additionally, we explore the cross-market effects of inventory pressures on other venues and how they influence dynamics at the local exchange. Our findings indicate that the probability of auctions increases during periods of less correlated orders, as these contribute less to inventory risks.

We also find that market makers' order imbalances have a significant negative effect on price improvement in the options market. This suggests that market makers are generally concerned about rising inventory risks associated with higher inventory pressures. To mitigate these risks, they execute trades at effective spreads closer to the quoted spreads, providing less price improvement as compensation for the increased inventory risk or as a deterrent to order flow.

When marginal costs are non-constant, market makers may further reduce price improvement to limit their risk exposure. We also highlight how price improvement auction environments can drive different price improvement strategies by market makers, depending on broader market conditions and their inventory risk profiles. In highly competitive environments, characterized by uniform order flows across multiple venues and intense price improvement auction settings, market makers with higher inventory imbalances may offer greater price improvement in auctions as a strategy to manage inventory risks. Finally, we find that market makers provide lower price improvements for short-maturity, deep out-of-the-money options compared to long-dated, deep in-the-money options, due to the higher adverse selection risks associated with short-tenor deep out-of-the-money option.

References

Andersen, T. G., N. Fusari, and V. Todorov (2017). Short Term Market Risks Implied by Weekly Options. *The Journal of Finance 72 (3)*, 1335-1385.

Baldauf, M., J. Mollner, and B. Z. Yueshen (2024). Siphoned apart: A Portfolio Perspective on Order Flow Segmentation. *Journal of Financial Economics 154*, p. 103807.

Barber, B. M., X. Huang, T. Odean, and C. Schwarz (2022). Attention-Induced Trading and Returns: Evidence from Robinhood Users. *Journal of Finance 77(6)*, 3141–3190.

Battalio, R., T. Griffith and R. Van Ness (2021). Do (Should) Brokers Route Limit Orders to Options Exchanges That Purchase Order Flow. *Journal of Financial and Quantitative Analysis 56 (1)*, 183–211.

Battalio, R., and C. W. Holden (2001). A Simple Model of Payment for Order Flow, Internalization, and Total Trading Cost. *Journal of Financial Markets 4 (1)*, 33-71.

Battalio, R., A. Shkilko, and R. Van Ness (2016). To Pay or Be Paid? The Impact of Taker Fees And Order Flow Inducements on Trading Costs in US Options Markets. *Journal of Financial and Quantitative Analysis 51 (5)*, 1637–1662.

Bollen, N. P. B., and R. E. Whaley (2004). Does Net Buying Pressure Affect the Shape of Implied Volatility Functions? *The Journal of Finance 59 (2)*, 711-753.

Bryzgalova, S., A. Pavlova, and T. Sikorskaya (2023). Retail trading in options and the rise of the big three wholesalers. *The Journal of Finance Forthcoming*.

Chan, K., Y. P. Chung, and W.-M. Fong (2002). The Informational Role of Stock and Option Volume. *Review of Financial Studies 15 (4)*, 1049–1075.

Chakravarty, S., H. Gulen, and S. Mayhew (2004). Informed Trading in Stock and Option Markets. *The Journal of Finance 59 (3)*, 1235-1258.

Chordia, T., and A. Subrahmanyam (2004). Order Imbalance and Individual Stock Returns: Theory and Evidence. *Journal of Financial Economics 72 (3)*, 485-518.

Daures, L., and S. Moinas (2022). Fragmentation and Strategic Market-Making. *Journal of Financial and Quantitative Analysis,* Forthcoming.

Dyhrberg, A. H., A. Shkilko, and I. M. Werner (2023). The Retail Execution Quality Landscape. *Working paper,* Fisher College of Business. *Available at SSRN 4313095* .

Easley, D., N. M. Kiefer, and M. O'Hara (1996). Cream-Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow. *The Journal of Finance 51 (3)*, 811–833.

Easley, D., M. O'Hara, and P. Srinivas (1998). Option Volume and Stock Prices: Evidence on Where Informed Traders Trade. *The Journal of Finance 53 (2)*, 431-465.

Eaton, G. W., T. C. Green, B. S. Roseman, and Y. Wu (2022). Retail Trader Sophistication and Stock Market Quality: Evidence from Brokerage Outages. *Journal of Financial Economics 146 (2)*, 502–528.

Ernst, T., and C. S. Spatt (2024). Payment for order flow and asset choice. Technical report, National Bureau of Economic Research.

Ernst, T., C. S. Spatt, and J. Sun (2023). Would Order-By-Order Auctions Be Competitive? *Available at SSRN 4300505* .

Han, S. (2024). Unveiling the Sophistication: Understanding Retail Investors' Trading Behavior in the U.S. Options Market. See https://cdn.cboe.com/resources/government_relations/Understanding-Retail-Investors-Dynamic-Trading-Behavior-in-the-US-Options-Market_2024.pdf

Hendershott, T., S. A. Khan, and R. Riordan (2023). Competition and Payment for Order Flow in Options. *Working Paper.*

Hu, J. (2014). Does Option Trading Convey Stock Price Information? *Journal of Financial Economics 111 (3)*, 625-645.

Jameson, M., and W. Wilhelm (1992). Market Making in the Options Markets and the Costs of Discrete Hedge Rebalancing. *The Journal of Finance 47 (2)*, 765-779.

Lee, C. M., and M. J. Ready (1991). Inferring Trade Direction from Intraday Data*. Journal of Finance 46 (2)*, 733–746*.*

Muravyev, D. (2016). Order Flow and Expected Option Returns. *The Journal of Finance 71 (2)*, 673-707.

Ni, S. X., N. D. Pearson, and A. M. Poteshman (2005). Stock Price Clustering on Option Expiration Dates. *Journal of Financial Economics 78 (1)*, 49-87.

Pan, J., and A. M. Poteshman (2006). The Information in Option Volume for Future Stock Prices. *Review of Financial Studies 19 (3)*, 871–908.

Schwarz, C., B. M. Barber, X. Huang, P. Jorion, and T. Odean (2023). The 'Actual Retail Price' of Equity Trades. *Working paper*

Stephan, J. A., and R. E. Whaley (1990). Intraday Price Change and Trading Volume Relations in the Stock and Stock Option Markets. *Journal of Finance 45 (1)*, 191-220.

Table 1
Data Summary Statistics

This table presents sample descriptive statistics computed from trades in the filtered October 2022 data sample. **Quoted spread** is (NBO-NBB)/2.0, while the **effective spread** is the difference between option price and midpoint, times trade direction. **Price improvement** is the difference between the quoted spread and the effective spread. **CALL** is a binary variable equal to one if the trade is trade on calls options and zero if on puts. **BUY** is a binary variable equal to one if the implied trade direction is a buy and zero if it is a sell. **Tick** is a binary variable that equals one if the trade price of the option series is $3.00 or greater. IVOL is the implied volatility in the option series at the time of the trade.

			Percentiles				
	mean	St. Dev	1%	25%	50%	75%	99%
Trade Size	5.27	27.62	1	1	1	4	58
Trade Price, $	5.03	11.38	0.05	0.96	2.38	5.35	42.10
IVOL	0.72	0.46	0.24	0.45	0.63	0.83	2.39
Stock Midpoint, $	139.23	128.46	3.14	54.01	119.43	216.76	496.49
Option Midpoint, $	5.03	11.37	0.05	0.97	2.38	5.35	42.13
Days to Expiry	49.72	113.20	0	3	10	39	616
Effective Spread	0.04	0.12	0	0.01	0.02	0.04	0.45
Quoted Option Spread	0.08	0.20	0.01	0.02	0.03	0.08	0.88
EQ	0.66	0.44	-0.06	0.25	1	1	1
Price Improvement, $	0.04	0.16	0	0	0	0.03	0.52
Vega	0.10	0.16	0	0.02	0.05	0.11	0.75
Gamma	0.054	0.11	0	0.01	0.03	0.06	0.46
Stock Volume, 1M	39.22	44.85	0.44	5.78	18.68	68.51	223.04
MCAP, 100M	4,003.73	5,721.02	3.79	299.30	1,284.67	6,670.75	23,774.70
$\lvert\Delta\rvert$	0.39	0.21	0.01	0.23	0.39	0.51	0.95
Tick	0.42	0.49	0	0	0	1	1
Quoted Stock Spread, $	0.04	0.16	0	0.01	0.01	0.03	0.37
CALLS	0.57	0.50	0	0	1	1	1
BUYS	0.50	0.50	0	0	1	1	1

Table 2

Pricing Models, Auction Types, and Contract Volumes Across U.S. Options Exchanges

This table presents information on various U.S. options exchanges, including their pricing models and whether they offer price improvement auctions (single-leg or multi-leg). PFOF stands for payment for order flow, MT for maker-taker and TM for taker-maker. The table also presents which exchanges use Designated Market Maker (DMM) preferencing. Additionally, the table shows the traded contracts volume and total number of observations in our October 2022 dataset for each trade mechanism. *SLAN* and *MLAN* are auction trades in single-leg and multi-leg auction mechanisms, respectively. *AutoEx* and *MLAutoEx* are simple limit order book trades and complex limit order book trades, respectively.

Exchanges	Pricing Model	Single-leg Auctions	Multi-leg Auctions	DMM Preferencing	Contracts Volume (%)				
					AutoEx	MLAutoEx	SLAN	MLAN	All
AMEX	PFOF	Yes	Yes	Yes	3.44	7.38	10.67	0.95	5.32
ARCA	PFOF	No	No	Yes	20.56	7.85			13.70
BOX	MT	Yes	Yes	No	4.60	1.05	4.83	0.45	3.92
BZX	MT	No	No	No	13.41				8.17
C2	MT	No	No	No	5.08	5.59			3.93
CBOE	PFOF	Yes	Yes	Yes	5.23	11.90	18.51	67.34	11.72
EDGX	MT	Yes	Yes	No	5.56	12.71	3.02	3.52	6.04
EMLD	MT	Yes	No	No	4.15	2.40	0.03		2.89
GEMX	MT	Yes	No	Yes	5.64		0.55		3.54
ISE	PFOF	Yes	Yes	Yes	0.84	31.58	7.00	4.37	6.79
MIAX	PFOF	Yes	Yes	Yes	1.83	11.66	12.64	14.27	5.98
MRX	MT	Yes	Yes	Yes	0.45	1.19	6.43	4.63	1.92
NASD	MT	No	No	No	16.89				10.30
NASDBX	TM	Yes	No	Yes	3.86		0.08		2.37
PEARL	MT	No	No	No	4.86				2.96
PHLX	PFOF	Yes	Yes	Yes	3.62	6.68	36.25	4.47	10.46
				Total Contracts Volume	117,511,248	28,782,481	37,492,078	9,048,308	192,834,115
				NObs.	22,441,079	5,089,143	7,350,436	1,738,246	36,618,904

Table 3

Trade Mechanisms and Execution Quality Across U.S. Options Exchanges

This table presents a comparison of price improvement (PI) and the ratio of effective spread to quoted spread (EQ) across various U.S. options exchanges for October 2022. *SLAN* and *MLAN* are auction trades in single-leg and multi-leg auction mechanisms, respectively. *AutoEx* and *MLAutoEx* are simple limit order book trades and complex limit order book trades, respectively.

	Limit Order Book				Auctions			
	AutoEx		MLAutoEx		SLAN		MLAN	
Exchanges	PI	EQ	PI	EQ	PI	EQ	PI	EQ
AMEX	-0.00	1.00	9.36	0.38	3.43	0.48	4.20	0.64
ARCA	0.00	1.00	21.78	0.37				
BOX	-0.05	1.02	2.80	0.88	4.02	0.60	1.85	0.79
BZX	2.39	0.63						
C2	5.81	0.56	8.54	0.32				
CBOE	1.54	0.84	11.50	0.34	3.85	0.41	7.85	0.25
EDGX	1.37	0.82	9.84	0.34	2.04	0.65	8.24	0.25
EMLD	-0.05	1.01	12.10	0.36	2.54	0.63		
GEMX	2.06	0.67			2.43	0.71		
ISE	0.81	0.95	10.96	0.31	1.56	0.64	10.92	0.33
MIAX	-0.11	1.02	10.87	0.34	3.21	0.49	6.01	0.22
MRX	0.05	1.01	8.77	0.44	3.06	0.56	5.88	0.50
NASD	2.71	0.68						
NASDBX	1.53	0.88			3.47	0.57		
PEARL	-0.03	1.01						
PHLX	0.84	0.94	14.63	0.44	4.02	0.34	6.00	0.48

Table 4
Difference-in-Means Analysis of Execution Quality Across Binary Regressors

This table presents the regression results comparing the average execution quality across different trade mechanisms. Columns (1) through (4) display various regression models for the dependent variables: PI (Price Improvement) and EQ (the ratio of effective half spread to quoted half spread). The models incorporate different combinations of fixed effects, including StockFE and DayFE, and cluster errors at the option and day levels where applicable. Significance levels are denoted as ***p < 0.01, **p < 0.05, and *p < 0.10.

	PI				EQ			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Constant	1.4918***	1.8020***			0.8291***	0.7791***		
	(0.003)	(0.004)			(0.000)	(0.000)		
SLAN	1.9249***	2.3096***	2.5312***	3.1740***	-0.3647***	-0.4283***	-0.3681***	-0.4320***
	(0.006)	(0.007)	(0.069)	(0.073)	(0.000)	(0.000)	(0.006)	(0.005)
MLAN	5.9811***	6.4278***	6.0401***	6.7922***	-0.5615***	-0.6356***	-0.5578***	-0.6322***
	(0.012)	(0.012)	(0.140)	(0.139)	(0.000)	(0.000)	(0.004)	(0.003)
MLAutoEx	10.2753***	10.5504***	9.3405***	9.8183***	-0.4812***	-0.5275***	-0.4815***	-0.5274***
	(0.007)	(0.008)	(0.223)	(0.221)	(0.000)	(0.000)	(0.004)	(0.004)
DMMP		-0.3664***		-0.2742***		0.0499***		0.0484***
		(0.010)		(0.089)		(0.000)		(0.010)
PFOF		-0.4428***		-1.0516***		0.0833***		0.0846***
		(0.010)		(0.080)		(0.000)		(0.011)
StockFE	No	No	Yes	Yes	No	No	Yes	Yes
DayFE	No	No	Yes	Yes	No	No	Yes	Yes
Clustered	No	No	Yes	Yes	No	No	Yes	Yes
R^2	0.052	0.055	0.052	0.054	0.237	0.254	0.236	0.252
NObs	36,618,904	36,618,904	36,618,904	36,618,904	36,618,904	36,618,904	36,618,904	36,618,904

Table 5
SLAN Trade Direction Classification

This table shows the implied trade direction classification for a sample of October 2022 single-leg price improvement option trades using Lee and Ready (1991) tick-test procedure and our procedure. "Sequence number" is the trade sequence number for the execution reported by OPRA. "Exchange" is the options exchange the trade was executed on. "LRTT" represents Lee and Ready (1991) trade direction classification, "OurTD" is trade direction classification using our procedure, and PhlxTD is the trade direction indicated by PHLX exchange for SLAN trades executed on PHLX.

stock	quote datetime	sequence number	expiration date	strike	type	exchange	trade price	best bid	best ask	midpoint	LRTT	OurTD	PhlxTD
AAPL	"10/3/2022 9:40:07.053"	120886338	10/7/2022	140	P	PHLX	3.83	3.80	3.85	3.82	buy	sell	sell
AAPL	"10/3/2022 9:40:07.053"	120886339	10/7/2022	140	P	PHLX	3.81	3.80	3.85	3.82	sell	sell	sell
AAPL	"10/3/2022 11:55:52.286"	1137821820	1/20/2023	130	P	MIAX	6.49	6.45	6.50	6.47	buy	sell	
AAPL	"10/3/2022 11:55:52.286"	1137821821	1/20/2023	130	P	MIAX	6.46	6.45	6.50	6.47	sell	sell	
AAPL	"10/3/2022 11:55:52.286"	1137821825	1/20/2023	130	P	MIAX	6.46	6.45	6.50	6.47	sell	sell	
COST	"10/3/2022 13:38:39.065"	2927380618	10/14/2022	425	P	PHLX	0.95	0.91	0.97	0.94	buy	sell	sell
COST	"10/3/2022 13:38:39.065"	2927380619	10/14/2022	425	P	PHLX	0.92	0.91	0.97	0.94	sell	sell	sell
COST	"10/3/2022 13:38:39.065"	2927380620	10/14/2022	425	P	PHLX	0.92	0.91	0.97	0.94	sell	sell	sell
AAPL	"10/3/2022 14:51:27.342"	1933674362	12/16/2022	145	C	PHLX	8.84	8.80	8.90	8.85	sell	buy	buy
AAPL	"10/3/2022 14:51:27.342"	1933674363	12/16/2022	145	C	PHLX	8.87	8.80	8.90	8.85	buy	buy	buy
AMD	"10/3/2022 15:32:53.224"	924101912	11/18/2022	80	C	PHLX	1.34	1.33	1.35	1.34	sell	buy	buy
AMD	"10/3/2022 15:32:53.224"	924101913	11/18/2022	80	C	PHLX	1.35	1.33	1.35	1.34	buy	buy	buy
AMZN	"10/3/2022 14:33:49.018"	529949441	10/7/2022	118	C	PHLX	1.56	1.55	1.58	1.57	sell	buy	buy
AMZN	"10/3/2022 14:33:49.018"	529949442	10/7/2022	118	C	PHLX	1.57	1.55	1.58	1.57	buy	buy	buy
ABNB	"10/3/2022 10:03:04.870"	365010563	12/16/2022	145	C	CBOE	1.26	1.14	1.37	1.25	buy	sell	

ABNB	"10/3/2022 10:03:04.870"	365010565	12/16/2022	145	C	CBOE	1.26	1.14	1.37	1.25	buy	sell
ABNB	"10/3/2022 10:03:04.870"	365010567	12/16/2022	145	C	CBOE	1.25	1.14	1.37	1.25	sell	sell
ABNB	"10/3/2022 10:03:04.870"	365010568	12/16/2022	145	C	CBOE	1.25	1.14	1.37	1.25	sell	sell
ABNB	"10/3/2022 10:03:04.870"	365010570	12/16/2022	145	C	CBOE	1.25	1.14	1.37	1.25	sell	sell
ABNB	"10/3/2022 10:03:04.870"	365010571	12/16/2022	145	C	CBOE	1.25	1.14	1.37	1.25	sell	sell
ALGN	"10/3/2022 10:35:04.923"	643521211	10/7/2022	225	C	AMEX	3.04	2.50	3.40	2.95	buy	sell
ALGN	"10/3/2022 10:35:04.923"	643521213	10/7/2022	225	C	AMEX	2.95	2.50	3.40	2.95	sell	sell
ALGN	"10/3/2022 10:35:04.923"	643521214	10/7/2022	225	C	AMEX	2.99	2.50	3.40	2.95	buy	sell
ALGN	"10/3/2022 10:35:04.923"	643521216	10/7/2022	225	C	AMEX	3.00	2.50	3.40	2.95	buy	sell
ALGN	"10/3/2022 10:35:04.923"	643521221	10/7/2022	225	C	AMEX	3.04	2.50	3.40	2.95	buy	sell
LNG	"10/3/2022 09:50:32.202"	349168692	10/21/2022	160	P	GEMX	3.40	3.30	3.60	3.45	sell	sell
LNG	"10/3/2022 09:50:32.202"	349168709	10/21/2022	160	P	GEMX	3.40	3.30	3.60	3.45	sell	sell
LNG	"10/3/2022 09:50:32.202"	349168716	10/21/2022	160	P	GEMX	3.40	3.30	3.60	3.45	sell	sell
LNG	"10/3/2022 09:50:32.202"	349168739	10/21/2022	160	P	GEMX	3.40	3.30	3.60	3.45	sell	sell
LNG	"10/3/2022 09:50:32.202"	349168770	10/21/2022	160	P	GEMX	3.40	3.30	3.50	3.40	mid	sell
LNG	"10/3/2022 09:50:32.202"	349168815	10/21/2022	160	P	GEMX	3.40	3.30	3.50	3.40	mid	sell
LNG	"10/3/2022 09:50:32.202"	349168829	10/21/2022	160	P	GEMX	3.40	3.30	3.50	3.40	mid	sell
LNG	"10/3/2022 09:50:32.202"	349168854	10/21/2022	160	P	GEMX	3.40	3.30	3.50	3.40	mid	sell
LNG	"10/3/2022 09:50:32.202"	349168994	10/21/2022	160	P	GEMX	3.40	3.30	3.40	3.35	buy	sell

Table 6

Price Improvements, Order Imbalance, PFOF and DMMs

This table presents the regression results examining the impact of various factors on the price improvement of options orders for the October 2022 sample period. The dependent variable, **Price improvement,** is defined as the difference between the quoted half-spread and the effective half-spread, measured in cents. **OI** (Order Imbalance) represents short-term inventory pressure on market makers. **Auction** is a binary variable equal to one if at least one trade within the interval was executed in a single- or multi-leg price improvement auction, and zero otherwise. **PFOF-DMMP** is a binary variable equal to one if the exchange has Designated Market Maker (DMM) preferencing and uses a payment for order flow pricing structure, and zero otherwise. **AvgSize** is the natural logarithm of the average trade size within the interval. **Call** is a binary variable equal to one if the option is a call. **MCAP** is the natural logarithm of the market capitalization of the underlying stock, and **StockVol** is the natural logarithm of the daily traded volume of the underlying stock. **Tick** is a binary variable equal to one if the average trade price of the option series within the interval is $3.00 or greater. **StockSpread** is the average spread of the underlying stock within the interval. The inverse of the average option and underlying stock quote midpoint is also included in the analysis. All specifications include fixed effects for the underlying stock, day, and exchange. Standard errors are double-clustered at the option and day levels and are reported in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.10

VARIABLES	(1)	(2)	(3)	(4)
OI	-0.0545***	-0.0563***	-0.0224**	-0.0224**
	(0.0071)	(0.0069)	(0.0090)	(0.0090)
OI x PFOF-DMMP			-0.0680***	-0.1134***
			(0.0099)	(0.0112)
OI x PFOF-DMMP x Auction				0.1042***
				(0.0139)
Auction	0.7509***	0.7522***	0.7516***	0.7533***
	(0.0495)	(0.0486)	(0.0486)	(0.0486)
AvgSize	0.0823***	0.0825***	0.0824***	0.0825***
	(0.0092)	(0.0092)	(0.0092)	(0.0092)
Call	-0.3303***	-0.3363***	-0.3364***	-0.3361***
	(0.0541)	(0.0539)	(0.0540)	(0.0539)
$\sqrt{\mathrm{DTE}}$	0.3860***	0.3836***	0.3836***	0.3836***
	(0.0199)	(0.0196)	(0.0196)	(0.0196)
AvgIVOL	1.6789***	1.6028***	1.6030***	1.6027***
	(0.1878)	(0.1768)	(0.1768)	(0.1767)
AvgDelta	12.4980***	12.5069***	12.5074***	12.5078***
	(0.3704)	(0.3674)	(0.3675)	(0.3675)
AvgGamma	1.4744***	1.5037***	1.5043***	1.5051***
	(0.3503)	(0.3428)	(0.3427)	(0.3429)
AvgVega	18.3195***	18.4542***	18.4540***	18.4534***
	(0.7358)	(0.7268)	(0.7267)	(0.7268)
1/OptionMidpoint	0.0617***	0.0628***	0.0629***	0.0630***
	(0.0053)	(0.0053)	(0.0053)	(0.0053)
MCAP	2.0175***	2.4030***	2.4034***	2.4042***
	(0.3580)	(0.2802)	(0.2801)	(0.2801)
Tick	-1.8803***	-1.8865***	-1.8866***	-1.8870***
	(0.1432)	(0.1416)	(0.1416)	(0.1416)
1/StockMidpoint		-0.8373***	-0.8379***	-0.8390***
		(0.2840)	(0.2838)	(0.2838)
StockSpread		6.7051***	6.7050***	6.7049***
		(0.4244)	(0.4244)	(0.4244)
StockVol		0.6500***	0.6500***	0.6494***
		(0.0704)	(0.0704)	(0.0704)
R^2	0.160	0.162	0.162	0.162
NObs.	20,246,444	20,246,444	20,246,444	20,246,444

Table 7

Price Improvements and Cross-Market Effects

This table presents the regression results examining cross-market effects on the price improvement of options orders for the October 2022 sample period. The dependent variable, **Price improvement,** is defined as the difference between the quoted half-spread and the effective half-spread, measured in cents. **OI** (Order Imbalance) represents short-term inventory pressure on market makers. **Auction** is a dummy variable equal to one if at least one trade within the interval was executed in a single- or multi-leg price improvement auction, and zero otherwise. **PFOF-DMMP** is a binary variable equal to one if the exchange has Designated Market Maker (DMM) preferencing and uses a payment for order flow pricing structure, and zero otherwise. **AvgSize** is the natural logarithm of the average trade size within the interval. **Call** is a dummy variable equal to one if the option is a call. **MCAP** is the natural logarithm of the market capitalization of the underlying stock, and **StockVol** is the natural logarithm of the daily traded volume of the underlying stock. **Tick** is a binary variable equal to one if the average trade price of the option series within the interval is $3.00 or greater. **OVOI** is the order imbalance on other exchanges. **SAME** is a binary variable set to one if the net order flow across other venues is in the same direction as the order flow on the local exchange in the time interval. **StockSpread** is the average spread of the underlying stock within the interval. The inverse of the average option and underlying stock quote midpoint is also included in the analyses. All specifications include fixed effects for the underlying stock, day, and exchange. Standard errors are double-clustered at the option and day levels and are reported in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.10

VARIABLES	(1)	(2)	(3)
OI	-0.0191***	-0.0141*	-0.0142*
	(0.0074)	(0.0077)	(0.0077)
SAME	-0.7948***	-0.7948***	-0.6739***
	(0.0237)	(0.0237)	(0.0351)
SAME x OI	0.0018		
	(0.0115)		
OVOI		-0.0155*	-0.0154*
		(0.0087)	(0.0087)
SAME x OI x OVOI			-0.1607***
			(0.0271)
OI x PFOF-DMMP	-0.0690***	-0.0711***	-0.0712***
	(0.0097)	(0.0097)	(0.0097)
Auction	0.6827***	0.6827***	0.6774***
	(0.0480)	(0.0480)	(0.0480)
AvgSize	0.0927***	0.0927***	0.0922***
	(0.0091)	(0.0091)	(0.0091)
Call	-0.3425***	-0.3425***	-0.3444***
	(0.0544)	(0.0544)	(0.0544)
$\sqrt{\mathrm{DTE}}$	0.3826***	0.3826***	0.3833***
	(0.0195)	(0.0195)	(0.0195)
AvgIVOL	1.6116***	1.6117***	1.6094***
	(0.1807)	(0.1807)	(0.1800)
AvgDelta	12.5134***	12.5140***	12.5089***
	(0.3670)	(0.3670)	(0.3671)
AvgGamma	1.5572***	1.5573***	1.5527***
	(0.3372)	(0.3372)	(0.3386)
AvgVega	18.4181***	18.4182***	18.4221***
	(0.7253)	(0.7253)	(0.7256)
1/OptionMidpoint	0.0619***	0.0619***	0.0621***
	(0.0053)	(0.0053)	(0.0053)
MCAP	2.4181***	2.4178***	2.4140***
	(0.2783)	(0.2783)	(0.2781)
Tick	-1.8942***	-1.8944***	-1.8921***
	(0.1416)	(0.1416)	(0.1417)

1/StockMidpoint	-0.8528***	-0.8531***	-0.8538***
	(0.2816)	(0.2816)	(0.2817)
StockSpread	6.7144***	6.7145***	6.7116***
	(0.4253)	(0.4253)	(0.4252)
StockVol	0.6651***	0.6653***	0.6606***
	(0.0701)	(0.0701)	(0.0702)
R^2	0.163	0.163	0.165
NObs.	20,246,444	20,246,444	20,246,444

Table 8

Auction Subsample Analysis: Price Improvements and Cross-Market Effects

This table presents regression results analyzing cross-market effects on price improvements for options orders during intervals that include at least one auction trade. The sample period covers October 2022. The dependent variable, **Price improvement**, is defined as the difference between the quoted half-spread and the effective half-spread, measured in cents. **OI** (Order Imbalance) represents short-term inventory pressure on market makers. **PFOF-DMMP** is a binary variable equal to one if the exchange has Designated Market Maker (DMM) preferencing and uses a payment for order flow pricing structure, and zero otherwise. **AvgSize** is the natural logarithm of the average trade size within the interval. **Call** is a dummy variable equal to one if the option is a call. **MCAP** is the natural logarithm of the market capitalization of the underlying stock, and **StockVol** is the natural logarithm of the daily traded volume of the underlying stock. **Tick** is a binary variable equal to one if the average trade price of the option series within the interval is $3.00 or greater. **OVOI** is the order imbalance on other exchanges. **SAME** is a binary variable set to one if the net order flow across other venues is in the same direction as the order flow on the local exchange in the time interval. **StockSpread** is the average spread of the underlying stock within the interval. The inverse of the average option and underlying stock quote midpoint is also included in the analyses. All specifications include fixed effects for the underlying stock, day, and exchange. Standard errors are double-clustered at the option and day levels and are reported in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.10

VARIABLES	(1)	(2)	(3)
OI	-0.0272**	-0.0230**	-0.0241**
	(0.0117)	(0.0117)	(0.0115)
SAME		-0.7940***	-0.9285***
		(0.0179)	(0.0286)
OVOI			0.0108
			(0.0093)
SAME x OI x OVOI			0.1982***
			(0.0245)
OI x PFOF-DMMP	0.0194*	0.0198*	0.0203*
	(0.0114)	(0.0117)	(0.0115)
AvgSize	0.0420***	0.0484***	0.0499***
	(0.0095)	(0.0095)	(0.0094)
Call	-0.3588***	-0.3468***	-0.3450***
	(0.0561)	(0.0556)	(0.0555)
$\sqrt{\text{DTE}}$	0.3059***	0.3004***	0.2993***
	(0.0213)	(0.0212)	(0.0212)
AvgIVOL	1.1706***	1.1808***	1.1819***
	(0.1929)	(0.1965)	(0.1975)
AvgDelta	14.1605***	14.1968***	14.2068***
	(0.4418)	(0.4403)	(0.4404)
AvgGamma	-0.7404**	-0.6831**	-0.6846**
	(0.3379)	(0.3301)	(0.3292)
AvgVega	30.9078***	30.8640***	30.8511***
	(1.3088)	(1.3064)	(1.3061)
1/OptionMidpoint	0.0704***	0.0695***	0.0692***
	(0.0051)	(0.0050)	(0.0050)
MCAP	2.4662***	2.5034***	2.5064***
	(0.2680)	(0.2676)	(0.2672)
Tick	-0.7518***	-0.7645***	-0.7673***
	(0.1471)	(0.1466)	(0.1465)
1/StockMidpoint	-0.5677	-0.5460	-0.5449
	(0.3615)	(0.3628)	(0.3628)
StockSpread	11.7901***	11.8280***	11.8325***
	(0.8474)	(0.8491)	(0.8490)

StockVol	0.7539*** (0.0744)	0.7862*** (0.0739)	0.7910*** (0.0740)
R^2	0.242	0.244	0.244
NObs.	5,411,428	5,411,428	5,411,428

Table 9

Price Improvements, Cross-Market Effects and Moneyness

This table presents the regression results examining leverage effects on the price improvements of options orders that are not trading on their expiration day during the October 2022 sample period. The dependent variable, **Price improvement,** is defined as the difference between the quoted half-spread and the effective half-spread, measured in cents. **OI** (Order Imbalance) represents short-term inventory pressure on market makers. **Auction** is a binary variable equal to one if at least one trade within the interval was executed in a single- or multi-leg price improvement auction, and zero otherwise**. Moneyness** is computed as the ln(Strike price/Stock price)/ √DTE, where DTE is the calendar days to expiration. **PFOF-DMMP** is a binary variable equal to one if the exchange has Designated Market Maker (DMM) preferencing and uses a payment for order flow pricing structure, and zero otherwise. **AvgSize** is the natural logarithm of the average trade size within the interval. **Call** is a dummy variable equal to one if the option is a call. **MCAP** is the natural logarithm of the market capitalization of the underlying stock, and **StockVol** is the natural logarithm of the daily traded volume of the underlying stock. **Tick** is a binary variable equal to one if the average trade price of the option series within the interval is $3.00 or greater. **OVOI** is the order imbalance on other exchanges. **SAME** is a binary variable set to one if the net order flow across other venues is in the same direction as the order flow on the local exchange in the time interval. **StockSpread** is the average spread of the underlying stock within the interval. The inverse of the average option quote midpoint is also included in the analyses. All specifications include fixed effects for the underlying stock, day, and exchange. Standard errors are double-clustered at the option and day levels and are reported in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.10

VARIABLES	All	Calls	Puts
Moneyness	5.0505***	-1.5279	5.5981***
	(1.0676)	(1.4164)	(2.0765)
OI	-0.0240***	-0.0045	-0.0525***
	(0.0070)	(0.0112)	(0.0149)
SAME	-0.8672***	-0.7861***	-0.9540***
	(0.0448)	(0.0550)	(0.0518)
OVOI	-0.0426***	-0.0381***	-0.0487***
	(0.0082)	(0.0097)	(0.0154)
SAME x OI x OVOI	0.0626*	0.0531	0.0620
	(0.0344)	(0.0506)	(0.0439)
OI x PFOF-DMMP	-0.0576***	-0.0429***	-0.0731***
	(0.0096)	(0.0098)	(0.0180)
Auction	0.5377***	0.6020***	0.4806***
	(0.0518)	(0.0494)	(0.0745)
AvgSize	0.1383***	0.1102***	0.1779***
	(0.0107)	(0.0084)	(0.0186)
Call	-0.4099***		
	(0.0767)		
AvgIVOL	0.9405***	1.1262***	0.9345***
	(0.1421)	(0.1593)	(0.1689)
AvgDelta	10.8021***	9.2525***	11.6069***
	(0.3298)	(0.4100)	(0.7168)
AvgGamma	-4.8021***	-3.8643***	-7.6415***
	(0.3864)	(0.3010)	(0.7445)
AvgVega	26.1091***	27.0839***	24.9021***
	(0.7506)	(0.8536)	(1.0308)
1/OptionMidpoint	0.0441***	0.0485***	0.0499***
	(0.0033)	(0.0056)	(0.0074)
MCAP	1.2387***	1.8442***	0.3269
	(0.3380)	(0.3095)	(0.7202)

Tick	-1.3231***	-1.0692***	-1.6385***
	(0.1144)	(0.1126)	(0.1790)
StockSpread	7.0404***	8.4926***	5.8901***
	(0.5438)	(1.0854)	(0.5389)
StockVol	0.7057***	0.6740***	0.7308***
	(0.0845)	(0.0768)	(0.1232)
R^2	0.157	0.165	0.147
NObs.	19,409,499	11,130,243	8,279,006

Table 10

Auction Subsample Analysis: Price Improvements, Cross-Market Effects and Moneyness

This table presents the regression results examining leverage effects on the price improvements of options orders that are not trading on their expiration day during the October 2022 sample period. The analyses focus exclusively on intervals that include at least one auction trade. The dependent variable, **Price improvement,** is defined as the difference between the quoted half-spread and the effective half-spread, measured in cents. **OI** (Order Imbalance) represents short-term inventory pressure on market makers. **Moneyness** is computed as the ln(Strike price/Stock price)/ √DTE, where DTE is the calendar days to expiration. **PFOF-DMMP** is a binary variable equal to one if the exchange has Designated Market Maker (DMM) preferencing and uses a payment for order flow pricing structure, and zero otherwise. **AvgSize** is the natural logarithm of the average trade size within the interval. **Call** is a dummy variable equal to one if the option is a call. **MCAP** is the natural logarithm of the market capitalization of the underlying stock, and **StockVol** is the natural logarithm of the daily traded volume of the underlying stock. **Tick** is a binary variable equal to one if the average trade price of the option series within the interval is $3.00 or greater. **OVOI** is the order imbalance on other exchanges. **SAME** is a binary variable set to one if the net order flow across other venues is in the same direction as the order flow on the local exchange in the time interval. **StockSpread** is the average spread of the underlying stock within the interval. The inverse of the average option quote midpoint is also included in the analyses. All specifications include fixed effects for the underlying stock, day, and exchange. Standard errors are double-clustered at the option and day levels and are reported in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.10

VARIABLES	All	Calls	Puts
Moneyness	5.4759***	-6.2271***	9.3966***
	(0.9173)	(1.4644)	(2.6096)
OI	-0.0365***	-0.0604***	-0.0129
	(0.0113)	(0.0223)	(0.0193)
SAME	-1.1340***	-1.0657***	-1.1967***
	(0.0404)	(0.0508)	(0.0553)
OVOI	-0.0203**	-0.0106	-0.0256
	(0.0101)	(0.0146)	(0.0161)
SAME x OI x OVOI	0.3978***	0.3376***	0.4879***
	(0.0323)	(0.0430)	(0.0557)
OI x PFOF-DMMP	0.0317**	0.0643***	-0.0029
	(0.0124)	(0.0209)	(0.0177)
AvgSize	0.0882***	0.0709***	0.1136***
	(0.0086)	(0.0110)	(0.0133)
Call	-0.4764***		
	(0.0796)		
AvgIVOL	1.0467***	1.5036***	1.2400***
	(0.1682)	(0.2262)	(0.1936)
AvgDelta	13.1969***	11.3060***	13.5207***
	(0.4537)	(0.5629)	(0.7323)
AvgGamma	-4.7083***	-4.2508***	-7.1708***
	(0.3469)	(0.3316)	(0.5231)
AvgVega	37.8391***	40.6023***	33.6691***
	(1.0529)	(1.0932)	(1.5673)
1/OptionMidpoint	0.0668***	0.0849***	0.0661***
	(0.0031)	(0.0056)	(0.0081)
MCAP	1.8624***	1.5122***	2.5110***
	(0.3440)	(0.3004)	(0.6036)
Tick	-0.6573***	-0.6472***	-0.6881***
	(0.1407)	(0.1442)	(0.1892)
StockSpread	12.2991***	15.2006***	9.9229***
	(1.0028)	(1.8740)	(0.9157)

StockVol	0.8053***	0.7981***	0.8006***
	(0.0922)	(0.0999)	(0.1044)
R^2	0.245	0.257	0.228
NObs.	5,151,514	3,118,538	2,032,688

Table 11

Probability of Auctions, Cross-Market Effects and Order Imbalance

This table presents the regression results examining order imbalance and cross-market effects on the probability of price improvement auction occurring during the October 2022 sample period. Regression data is trade data from exchanges that have price improvement auction mechanisms. The dependent variable, **Auction,** is a binary variable equal to one if at least one trade within the interval was executed in a single- or multi-leg price improvement auction, and zero otherwise. **OI** (Order Imbalance) represents short-term inventory pressure on market makers. **Moneyness** is computed as the ln(Strike price/Stock price)/ √DTE, where DTE is the calendar days to expiration. **PFOF-DMMP** is a binary variable equal to one if the exchange has Designated Market Maker (DMM) preferencing and uses a payment for order flow pricing structure, and zero otherwise. **AvgSize** is the natural logarithm of the average trade size within the interval. **Call** is a dummy variable equal to one if the option is a call. **MCAP** is the natural logarithm of the market capitalization of the underlying stock, and **StockVol** is the natural logarithm of the daily traded volume of the underlying stock. **Tick** is a binary variable equal to one if the average trade price of the option series within the interval is $3.00 or greater. **OVOI** is the order imbalance on other exchanges. **SAME** is a binary variable set to one if the net order flow across other venues is in the same direction as the order flow on the local exchange in the time interval. The inverse of the average option and underlying stock quote midpoint is also included in the analyses. **OptionSpread** and **StockSpread** are the average spreads of options and their underlying stock within the interval. All specifications include fixed effects for the underlying stock, day, and exchange. Standard errors are double-clustered at the option and day levels and are reported in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.10

VARIABLES	(1)	(2)	(3)	(4)
OI	-0.0059***	-0.0041***	-0.0036***	-0.0018***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)
$Auction_{t-1}$				0.2196***
				(0.0035)
SAME			0.0010	0.0072***
			(0.0025)	(0.0019)
OVOI			-0.0013***	0.0001
			(0.0004)	(0.0004)
SAME x OI x OVOI			-0.0832***	-0.0712***
			(0.0027)	(0.0021)
OI x PFOF-DMMP		-0.0031***	-0.0030***	-0.0017***
		(0.0005)	(0.0005)	(0.0006)
AvgSize	-0.0174***	-0.0174***	-0.0166***	-0.0179***
	(0.0010)	(0.0010)	(0.0010)	(0.0011)
Call	0.0318***	0.0318***	0.0303***	0.0223***
	(0.0020)	(0.0020)	(0.0020)	(0.0017)
$\sqrt{\text{DTE}}$	-0.0086***	-0.0086***	-0.0082***	-0.0076***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
AvgDelta	-0.1178***	-0.1177***	-0.1178***	-0.0772***
	(0.0047)	(0.0047)	(0.0045)	(0.0039)
AvgGamma	0.0578***	0.0579***	0.0609***	0.0420***
	(0.0053)	(0.0053)	(0.0051)	(0.0063)
AvgVega	-0.0525***	-0.0525***	-0.0505***	-0.0410***
	(0.0054)	(0.0054)	(0.0052)	(0.0071)
1/OptionMidpoint	-0.0005***	-0.0005***	-0.0004***	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
OptionSpread	0.0000	0.0000	-0.0026	-0.0130***
	(0.0034)	(0.0034)	(0.0034)	(0.0041)
MCAP	-0.0490***	-0.0490***	-0.0470***	-0.0179***
	(0.0083)	(0.0083)	(0.0078)	(0.0011)
Tick	-0.0447***	-0.0447***	-0.0440***	0.0223***
	(0.0024)	(0.0024)	(0.0022)	(0.0017)
1/StockMidpoint	0.0164	0.0164	0.0159	-0.0076***
	(0.0135)	(0.0135)	(0.0130)	(0.0004)

StockSpread	0.0027 (0.0039)	0.0027 (0.0039)	0.0025 (0.0037)	-0.0772*** (0.0039)
R^2	0.348	0.348	0.354	0.398
NObs.	11,877,865	11,877,865	11,877,865	7,513,323

Table 12

PFOF-DMMP Exchanges: Probability of Auctions, Cross-Market Effects and Order Imbalance

This table presents the regression results examining order imbalance and cross-market effects on the probability of price improvement auction occurring during the October 2022 sample period. Regression data is trade data from exchanges that have price improvement auction mechanisms, uses DMM preferencing and utilize PFOF pricing model. The dependent variable, **Auction,** is a binary variable equal to one if at least one trade within the interval was executed in a single- or multi-leg price improvement auction, and zero otherwise. **OI** (Order Imbalance) represents short-term inventory pressure on market makers. **Moneyness** is computed as the ln(Strike price/Stock price)/ √DTE, where DTE is the calendar days to expiration. **PFOF-DMMP** is a binary variable equal to one if the exchange has Designated Market Maker (DMM) preferencing and uses a payment for order flow pricing structure, and zero otherwise. **AvgSize** is the natural logarithm of the average trade size within the interval. **Call** is a dummy variable equal to one if the option is a call. **MCAP** is the natural logarithm of the market capitalization of the underlying stock, and **StockVol** is the natural logarithm of the daily traded volume of the underlying stock. **Tick** is a binary variable equal to one if the average trade price of the option series within the interval is $3.00 or greater. **OVOI** is the order imbalance on other exchanges. **SAME** is a binary variable set to one if the net order flow across other venues is in the same direction as the order flow on the local exchange in the time interval. The inverse of the average option and underlying stock quote midpoint is also included in the analyses. **OptionSpread** and **StockSpread** are the average spreads of options and their underlying stock within the interval. All specifications include fixed effects for the underlying stock, day, and exchange. Standard errors are double-clustered at the option and day levels and are reported in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.10

VARIABLES	(1)	(2)	(3)
OI	-0.0066***	-0.0059***	-0.0032***
	(0.0007)	(0.0006)	(0.0006)
Auction_{t-1}			0.1967***
			(0.0030)
SAME		-0.0078**	-0.0012
		(0.0033)	(0.0026)
OVOI		-0.0019***	-0.0000
		(0.0006)	(0.0006)
SAME x OI x OVOI		-0.1166***	-0.0974***
		(0.0033)	(0.0024)
AvgSize	-0.0188***	-0.0178***	-0.0199***
	(0.0018)	(0.0018)	(0.0019)
Call	0.0480***	0.0464***	0.0341***
	(0.0028)	(0.0028)	(0.0025)
$\sqrt{\text{DTE}}$	-0.0129***	-0.0125***	-0.0120***
	(0.0005)	(0.0005)	(0.0007)
AvgDelta	-0.1699***	-0.1681***	-0.1172***
	(0.0058)	(0.0055)	(0.0052)
AvgGamma	0.0788***	0.0873***	0.0617***
	(0.0075)	(0.0076)	(0.0082)
AvgVega	-0.0780***	-0.0750***	-0.0553***
	(0.0080)	(0.0079)	(0.0102)
1/OptionMidpoint	-0.0007***	-0.0007***	-0.0001
	(0.0002)	(0.0002)	(0.0002)
OptionSpread	0.0257***	0.0203***	0.0108**
	(0.0046)	(0.0046)	(0.0049)
MCAP	-0.0674***	-0.0646***	-0.0608***
	(0.0107)	(0.0102)	(0.0096)
Tick	-0.0633***	-0.0630***	-0.0509***
	(0.0029)	(0.0028)	(0.0024)
1/StockMidpoint	0.0065	0.0050	0.0090
	(0.0160)	(0.0154)	(0.0165)
StockSpread	-0.0001	0.0023	0.0201**
	(0.0056)	(0.0054)	(0.0085)
R^2	0.156	0.167	0.199

NObs.	7,250,369	7,250,369	4,739,210