April 21, 2026

Vanessa Countryman, Secretary
Securities and Exchange Commission
100 F Street, N.E.
Washington, D.C. 20549-1090

Re: File Number 4-887, Roundtable on Options Market Structure

Dear Ms. Countryman:

Thank you for the opportunity to submit our views on options market structure in connection with the Commission's Roundtable on Options Market Structure held on April 16, 2026. We are finance professors at Syracuse University and the University of Illinois at Urbana-Champaign with a long-term interest in options market structure. We attach our current paper, "Does Internalization Impact Quote Competition?" which provides empirical evidence directly relevant to one of the roundtable's topics on facilitating competition in a quote-driven market.

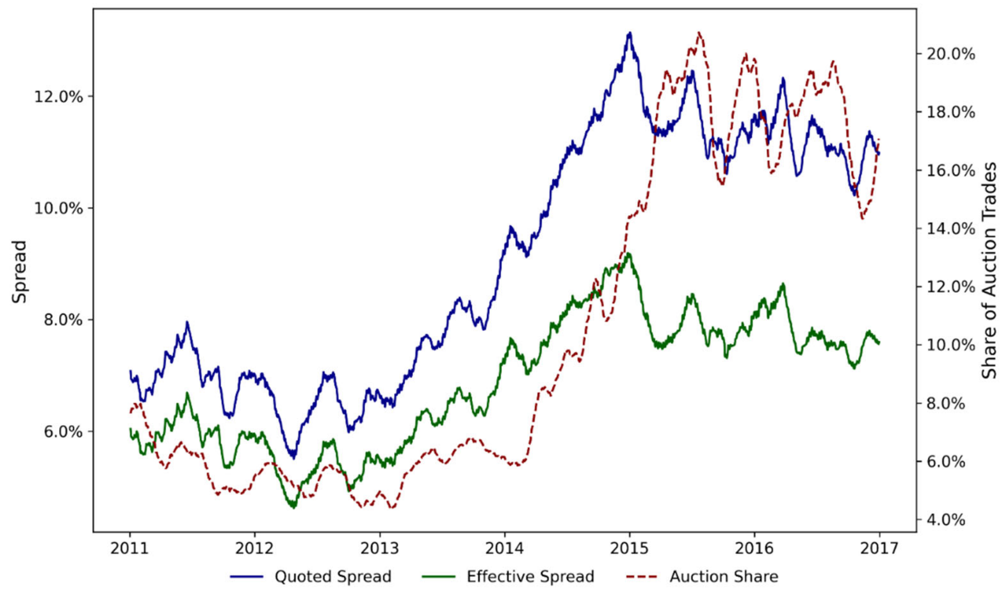
Our paper examines the effects of internalization on quote competition in options markets. We test a simple mechanism: internalization creates a disincentive for market makers to compete on quotes, since narrowing the NBBO reduces profits from internalizing the order flow they have purchased. Market makers routinely internalize retail order flow through on-exchange auctions, which allow them to trade without quoting the best price, disconnecting trading from quoting.

We present three sets of findings. First, we show that market makers use auctions tactically to execute trades when their quotes are uncompetitive. Exchanges offering auctions ("auction exchanges") are 31 percentage points more likely to trade in an auction when they are not at the best quoted price. Within those auctions, price improvement is 17 percentage points less likely when the exchange is not at the best price than when it is. These results indicate that auctions are often used to match the NBBO without displaying competitive quotes, rather than strictly as price improvement mechanisms.

Second, we find that auction exchanges are approximately 12 percentage points less likely to quote at the NBBO than non-auction exchanges. This gap is more pronounced at 30 percentage points in setting the best quote.

Third, we examine an exogenous rule change that restricts auctions. We find that restricting auctions increases auction exchanges' quote competitiveness, and NBBO quoted spreads narrow significantly. Effective spreads show smaller declines, since narrower quoted spreads also reduce the scope for price improvement. An interesting mechanical consequence is that the effective-over-quoted (EQ) ratio increases (potentially signaling worsening execution quality) simply because quoted spreads narrow more than effective spreads.

Long-term trends in the data are consistent with these results. Figure 2 in the paper (reproduced below) plots quoted spreads, effective spreads and auction use over the 2011–2016 period. Quoted and effective spreads track each other closely in the 2011–2013 period (a trend extending back to at least 2004) but diverge significantly in 2013–2014. This is also the time when auction use increases as auctions are used more for retail internalization. It is widely noted that quoted spreads have declined in equities markets; less discussed is the increase in options quoted spreads. Figure 2 indicates that, over time, quoted spreads have become less meaningful indicators of ex-ante liquidity in options.



The Commission's focus on quote competition is especially important in options, where displayed liquidity relies more heavily on market maker quotes than in equities, options market making is concentrated among a small number of firms, and internalization incentives are more prominent due to larger payments for order flow. Our evidence shows that the current auction framework weakens the incentive to compete on quotes. It also implies that initiatives to enhance quote competition should focus on reconnecting quoting to trading.

We also suggest caution around the use of EQ ratio as an execution quality metric. Because internalization widens quoted spreads, the benchmark against which price improvement is measured is itself inflated by the practice. As noted above, our 2017 event study shows that EQ ratios worsen even as effective spreads decline, because quoted spreads decline more. In the long-term time-series, quoted and effective spreads both rise as auction use increases, but the EQ ratio mechanically declines since quoted spreads increase more.

On a related point, while we use public data in our analysis, a potential disclosure requirement (similar to Rule 605 for equities) could provide granular data on the execution quality of internalized orders, in auctions and in the limit order book.

We appreciate the Commission's attention to options market structure.

Sincerely,

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Attachment: "Does Internalization Impact Quote Competition?"

Does internalization impact quote competition? [*]

Amber Anand, Dmitriy Muravyev

Abstract

Market makers traditionally compete for client orders by posting better bid and ask prices. But internalization mechanisms – such as price improvement auctions in options – let market makers trade without posting competitive quotes. We examine how internalization affects quote competition in the options markets, where major market makers are primarily responsible for both posting quotes and internalizing retail order flow. We find that internalization reduces quote competition. Market makers route trades to auctions to match best prices when their quotes are uncompetitive: auction trades are 31 percentage points more likely to occur, but 17 percentage points less likely to receive price improvement when an exchange is not posting the best price. Exchanges that offer auctions are 12 percentage points less likely to quote the best price. To examine how internalization affects spreads, we analyze a market-wide rule change that restricted auctions for certain options. For affected options, quoted spreads narrowed by 23% while effective spreads show much smaller changes. We also document a long-term widening of the gap between quoted and effective spreads alongside an increase in auction use, consistent with our findings of internalization reducing quote competition.

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1. Introduction

We study how internalization affects quote competition and quoted bid-ask spreads in options markets. Internalization, which allows market makers to trade directly with retail orders routed to them by brokers, has become a dominant feature of U.S. equity and options markets. This structure is intertwined with payments for order flow (PFOF) from market makers to brokers for routing these retail orders. In equities, retail orders are internalized off-exchanges, allowing market makers to trade without competing on quoted prices. Auctions on options exchanges serve the same purpose. The recent surge in options trading and options PFOF, which now exceeds that in equities, has brought new attention to retail trading in options. Recent research primarily evaluates price improvement offered to retail traders, while we focus on the broader effects on quote competition.[1]

Theoretical models predict that internalization can weaken quote competition. Easley, Kiefer, and O'Hara (1996) show that when a relatively uninformed segment of order flow is diverted away from public competition, the adverse selection risk increases for those who continue to post quotes, thereby widening bid-ask spreads. In addition, Dutta and Madhavan (1997), Bloomfield and O'Hara (1998), and van Kervel and Yueshen (2024) model the anti-competitive effects associated with internalization of order flow.

We propose and directly test a complementary mechanism based on incentives. When market makers are guaranteed a steady stream of internalized order flow, their need to compete aggressively by posting the best prices on public exchanges diminishes. As Citadel Investment Group (2005) notes, "Displaying a better quote will 'only' improve the overall market price, which is the last thing a market maker wants to do if it has captive order flow that it can internalize." This creates a disincentive for market

[1] Battalio and Jennings (2023), Brown, Johnson, Kothari and So (2024), Dyhrberg, Shkilko and Werner (2023) and Schwarz, Barber, Huang, Jorion and Odean (2025) examine price improvement in equities. Bryzgalova, Pavlova and Sikorskaya (2023), Hendershott, Khan and Riordan (2025) and Ernst and Spatt (2025) focus on retail executions in options markets.

makers to improve public quotes, as better quotes would reduce the profits from internalized trades, which are benchmarked against those same quotes.[2]

Despite the strong theoretical predictions, empirical studies rarely find a large effect of internalization on quoted spreads (e.g., Battalio, 1997; Battalio, Greene, and Jennings, 1997; Bessembinder, 2003). Prior work focuses on equities, where a complex market structure complicates this analysis. Internalization in equities occurs off-exchange, and public data do not cleanly separate these trades from other off-exchange activity. Public data also do not allow researchers to link these off-exchange trades to the quoting behavior of the market makers who execute them, because other investors, such as high-frequency traders, often set the best quotes.[3]

While the options and equity market structures are similar in allowing market makers to internalize without corresponding quoting requirements (off-exchange trading in equities and auctions in options), the unique features of the U.S. options market overcome many of these challenges and provide a better setting for our research question. Unlike equities, all option trades, including internalized ones, must occur on an exchange. Market makers widely internalize trades in auctions. Auctions are initiated after receiving an order, and the market maker does not need to have quoted the best price beforehand, which reduces the incentive to post competitive quotes. As Bryzgalova et al. (2023) note, the fee structure discourages competition in auctions from other market participants. Since auctions occur on exchanges, auction trades are clearly identified in public data. Further, option market makers set the best quoted prices (NBBO) most of the time (SEC, 2021), as customer liquidity is scarce and fragmented across a large number of option

[2] Similar to equities, options exchanges prohibit trading through a better price on another exchange, requiring a market maker to be at the best price before order arrival, or to route the order to the better price on another exchange. Instead, a market maker can match or improve the best price in an auction after receiving the order. Figure 1 provides an illustration of the possibilities for a market maker to trade with purchased options order flow.
[3] The presence of endogenous liquidity providers may also affect findings under the Bloomfield and O'Hara (1998) framework, where internalization's impact depends on market maker competition. Markets with less competition may yield different results.

contracts.[4] Overall, market makers' dual role creates a direct, observable link between their internalization activity and their public quotes.

We examine public OPRA data covering all equity option trades from May 2021.[5] We focus on single-leg trades, with more than two million option trades for 2,444 common stocks on an average day in the sample. Auctions account for 19.4% of all trades. Furthermore, the wide bid-ask spreads, averaging nearly 9%, create strong incentives for market makers to internalize retail order flow.

We first show that market makers use auctions tactically, consistent with our proposed mechanism. On exchanges that offer auctions, a trade is 31 percentage points more likely to occur in an auction when the exchange is not quoting the best price. These auction trades are also 17 percentage points more likely to match the best quote available elsewhere rather than provide any price improvement. These results are consistent with market makers using auctions to satisfy their trade-through obligations when they are not quoting the best price. As noted earlier, we can establish this link between market maker quotes and internalization only because of the unique characteristics of the options market.

The quote matching behavior has a market-wide impact on quote competition. Exchanges with auctions are 12 percentage points less likely to quote at the national best bid or offer (NBBO) than non-auction exchanges. When a single exchange sets the best price, it is nearly 30 percentage points more likely to be a non-auction exchange. The effect also spills over across venues. When a designated market maker (DMM) has access to auctions for an option class on one exchange, its quotes for that same option on a non-auction exchange become less competitive. Specifically, when a DMM on the non-auction NYSE Arca exchange also has auction access for the same option class elsewhere, Arca is 8.5 percentage points less likely to quote at the best price under these overlapping DMM assignments.

[4] https://www.nasdaq.com/articles/whats-driving-the-growth-in-options-trading notes that there are approximately 1.5 million different securities traded in the US options markets.

[5] In Appendix Table 3, we show that the results are similar over a longer period from January to June 2021.

To examine whether weaker quote competition translates into broader market quality effects, we study a 2017 market-wide rule change that exogenously restricted auction usage. To make the auction pilot program permanent, exchanges simultaneously adopted rule changes that restricted or prevented the initiation of an auction if the NBBO spread was at its minimum of one penny.[6] This natural experiment allows us to use a difference-in-differences design that compares option classes frequently affected by this restriction to those that were less affected, before and after the rule was implemented.

We find that, as intended, the rule change reduced auction usage for the affected options.[7] The reduction in auctions is accompanied by an increase in quote competition from auction exchanges and an overall decline in quoted spreads. For more affected options, relative to less affected, NBBO quoted dollar spreads declined by 0.6 cents from a pre-period average of 2.6 cents, a 23% reduction. This finding provides causal evidence that the ability to use auctions (before the rule change) is associated with wider quoted spreads, which affect all market participants. Effective spreads show a smaller decline with mixed statistical significance, indicating that price improvement in auctions partly offsets the harm from wider displayed spreads. Because quoted spreads fell more than effective spreads, the Effective-to-Quoted (EQ) ratio increased, suggesting an apparent decline in execution quality even though spreads do not show such a decline. These results suggest caution against relying solely on EQ ratios to assess retail execution quality.

Finally, we examine aggregate market trends in internalization and bid-ask spreads in the years when auctions were adopted for retail internalization. Figure 2 shows that the auction share of all option trades increased rapidly in late 2014, consistent with changes made by exchanges over this period to expand auction use for retail internalization. Quoted and effective spreads closely track each other in the 2011-2013 period. Theis changes in the 2013-15 period, when both increase, but quoted spreads do so sharply from

[6] Penny pilot option classes have tick sizes of $0.01 for option series priced below $3, and $0.05 for option series above $3. Non-penny option classes trade in corresponding price increments of $0.05 and $0.10. An option class refers to all traded options on an underlying stock. An option series specifies a combination of the underlying stock, call/put, expiration date and strike price.

[7] Since this analysis predates the availability of public auction flags in OPRA, we use an alternative proxy to identify auction trades before 2019 using available trade flags. Anand, Hua and Puckett (2025) provide a detailed exploration of the methodology for identifying auction trades before the auction trade identifier becomes available.

approximately 7% to nearly 12%, while effective spreads show a smaller increase. The widening gap between quoted and effective spreads coincides with the increase in the use of auctions. The results of our 2017 event study suggest that internalization in auctions contributed (at least in part) to the growing disconnect between quoted and effective spreads.

We primarily contribute to the classic literature on market-wide effects of internalization. Microstructure theory (e.g., Parlour and Rajan, 1993, Easley, Kiefer and O'Hara, 1996, Dutta and Madhavan, 1997, Bloomfield and O'Hara, 1998, Kandel and Marx, 1999, Lescourret and Robert, 2011) predicts that internalization diverts relatively uninformed retail flow from exchanges, reduces market maker competition, weakens market makers' incentives to post aggressive quotes, and widens bid-ask spreads.

Several empirical studies, such as Bessembinder and Kaufman, (1997), Bessembinder (2003), Chung, Chuwonganant, and McCormick (2004), O'Hara and Ye (2011), Hatheway, Kwan, and Zheng (2017), examine cross-sectional effects of internalization in the US equities markets with mixed results. Hansch, Naik, and Viswanathan (1999) find no cross-sectional link between internalization and spreads on the London Stock Exchange. Battalio (1997) and Battalio, Greene, and Jennings (1997) study the entry of internalizing dealers in U.S. markets and find no adverse effects. Comerton-Forde, Malinova, and Park (2018) find that restricting internalization on dark venues in Canada raised quoted depths on lit markets while spreads stayed roughly unchanged. These weak results may arise from the challenge of isolating, within the complex equity market structure, a direct link between internalization and quote competition.

We study a recent period in equity options, which allows us to directly link internalization to quote competitiveness and exploit an exogenous change to the auction mechanism. We find that internalization reduces quote competition and widens overall quoted bid-ask spreads. Our results support the model in van Kervel and Yueshen (2024), where benchmarking internalized trades to public quotes discourages market makers from posting competitive quotes.

We also extend recent work on retail trading in options. Bryzgalova et al. (2023) introduce auction trades as a proxy for retail trading. Hendershott, Khan, and Riordan (2025) find better execution quality in option auctions than regular trades, recommending more orders trade via auctions. They also find that PFOF affects order routing. Ernst and Spatt (2025) find smaller price improvement and larger market maker profits for internalized options trades compared to equities.[8] We add to the understanding of internalization in auctions by showing that auctions make exchange quotes less competitive and increase quoted bid-ask spreads.

Our findings reveal a hidden cost of internalization. Internalized trades may benefit from price improvement, but the practice reduces overall quote competition and widens quoted spreads. The wider quoted spreads hurt traders who trade at the quote. Models by Chordia and Subrahmanyam (1995) and Kandel and Marx (1999) also suggest that wider spreads encourage PFOF. Combined with these predictions, our results suggest that the two, PFOF and wider quoted spreads, can reinforce one another. The effects apply even to internalized trades, since larger quoted spreads allow greater leeway to market makers and brokers to negotiate PFOF and price improvement as documented by Huang, Jorion, and Schwarz (2025). Our findings can inform future policy discussions around internalization, such as the now withdrawn SEC Proposed Rule 615, which would have introduced qualified auctions for equity internalization (SEC, 2022).

2. Internalization in options markets

Unlike equity markets, where market makers internalize trades off-exchanges, all option trades occur on exchanges. Exchanges that facilitate internalization charge a marketing fee to executing market makers. The executing market makers include DMMs as well as other exchange appointed market makers.[9]

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[8] In equities, Dyhrberg, Shkilko and Werner (2023), and Battalio and Jennings (2023) conclude that market makers provide valuable price improvement to retail traders. Schwarz, Barber, Huang, Jorion and Odean (2023), Huang, Jorion, Lee and Schwarz (2023) and Ernst, Malenko, Spatt and Sun (2024) describe broker monitoring of market maker price improvement.

[9] DMMs have higher quoting responsibilities and privileges than other market makers.

This fee is distributed through DMMs to pay to bring order flow to the exchange. Market makers typically supplement these marketing fees to pay PFOF to brokers. There are two primary mechanisms for trading with the purchased order flow a market maker brings to an exchange. If the order is for less than five contracts, the DMM can trade with the order in the limit order book if the DMM is quoting at the relevant (bid or ask) best price in the market. That is, the DMM can jump ahead of other market makers who are quoting the same price and trade with any small order of less than five contracts. This allows the DMM to trade with 100% of the incoming order, but it requires quoting at the best price before the order arrives. Displaying quotes exposes market makers to trading with less preferred counterparties, such as professional traders and other market makers.

Auctions provide the other mechanism for market makers to internalize order flow. Unlike the small order allocation discussed above, auctions do not require the market maker to be quoting at the best price. The market maker who brings the order to the exchange initiates the auction, specifying a limit price at which the market maker is willing to trade the order. The limit price cannot be worse than the NBBO. The initiating market maker can also choose to automatically match other market makers' auction responses up to a specified price. The exchange disseminates the auction message to other participants. The message provides details on the option series and the order (the trade direction and order size). Exchanges differ on whether the initiating market maker's starting limit price is included in the message. Auctions typically run for 100 milliseconds. The initiating market maker's allocation depends on the responses received in the auction, ranging from 100% (no other market makers matching the price), to 50% (one other market maker), or 40%.

While auctions allow for competition from multiple market makers, exchange rules and fees favor the initiating market maker. Hendershott et al. (2025) estimate that the initiating market maker faces no competition in over 90% of auctions, indicating minimal risk of losing purchased orders. Auctions allow market makers to provide price improvement, which brokers monitor using metrics such as the EQ ratio.

The history of auctions in options markets includes the 2017 event we study in our analysis when auctions, which were permitted under a pilot program, become permanent. The event is unique in restricting auction access in some circumstances market-wide, coordinated to be implemented on the same date. As a part of the pilot, exchanges were required to report statistics related to price improvement in auctions. In the analysis of the statistics, it became apparent that price improvement was rare when the NBBO spreads were at $0.01. This finding led to exchanges either eliminating the possibility of auctions when arrival-time spreads equal $0.01 (Miax, Amex and BOX) or restricting their use in these situations by requiring a minimum price improvement of $0.01 (Phlx, BX, ISE, BATS, GEMX and MRX). The exchange proposals for these changes were approved by the SEC on January 18, 2017, which we use as our event date. The changes, which make the use of auctions more difficult, on the same date, indicate that these changes came about in active consultation with the SEC.

3. Data and sample

We use publicly available data drawn from the Options Price Reporting Authority (OPRA) data, processed by the CBOE (formerly the Livevol data). This widely used dataset includes comprehensive information for trades, including trade price and size, a trade condition identifier and the exchange where the trade occurs. Crucially for our analysis, the data include the NBBO and each exchange's best bid and ask quotes at the time of each trade. The CBOE consolidated trade-quote dataset provides a manageable alternative to processing massive OPRA quote records.

We examine data from the month of May 2021 for our analysis of a recent period when auction trades are identified in OPRA. Robustness tests across January to June 2021 yield similar results (Appendix Table 3).[10] Following Bryzgalova et al. (2023) and Hendershott et al. (2025), we focus on single-leg trades executed as regular (auto executed) or auction trades. We exclude observations where either the NBB or NBO equals zero, the NBB is greater than or equal to the NBO, the quoted spread is greater than $20, or

[10] CBOE has retrospectively removed exchange quotes in the data. June 2021 is the last month where we have exchange quotes available in the dataset.

the effective spread is greater than three times the quoted spread. We combine the CBOE/Livevol data with Optionmetrics and CRSP databases. We restrict our sample to options on common stocks (share codes 10 and 11 in CRSP), option series with less than 365 days to maturity, and options with standard settlement in Optionmetrics.

Table 1 describes our sample. We calculate averages every day and then average across days in the month. On an average day in the month, our sample includes approximately 2,444 option classes, with an average of 2.37 million trades. Since we observe quotes only when a trade occurs, quote observations match total trades. These trades account for 11.8 million contracts traded on an average day. Similar to previous studies examining single leg trades, most trades are in call options. As documented by earlier studies (e.g., Muravyev and Pearson, 2020), spreads are large in options markets. The average quoted spread (across all observations in a day) is close to 9% on an average day, effective spreads are smaller at 6.87%. The EQ ratio is a measure of price improvement with lower ratios indicating larger price improvement. In the overall sample, the EQ ratio is 0.82. On an average day, 19.4% of sample trades occur in auctions. Eleven of the 16 exchanges include auctions and these account for 53.3% of trades on an average day.

We disaggregate the sample by exchanges that include auctions (“auction exchanges”) and those that do not (“non-auction exchanges”), as well as by trade type (auction trades and regular trades) in Table 2. Trades on auction exchanges have lower EQ ratios indicating larger price improvement. Trades also appear to occur on auction exchanges when spreads are larger, which may allow greater possibility for price improvement. The difference in EQ ratios is striking when comparing auction and regular trades: auction trades have an EQ ratio of 0.49, indicating that orders executed in auctions pay effective spreads that are half of quoted spreads. Regular trades show an average EQ of 0.90.

4. Results

4.1 The use of the auction mechanism

We begin our analysis of the link between the ability to internalize in auctions and quote competitiveness by examining the probability that an exchange is at the best quote when it executes a trade. Trade through rules in options markets prohibit an exchange from executing a trade at a price worse than the best bid or ask quote in the market (the national best bid or offer, NBB/O). With auctions, a market maker can match or improve on the NBB or NBO price after receiving the order, even if the market maker was not quoting the best price when the order was received. We examine whether the use of the auction mechanism is more likely when an exchange is not quoting the best price than when it is. For this analysis, we classify trades above the quote midpoint as buyer-initiated and below the midpoint as seller-initiated. We exclude midpoint trades.

We create an indicator variable, "*ExchangeBestWhenTrade*", which equals one if the exchange (where the trade occurs) is quoting at the NBO for buyer-initiated trades and the NBB for seller-initiated trades.[11] Table 2 presents the average of this variable. We find that an auction exchange is 23.5 percentage points less likely to be at the best quoted price when a trade occurs on the exchange than a non-auction exchange is when it executes a trade. If this difference is related to the likelihood of trading an order in an auction when an exchange is not at the best quote, we should see a large difference in the propensity to be at the best quoted price between regular and auction trades. We find that to be the case: exchanges are 52.5 percentage points less likely to be at the best quote for auction trades relative to regular trades.

We confirm that the auction exchange level aggregation is not dominated by a particular exchange. In Appendix Table 1, we calculate the proportion of trades that occur in auctions for each exchange each day, as well as the "*ExchangeBestWhenTrade*" measure. The average across days is presented in the table. Exchanges are ranked in descending order by the proportion of their trades in auctions. The bottom five exchanges are non-auction exchanges. While the relationship is not strictly monotonic, we see a trend that

[11] Since price improvement is more likely in auctions, omitting midpoint trades may affect our analysis. We analyze an alternate measure where *ExchangeBestWhenTrade* is enhanced to include midpoint trades by assigning the indicator variable a value of one for midpoint trades if either the exchange's bid equals the NBB or the exchange's ask equals the NBO. Results are similar to those presented in the paper.

exchanges with more trading concentrated in auctions are less likely to be at the best quotes at the time of the trade. We calculate the daily correlation between the two variables for the 16 exchanges. The average daily correlation is -0.87.[12]

We examine more rigorously whether the choice of an auction trade is related to an exchange quoting the best price in Table 3. The models in Table 3 are estimated within the sample of trades occurring on auction exchanges since the choice of executing a trade in an auction only exists within auction exchanges. We estimate the following model:

$$AuctionTrade_i = \beta_1 ExchangeBestWhenTrade_i + \beta'\mathbf{X} + FE + \epsilon_i, \quad (1)$$

where $AuctionTrade_i$ is an indicator variable that equals one if trade *i* is executed in an auction and zero if it is a regular trade. The variable of interest, *ExchangeBestWhenTrade*, equals one for trade *i* if the trade reporting exchange is quoting at the NBO for buyer-initiated trades or the NBB for seller-initiated trades, **X** is a vector of control variables: the NBBO quoted spread at the time of the trade, the delta, gamma and vega of the option series (option series variables are drawn from Optionmetrics), the NBBO quote midpoint and the tick size. Models 1 and 2 include underlying stock and date fixed effects, while models 3 and 4 include underlying stock and exchange fixed effects. T-statistics and p-values are based on standard errors clustered at the stock and date level.

The first model, serving as the baseline, is estimated without our variable of interest. Consistent with Hendershott et al. (2025), we find that auctions are more likely when quoted spreads are wider, likely because there are greater opportunities for price improvement. In the second model, we add *ExchangeBestWhenTrade* to the estimation. The results show that, within auction exchanges, an auction is

[12] Outside of auctions, trades can occur at exchanges when they are not displaying the best price. The mechanisms that could allow these trades include the hidden liquidity in price improvement orders on Nasdaq, C2 and BATS options exchanges, and the possibility of flashing orders on several exchanges including the CBOE, AMEX, PHLX, ISE and Miax. Order flashing involves the exchange offering the opportunity to its market makers to match or improve on the NBBO when the exchange receives an order and is not quoting at the best price. We note that flashing is not an effective way to internalize since the market maker bringing the order does not have any privileges in trading with the order in the flash mechanism.

48.3 percentage points more likely if the exchange is not at the best quote than when it is.[13] Model 4 is similar to model 2 but includes exchange fixed effects to control for heterogeneity within auction exchanges. Model 4 shows that an auction on an auction exchange is 31 percentage points more likely if the exchange is not at the best quote than when it is. These results indicate that trades on an auction exchange are more likely to occur outside auctions, in the limit order book, when the exchange is quoting the best price, and within auctions when it is not.[14]

In Table 4, we examine whether price improvement for auction trades differs based on whether the exchange is quoting at the best price or not. Table 3 shows that auction trades are more likely when the exchange is not quoting the best price. If this occurs because the opportunity for price improvement is larger when the auction exchange is not at the best quote, we expect auction trades executed at such times to receive larger price improvement. Alternatively, if auctions help market makers match the NBBO price and satisfy the trade-through prohibition, we may find that auction trades, when the exchange is not quoting the best price, are less likely to receive price improvement.

In Table 4, Models 1 and 3, the dependent variable equals one if the trade occurs within the NBBO (and thus receives price improvement) and zero if it trades at the best quote (no price improvement).[15] The explanatory variables include our variable of interest, *ExchangeBestWhenTrade*, the quoted spread at the time of a trade, and option series characteristics. Model 1 includes stock and date fixed effects, and model 3 include stock and exchange fixed effects. Standard errors are clustered by stock and date. The models are estimated within the subsample of trades that execute in auctions, thus, the comparison in this analysis is between auction trades that occur when the exchange is quoting the best price and auction trades that occur when it is not.

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[13] In Appendix Table 2, we present average coefficients of daily estimations. The minimum and maximum coefficients indicate that effect ranges between 45 and 50 percentage points across days in our sample. The associated t-statistics indicate high levels of statistical significance.
[14] We also estimate a model with a combined exchange-stock-day fixed effect. The results are similar to model 4.
[15] A small number of trades that occur at prices worse than the NBBO are excluded in this estimation.

The coefficient on *ExchangeBestWhenTrade* suggests that when an exchange is quoting the best price, there is a 17 percentage point greater likelihood of the trade executing inside the NBBO. Put another way, given our construction of the dependent variable, an auction trade is 17 percentage points more likely to simply match the NBBO quoted price when the exchange is not quoting the best price, than when it is. This result is consistent with market makers, at times, using auctions to match the NBBO prices without displaying their quotes at those prices. In Table 4, Models 2 and 4, we use the EQ ratio as the dependent variable. The EQ ratio is approximately 0.16 lower (i.e., the price improvement is larger) when the exchange quote equals the best quoted price than when it does not.

The results in Tables 3 and 4 are consistent with auctions providing market makers a way to execute trades when their quotes are not at the best prices available in the market. We note that the results are not obvious. Market makers can use auctions strictly as price improvement mechanisms, which would not be related to whether they are quoting at the NBB/O or not.

4.2 Quote competition

We examine whether the results in Tables 3 and 4 have broader implications for quoting competitiveness. In Table 5, we measure quoting competitiveness across all observed quotes in our sample. For each observed quote, we create an indicator variable that equals one if any of the 11 auction exchanges is at the best quoted price (separately for the NBB and NBO), and zero if none of the 11 is at the best quote. We create a similar measure for the five non-auction exchanges. We calculate the difference between the two indicator variables (auction minus non-auction) for each quote observation. This difference between auction and non-auction exchanges is perfectly matched since it is calculated at the same moment in time for the same option series. This is important because, even though the difference between auction and non-auction exchanges may be related to other variables, there is no structural impediment for either set of exchanges to quote the best price; thus, the univariate differences provide a result that does not necessarily require additional controls. We average these variables each day and present the average across days separately for NBB and NBO quotes in Table 5.

For the overall sample, Table 5 shows that the aggregate set of 11 option exchanges is approximately 12 percentage points less likely to be at the NBB or NBO than the set of five non-auction exchanges on an average day in our sample. We also present the average of daily t-statistics and p-values associated with the difference. The daily calculated tests of significance are clustered at the underlying stock level. T-statistics indicate that the difference in quote competitiveness between auction exchanges and non-auction exchanges is highly statistically significant.

Setting the best quoted price in the market is an important dimension of quote competition for liquidity (since a better quoted price narrows the spread) and for price discovery. Our data constraints do not allow us to directly observe which exchanges change their quotes to narrow the NBBO prices. Within these constraints, we disaggregate our sample by the number of exchanges at the NBB or NBO. When there is only one exchange at the best quote, it can arise from an exchange improving on the best quoted price or the exchange being the last one left at a quoted price. Thus, the behavior of improving on the NBB/O is captured, admittedly imperfectly, within the observations with only one exchange at the best price. We argue that the scenario with only one exchange at the best price reflects situations when the exchange quote is most valuable. Exchanges recognize this in providing priority in the limit order queue to “market turners” (the market maker who improves on the NBB/O).[16] At the other extreme, a large number of exchanges at the NBB/O likely reflects easier quoting conditions, and the value of each individual quote is reduced.

Table 5 presents the disaggregated results by the number of exchanges at the NBB and NBO. We create five buckets: observations with one exchange at the quote, two exchanges, three exchanges, four to six exchanges, and those with seven to 16 exchanges. To look at the results by number of exchanges at the best bid, we draw attention to the “At NBB” column. We find that when there is only one exchange at the best bid, it is a non-auction exchange 64.7% of the time and an auction exchange 35.4% of the time. The 29.4 percentage point difference is large and statistically significant. The corresponding difference (in the

[16] For example, see page 261 of CBOE (C1) Exchange rule book.

"At NBO" column) when there is only one exchange at the best ask is 30.1 percentage points. Thus, the price setting exchange in options markets is significantly more likely to be a non-auction exchange. We further find that the difference between auction and non-auction exchanges gets smaller with increasing number of exchanges at the NBB/O with the difference largely vanishing when there are seven or more exchanges at the best quote.

In Table 6, we examine the difference in the propensity of auction and non-auction exchanges to be at the best quote in a regression setting. For each observed quote, we use the indicator variable discussed above which equals one if the auction/non-auction exchanges, in aggregate, are quoting at the NBB/O as the dependent variable. As mentioned earlier, the comparison is perfectly matched for each observation. That is, any option characteristics or market conditions at a particular time that affect quoting propensity affect both auction and non-auction exchanges. The regression framework includes stock and date fixed effects. Further, for consistency, we also present a model that includes the control variables used in previous tables. T-statistics and p-values are based on standard errors clustered by underlying stock and date. The results are almost identical to the univariate results in Table 5. Across different specifications, auction exchanges, in aggregate, are approximately 12 percentage points less likely to be at the NBB/O than non-auction exchanges.[17]

We examine whether the results from May 2021 apply to a longer period. In appendix Table 3, we replicate the main results from Tables 3, 4 and 6 for each of the six months from January to June 2021. The results are similar to those for May 2021. CBOE has retrospectively removed exchange quotes in the data. These are the last months of data available to us which include the exchange-specific quotes.

4.3 Auction market maker behavior on a non-auction exchange

[17] In Appendix Table 1, we include exchange level statistics on the propensity to be at the NBB/O. Exchanges are sorted by the proportion of an exchange's volume that is executed in auctions. A visible trend is the greater likelihood of non-auction exchanges than auction exchanges to be at the best quotes. We calculate a correlation each day between the exchange proportion of trades in auctions and the likelihood of their quotes at the NBB/O. The average daily correlation is -0.75 for both NBB and NBO. These results indicate that the aggregation at the auction / non-auction level is not overly affected by market maker behavior on one exchange.

So far, our results indicate that auction exchange market makers may not compete aggressively on quotes. Given that market makers operate across exchanges, are there implications for their quoting behavior on non-auction exchanges?

Public data do not allow us to directly observe market maker quotes. In our earlier discussion, we point to the salience of the DMM in providing liquidity in assigned option classes on an exchange. In this section, we use the fact that one important non-auction exchange, NYSE Arca, uses DMMs in its market structure. As shown in Appendix Table 1, Arca behaves in expected ways as a non-auction exchange: 99.7% of trades at Arca occur when it is quoting at the best relevant quote, and it is at the best quote for 62% of observed quotes in our sample, in line with other non-auction exchanges. Arca is also one of the larger exchanges in our sample with 12.8% of trades and 10.7% of contract volume. Thus, for one significant non-auction exchange, we have information on the important market maker for each option class.

A second feature of the options markets, that helps us overcome the challenges around making inferences about market maker behavior, is that there are only a few large market making firms that serve as DMMs across all option exchanges. As a result, the same firm is frequently the DMM for the same option class across multiple exchanges. In our Arca sample of option classes, 79.5% of option classes (associated with 84.2% of observations) are handled by an Arca DMM who is also the DMM for the same option class on another exchange. Since all other exchanges that use DMMs are auction exchanges, this translates to Arca DMMs having DMM assignments where they have access to an auction mechanism on another exchange. At the same time, there are option classes where the Arca DMM does not have overlapping DMM assignments. The variation, within a DMM firm, across option classes with and without access to auctions, allows us to examine spillovers of our quote competitiveness results to non-auction exchanges.

The comparison across option classes, within a DMM's portfolio, raises the additional challenge that there may be differences across option classes on any given exchange's propensity to be at the best quote. To control for this variation, we construct a difference measure for each observation associated with Arca listed options. Specifically, the measure is the difference between an indicator variable that equals one if the Arca quote equals the NBB/O (zero otherwise) and an indicator variable that equals one if any of the four other non-auction exchanges' quote equals the NBB/O (zero otherwise). This difference variable controls for differences between option classes and is specific to quoting characteristics of non-auction exchanges. In Table 7, we present results from a regression model where the difference variable is the dependent variable. The variable of interest is "*DMM on Auction Exchange*" which equals one if the DMM assigned to an option class on Arca is also the DMM for the same option class on at least one auction exchange.[18] We present the results using bid quotes in Table 7.

Table 7, Model 1, includes only *DMM on Auction Exchange* as the explanatory variable. The model also includes DMM firm and date fixed effects. Thus, the model is a difference-in-differences setup comparing, within an Arca DMM's assigned portfolio, quote competitiveness (relative to other non-auction exchanges) for option classes where Arca DMM is also the DMM on an auction exchange with those where it is not. The results show that having access to auctions on another exchange is associated with an 8.5 percentage point lower likelihood of quoting at the NBB. Model 2, which includes other control variables, shows a smaller magnitude of a 4.9 percentage lower likelihood of quoting at the NBB. T-statistics and p-values are based on standard errors clustered by underlying stock and date.

In Table 8, we explore the possibility that the effects of having access to auctions differ across DMM firms. There are six DMM firms on Arca. One of these firms has no option class overlap with other exchanges and is excluded from this analysis. Table 8, Panel B presents the results of models similar to Table 7, estimated separately for each of the remaining five DMM firms. We present results for Models 1 and 2. Model 2 coefficients on control variables are suppressed in the table. Both models include date fixed effects, and t-statistics and p-values are based on standard errors clustered by underlying stock and date.

[18] That is, the DMM firm on NYSE Arca is also the DMM for the same option class on any of the following: CBOE, EDGX, MIAX, EMLD, ISE, GEMX, MRX, PHLX and BX. We exclude AMEX from this list since it has two primary market makers associated with each option class.

We find a negative coefficient on *DMM on Auction Exchange* for three of the five DMM firms. We note that for two of the five firms (DMM1 and DMM4), observations in the sample overwhelmingly tilt towards option classes where the Arca DMM firm in an option class is also the DMM on an auction exchange. For example, Table 8 Panel A shows that for DMM1, 93.6% of option classes associated with almost all (99.7%) of the quote observations have an overlapping DMM assignment. DMM2 tilts the other way with only 5.6% of observations associated with overlapping DMM assignments. Given these numbers, we do not draw any conclusions from the analysis for DMM1, DMM2 and DMM4. However, DMM3 has a reasonable split between option classes with and without overlapping auction exchange DMM assignments. We find that DMM3 is 9.9 percentage points less likely (in the model with control variables) to be at the NBB when it is also the DMM for the option class on an auction exchange than when it does not have an overlapping DMM assignment.

Thus, for one of the two DMM firms where this analysis is reasonable, having access to the opportunity to internalize in auctions is associated with a sharply lower propensity to be at the best quotes.

4.4 Auctions and spreads

We examine the implications of auctions on spreads. Lower quote competition from auction exchanges may matter less if non-internalizing market makers narrow spreads to competitive levels. On the other hand, these market makers may be dissuaded by the unresponsiveness of order flow to quotes, and may be able to undercut auction exchange spreads without moving spreads to competitive levels. Dutta and Madhavan (1997), Bloomfield and O'Hara (1998) and Easley et al. (1996) show that spreads can be larger than competitive levels in a market with payment for order flow. For this analysis, we focus on an exogenous change in the ability to conduct an auction.

As discussed earlier, on January 18, 2017, the SEC approved rule changes to either make an order ineligible for auctions (implemented by BOX, Miax, Amex), or require price improvement of at least $0.01 over the NBBO (implemented by Phlx, BX, ISE, BATS, GEMX, MRX), when the spread at order arrival equals \$0.01. Since the rule changes makes auctions more difficult, they are unlikely to be a competitive response to other exchanges. A more likely explanation is that the SEC was actively involved in the discussion around auctions and coordinated the rule changes across exchanges. Thus, the rule changes exogenously inhibit auction use across exchanges on the same date. Further, while the rule change affects all penny-pilot option classes, we expect the effects to be larger for those option classes where the likelihood of a spread of \$0.01 is higher before the rule change. We note that this event restricting auctions is unique in options in its market-wide reach and clear implementation date.

We use the rule change for a difference-in-differences analysis where we compare spreads in option classes with higher and lower propensity to have spreads at \$0.01, before and after the rule change. Since spreads of \$0.01 are only possible for options priced below \$3 in penny-pilot options, we restrict our analysis to this subsample of options. We define the pre-period as December 1, 2016 to January 17, 2017 and the post-period as January 18, 2017 to February 28, 2017. We calculate the proportion of observed quotes (for options priced below \$3) with a spread of \$0.01 in the pre-period for each of the 204 penny-pilot option classes in our sample. We divide these into two groups based on the calculated proportion as high-bind (an average of 46% of observed quotes) and low-bind (approximately 13% of quotes) samples. The data used and the filters applied are the same as those discussed in section 3.

We first verify that auction activity changes following the rule changes. As discussed earlier, the auction identifier in the data was added in November 2019. Thus, there is no clear auction identifier in our 2017 sample. However, we proxy for auction trades using the "stopped trade" indicator in the data.[19] The auction process requires that the market maker "stop" a trade at a price no worse than the NBBO when the order is received and then initiate an auction. Thus, several exchanges were reporting auction trades as stopped trades prior to the change in trade identifiers. Appendix Figure 1 plots the frequency of single-leg trade identifiers in OPRA data around the November 2019 date when the auction identifier is introduced.

[19] Anand, Hua and Puckett (2025) describe and validate this approach in more detail.

As can be seen in the figure, the stopped trade frequency prior to the switch closely follows the auction frequency after the switch. We also plot the proportions for regular orders and Intermarket Sweep Orders (ISO). The ISO series appears consistent throughout the period. Regular trades show a decline indicating that some exchanges were marking auctions as regular trades. For our purposes, stopped trades provide an imperfect, but reasonable, proxy for auctions.

Figure 3.A. plots the difference in the proportion of stopped trades for the high-bind and the low-bind samples. In the pre-period, the difference is positive, indicating that stopped trades are more frequent in the high-bind sample prior to the change. There is a sharp drop around the event date causing the difference to turn negative after the rule change. Thus, auctions show a decline associated with the event date for our treatment sample relative to the control sample. Figure 3.A. reflects market-wide trends. Trades can be stopped for reasons other than auctions. To further associate the decline with auctions, Figure 3.B. plots the difference in the proportions for the high-bind and the low-bind samples, separately for auction and non-auction exchanges. Non-auction exchanges, represented by the dashed blue line, show no differences between the high- and low-bind samples in the pre or post-periods. In fact, stopped trades are negligible in non-auction exchanges in both periods, which causes the dashed line to be stay flat at zero. On the other hand, the plot for auction exchanges shows that the trends in Figure 3.A. are driven by auction exchanges. Thus, we conclude that the rule change significantly affected the use of auctions in the high-bind sample.

Table 9, Model 1 examines the difference-in-differences estimate for stopped trades using the following model:

$$StoppedTrade_i = \beta_1 Highbind * Post + \beta'\mathbf{X} + FE + \epsilon_i, \qquad (2)$$

where $StoppedTrade_i$ is an indicator variable that equals one if trade i is a stopped trade and zero if it is a regular trade. *Highbind*, equals one for option classes with above-median proportion of spreads at \$0.01 in the pre-period, and zero for option classes below that level. *Post* equals one in the post-period and zero in the pre-period. **X** is a vector of control variables: the quoted spread, delta, gamma and vega of the option series and the NBBO quote midpoint. The model includes underlying stock and date fixed effects. Standard errors are clustered by underlying stock and date. The coefficient of *Highbind* Post* indicates that stopped trades decline by 5.3 percentage points for the high-bind sample relative to the low-bind sample. The coefficient is highly statistically significant and confirms the trends in Figure 1. The pre-period average for the treatment sample is 19%. Thus, the decline is economically significant. In Model 2, we restrict the analysis to auction exchanges only. As expected, the decline in stopped trades is larger in this sample with a decline of 11 percentage points for the high-bind sample relative to the low-bind sample.[20]

Models 3 and 4 confirm our earlier findings that auctions are related to auction exchanges' propensity to quote at the NBBO. In Model 3, we use the quote competition measure from Table 5 as the dependent variable. The variable is the difference between two indicator variables – auction exchanges as a group at best bid minus non-auction exchanges as a group at best bid – for each quote observation. Auction exchanges' relative (to non-auction exchanges) propensity to be at the NBB for the high-bind sample increases by 5.1 percentage points after the rule change. Model 4 reports similar results for NBO.

Table 10 presents the results for spread variables. Panel A presents the results for NBBO quoted (dollar and percentage) spreads, effective (dollar and percentage) spreads and EQ ratios for the overall sample. The difference-in-difference coefficient in Model 1 shows that NBBO quoted dollar spreads decline by 0.6 cents for the high-bind sample after the rule change. For context, the pre-period average NBBO spread for the high-bind sample is 2.6 cents. Model 2 shows a decline in NBBO percentage spreads of 90 basis points. Since these are low priced options, percentage spreads are large with a pre-period mean of 6.90%. The results for effective spreads are mixed with dollar spreads showing an insignificant decline in

[20] There are differential incentives for internalizing trades in an auction depending on the trade size. For example, one contract orders cannot be split with a competing market maker, allowing the initiating market maker to trade in an auction without fear of competition (holding price constant). Another example concerns orders for one to five contracts. Exchange rules allow DMMs to internalize trades up to five contracts if the DMM is quoting the best price when the order arrives. This ability may lower the DMM's incentives to initiate an auction for five (or fewer) contract orders relative to six contract or larger orders. Ernst and Spatt (2025) examine the role of trade size on auctions. In Appendix Figure 2, we plot the coefficient (as in equation 2 above) for change in auctions for different trade sizes. The estimations across trade sizes do not show changes due to the 2017 rule change that are statistically significantly different across trade sizes.

Model 3 and effective percentage spreads declining statistically significantly in Model 4. The expectations for effective spreads are also less clear. Narrowing quoted spreads would narrow effective spreads for trades that occur at the quote, but may also lower opportunities for price improvement. The magnitude of the effective percentage spread reduction in Model 4 is about half of the reduction in quoted spreads. The corresponding magnitude for effective dollar spreads is a third of the reduction in quoted spreads. The net effect of the two is that the difference between effective and quoted spreads declines which is reflected in the increase in the EQ ratio in Model 5.

The results in Panel A show the outcomes for all trades, including ones that are not from retail traders. Outside of auctions, it is difficult to identify internalized retail trades in the data. Since the event reduces the likelihood of the use of auctions, we use small trades as a proxy for retail trades. We present execution outcomes for small trades (one to five contracts) in Table 10, Panel B. These trades also include trades from non-retail traders but are likely to more closely reflect retail trading than the overall sample. The results are similar to those in Panel A – an insignificant decline for effective spreads and a significant increase in EQ ratios. In unreported results, we also estimate a model restricted to one contract trades only, with similar results.

These results indicate a point of caution in examining changes in EQ ratios. In the event we analyze, quoted as well as effective spreads decline, but because the decline in quoted spreads is larger, EQ ratios increase, even though no clear worsening in execution quality is visible in effective spreads.

The analysis of the rule changes confirms the effects of auctions on quote competition from our 2021 sample and provides evidence of the impact of auctions on overall spreads.

4.4.1 Competition in auctions among market makers

Bloomfield and O'Hara (1998) show that greater competition among market makers mitigates the impact of internalization on spreads. In the context of the 2017 event we examine, the model would predict that option classes, with higher market maker competition in the pre period, are more likely to already have spreads at competitive levels and are consequently less likely to experience a reduction in spreads. The challenge for this analysis is that OPRA data do not include any information on the identity or the number of market makers active in an option class, which makes it difficult to observe market maker competition. We take an indirect approach by examining competition within auctions.

We follow Hendershott, Khan, and Riordan (2025) in proxying whether an auction is competitive by counting the number of trades that occur in an auction on an exchange in an option series at the same time. When there is more than one observed trade, the auction can be identified as competitive with at least two market makers competing for the customer trade. Conversely, only one observed trade includes the cases where no other market maker responded to trade in the auction.[21] Since one contract orders cannot be split, we focus this analysis on trades where the aggregated trade size (indicating the order size) in the auction exceeds one contract. We classify trades with more than one reported trade as competitive auctions. We also calculate a proxy for the proportion that the initiating market maker is able to internalize as the largest trade size in the sequence of aggregate trades as a proportion of the aggregated trade size.

We first analyze the nature of competition in auctions. An obvious starting point is whether competition in auctions is associated with larger price improvement. We expect that when market makers compete for an order, the order benefits through larger price improvement. The first column in Table 11, Panel A examines the relation between market maker competition and price improvement measured by the EQ ratio. We estimate the regression using the sample of auctions in the pre-period with an aggregated size greater than one contract. Contrary to our expectation, we find that competitive auctions are associated with higher EQ ratios (i.e., lower price improvement). The finding points to the possibility that market makers are more likely to enter an auction when they expect less price competition.

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[21] One trade cases will also include those where there was competition in the auction but one market maker strictly dominated on the offered price. Separately, it is also possible that some exchanges report consolidated trades making it more difficult to identify competitive auctions on those exchanges. Since our focus is less on measuring the level of competition and more on characterizing the nature of competition and whether competition interacts with changes in spreads, our analysis is less likely to be affected by differences in trade reporting practices.

To further examine this possibility, we examine the relation between our price competition variable and an indicator variable that equals one when the spreads are binding at trade time. As noted earlier, the 2017 rule changes are driven by the fact that price improvement is extremely rare when the spreads are binding at a penny. Thus, these situations are the ones where market maker competition is likely to match the quoted price, and no market maker offers price improvement. In the second column, we find that a competitive auction is 11.9 percentage points more likely when the spreads are binding. The third column confirms this result with the proportion of largest trade as the dependent variable – the largest trade is 6.1 percentage points smaller (indicating lower allocation to initiating market maker) when the spread is binding. These results indicate that market makers strategically enter auctions to trade when they know that price competition is inhibited. In column 4, we restrict the regression to only those cases where the spread is not binding to examine whether the relation between EQ ratios and competitive auctions extends to this subsample. We find that to be the case – competitive auctions are associated with lower price improvement.[22]

The results discussed above suggest that the market maker motivation to compete in auctions is likely to be related to their ability to strategically trade with orders without necessarily competing on price. This form of competition appears to be less in line with that conceived in Bloomfield and O'Hara (1998). However, it may be that market makers compete more aggressively on quoted prices outside of auction. We next use our measure of competition to proxy for market maker competition in an option class. The assumption in the analysis is that competition in auctions indicates the level of market maker activity in an option class, which may also affect the competition in quoted prices. Since market maker activity is correlated with the *Highbind* variable discussed above, we classify option classes by the average propensity of competitive auctions in the pre-period within *Highbind* subsamples. As an example, we divide option

[22] We separately examine whether our measures of competition change in the post period using the same difference in differences specification in Tables 9 and 10. We do not find a significant change. The results are included in Appendix Table 4.

classes into those with low and high competition (using the median) within the subsample where *Highbind* equals one.

Table 11, Panel B presents the results for this subsample. The table examines whether higher levels of pre-period market maker competition are associated with differential effects on spreads due to the 2017 rule changes. As discussed earlier, if higher market maker competition makes the spreads more competitive in the pre-period, the restriction on auctions will have a smaller effect on spreads for more competitive option classes. In Panel B, the variable of interest interacts the *High Competition* indicator variable with the *Post* indicator variable. Similar to Table 10, Panel B, we examine changes in quoted and effective spreads and EQ ratios. We do not find significant changes for any of the variables.[23]

The interpretation of these results is ambiguous. At first brush, the results suggest that the level of market maker competition does not indicate spreads reaching competitive levels in the pre-period. However, our results in Panel A also suggest that the kind of competition we measure is not the price competition envisaged in Bloomfield and O'Hara (1998), raising the possibility that access to better data on market maker competition may yield different results.

5. Long-term trends in auctions and bid-ask spreads

We examine long term trends in spreads and the use of auctions in options markets. Auctions in options were originally designed to help large traders, with early auction mechanisms explicitly emphasizing block trades.[24] In support of this objective, exchange rules differed based on whether the trade size was smaller or greater than 50 contracts, with greater restrictions on initiating auctions if the trade size was smaller than the 50-contract threshold. For example, for smaller trades, auctions could only be initiated at prices better than the NBBO quotes, while larger orders could be priced to match NBBO quotes in

[23] We report similar results for *Highbind* equals zero subsample in Appendix Table 5.
[24] BOX launched in 2004 with its Price Improvement Period (PIP), ISE's Price Improvement Mechanism (PIM) won SEC approval that December, and Cboe started its Automated Improvement Mechanism (AIM) in March 2006, each offering brief exposure periods to compete for price improvement on paired orders.

auctions. Exchanges started to eliminate the differential treatment in the 2013-2014 period (see, for example, SR-Phlx-2013-76 filed by PHLX). In addition, Miax significantly expanded its market share by capitalizing on auctions for sub-50-contract orders. These changes converted auctions from a block-trading utility into a channel for retail internalization, but they rolled out gradually over time, which makes a clean event study difficult. However, a long-horizon view is still informative in understanding the evolution of auctions and spreads in options markets.

Figure 2 covers January 2011 through June 2018 and plots three market-wide series: percentage quoted spreads, percentage effective spreads, and the share of single-leg trades that execute in auctions (on the right scale). Because OPRA did not publish auction flags during this period (which were introduced in 2019), we proxy auctions with "stopped" executions using available trade flags. We build each day's statistics at the option-class level and then average across classes using contract-volume weights. To smooth noise and highlight trends, we plot 30-day moving averages.

We draw attention to three trends in Figure 2. First, the auction share rises quickly starting in late 2014 – from under 6% early in the sample to well above 10% after 2015, with peaks approaching one-fifth of trades. Second, quoted spreads move from one plateau to another. They sit near 7% in 2011–2013, rise sharply through 2014–2015, and then stabilize near 12% in 2015–2018. Third, effective spreads also rise but by less, causing the gap between quoted and effective spreads to widen around 2014. Early in the sample quoted and effective spreads track each other closely; in the later period, quoted spreads pull away from effective spreads.[25] While we do not claim causality from Figure 2, we note that the divergence between quoted and effective spreads is the predicted outcome from our analysis. Our earlier results would suggest that as auctions are increasingly used for internalization, quoted spreads would increase more than effective spreads.

[25] As expected, the divergence between quoted and effective spreads shows up as a sharp decline in EQ ratios over this period. We believe that this is not a signal of better execution quality, but reflects greater discretion by market makers.

Figure 2 raises the question of whether an increase in quoted spreads matters if effective spreads stay contained. Wider quoted spreads raise the cost of immediacy for anyone who crosses the spread and lessen the value of displayed liquidity as an execution benchmark. Wider quoted spreads also give more room to improve prices and they expand the scope for broker-level bargaining over PFOF and price improvement. Consistent with this view, Huang, Jorion, and Schwarz (2025) report large differences in PFOF and price improvement across brokers, and Hendershott, Khan, and Riordan (2025) show that auctions are more likely when quoted spreads are larger, which is consistent with more price discrimination when quotes widen.

6. Conclusion

Internalization is widespread in equities and options markets. In equities, market makers can internalize off exchange without a corresponding requirement to post the best quotes. In options markets, internalization occurs on exchanges, but auctions similarly allow internalizing without a requirement to be quoting the best price. With the growth in options trading and the salience of options PFOF for some brokers, academic attention has appropriately focused on price improvement offered in auctions. We add to this literature by examining whether internalization inhibits quote competition by using the context of auctions in options.

We find that auctions in options markets are frequently used when the relevant exchange (where the trade occurs) is not quoting the best price. Quote matching, rather than price improvement, is more likely in auctions when the auction exchange is not quoting the best price. These results suggest that auctions allow market makers to trade at NBBO quotes without displaying their prices. Market makers on auction exchanges are less likely to quote at the best prices in the market, and especially to be alone at the best quoted price. The evidence points to the disconnect between quote display and order flow routing feeding into a broader pulling back from competitive quoting.

To test for aggregate effects of auctions on spreads, we examine a rule change that restricts the use of auctions if the spread at the time of order arrival equals \$0.01. Using a difference-in-differences test, we find that the rule change is associated with a decline in NBBO spreads, and a smaller decline in effective spreads. Our results suggest that auctions reduce quote competition in options markets.

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Table 1: sample characteristics

This table describes our sample of options trades in May 2021. The statistics presented below are averages of daily averages calculated across all observations during the trading day. The sample is limited to equity options (CRSP share codes 10 and 11) with underlying price greater than $1. We exclude option series with greater than 365 days to maturity. Our sample only includes single-leg trades marked as regular and auction that occur between 9.30 a.m. and 4.00 p.m. There are a total of 16 options exchanges during our sample period, out of which 11 include an auction mechanism and five do not. Quoted spreads are the difference between the quoted best bid and ask (NBBO) prices observed at the time of the trade and are calculated as simple averages across all trades on the day. Effective spreads are calculated as twice the difference between the trade price and the midpoint of the NBBO. Effective to quoted ratio is a measure of the price improvement for a trade.

Trading days	20
Option classes traded	2,443.8
Number of trades	2,367,773.5
Number of contracts	11,815,925.2
Call option proportion	67.69%
Days to maturity	28.30
Trade size	4.98
Quoted spread	0.174
Quoted spread (%)	8.90%
Effective spread (%)	6.87%
Effective to quoted ratio	0.82
Tick size	0.029
Trade occurred in auction	19.40%
Trade occurred at auction exchange	53.29%

Table 2: sample characteristics, by auction exchange and auction mechanism

This table describes our sample, disaggregated by type of exchange (auction or non-auction) and by trade type (regular or auction). The statistics presented below are averages of daily averages calculated across all observations during the trading day. The sample is limited to equity options (CRSP share codes 10 and 11) with underlying price greater than \$1. We exclude option series with greater than 365 days to maturity. Our sample only includes single-leg trades marked as regular and auction that occur between 9.30 a.m. and 4.00 p.m. There are a total of 16 options exchanges during our sample period, out of which 11 include an auction mechanism and five do not. Quoted spreads are the difference between the quoted best bid and ask (NBBO) prices observed at the time of the trade and are calculated as simple averages across all trades on the day. Effective spreads are calculated as twice the difference between the trade price and the midpoint of the NBBO. Effective to quoted ratio is a measure of the price improvement for a trade. "Exchange at best quote for trade" presents the probability that the exchange where a trade executes is at the best quote on the side of the trade (NBO for buy and NBB for sell) at the time of the trade. Trades with prices above the NBBO midpoint are classified as buys and those below as sells.

	By exchange type		**By trade type**	
	Non-auction exchanges	**Auction exchanges**	**Regular trade**	**Auction trade**
Number of trades	1,106,682.5	1,261,091.0	1,909,031.9	458,741.6
Number of contracts	5,187,031.7	6,628,893.5	9,117,983.8	2,697,941.4
Trade size	4.69	5.25	4.77	5.87
Quoted spread	0.164	0.184	0.167	0.204
Quoted spread (%)	7.4%	10.2%	8.3%	11.6%
Effective spread (%)	6.2%	7.5%	7.1%	5.8%
Effective to quoted ratio	0.88	0.77	0.90	0.49
Trade occurred in auction	0.0%	36.4%	0.0%	100.0%
Exchange at best quote for trade	89.7%	66.2%	86.9%	34.4%

Table 3: Use of the auction mechanism

This table presents the results of regression models explaining the use of the auction mechanism. The regression models are estimated over all trades within the specified subsample during the month of May 2021. The dependent variable equals one if the trade occurs using the auction process and zero if it is a regular trade. The explanatory variables include: "At best quote when trade" which equals one if the exchange where a trade occurs is at the best quote on the side of the trade (NBO for buy and NBB for sell) at the time of the trade, and zero otherwise. Trades with prices above the NBBO midpoint are classified as buys and those below as sells; the dollar NBBO quoted spread at the time of the trade, the tick size for the particular option series in which the trade occurs, and option series characteristics. The models are estimated within all trades that occur on auction exchanges. Models 1 and 2 include stock and date fixed effects. Models 3 and 4 include stock and exchange fixed effects. T-statistics and p-values are based on standard errors clustered by underlying stock and date

	Dependent variable:			
	Auction trade			
	(1)	(2)	(3)	(4)
At best quote when trade		-0.483***		-0.310***
		(0.010)		(0.005)
Quoted spread	0.104***	0.097***	0.039***	0.055***
	(0.007)	(0.007)	(0.003)	(0.005)
Tick size	-0.332	0.943***	-0.537***	0.328*
	(0.341)	(0.293)	(0.169)	(0.157)
Abs (delta)	0.058**	0.043***	0.077***	0.061***
	(0.025)	(0.011)	(0.014)	(0.008)
Gamma	0.082**	0.005	0.048*	0.007
	(0.038)	(0.019)	(0.026)	(0.016)
Vega	-0.0004***	-0.0002***	-0.0002***	-0.0001***
	(0.0001)	(0.00002)	(0.00002)	(0.00003)
Price (midpoint)	-0.002***	-0.002***	-0.001***	-0.001***
	(0.001)	(0.0004)	(0.0004)	(0.0003)
Stock FE	Y	Y	Y	Y
Date FE	Y	Y	N	N
Exchange FE	N	N	Y	Y
Sample	Auction exchanges	Auction exchanges	Auction exchanges	Auction exchanges
Observations	22,364,657	21,191,117	22,364,657	21,191,117
Adjusted R^2	0.029	0.256	0.355	0.425
Note:				*p<0.1; **p<0.05; ***p<0.01

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Table 4: price improvement within auctions and exchange at best quote

This table presents the results of regression models examining whether price improving trades within auctions are more or less likely when an exchange is at the best quote. The regression models are estimated within trades that occur in auctions in our sample during the month of May 2021. The table presents results for two measures of price improvement: first, an indicator variable that equals one if the trade occurs at a price better than the quoted price, and zero otherwise; and, second, the effective to quoted spread ratio. The explanatory variables include: "At best quote when trade" which equals one if the exchange where a trade occurs is at the best quote on the side of the trade (NBO for buy and NBB for sell) at the time of the trade, and zero otherwise. Trades with prices above the NBBO midpoint are classified as buys and those below as sells; the dollar NBBO quoted spread at the time of the trade, the tick size for the particular option series in which the trade occurs, and option series characteristics. The models are estimated within all trades that occur on auction exchanges. Models 1 and 2 include stock and date fixed effects. Models 3 and 4 include stock and exchange fixed effects. T-statistics and p-values are based on standard errors clustered by underlying stock and date.

	Dependent variable:			
	Trade inside quote	EQ ratio	Trade inside quote	EQ ratio
	(1)	(2)	(3)	(4)
At best quote when trade	0.170^{***}	-0.157^{***}	0.167^{***}	-0.155^{***}
	(0.014)	(0.008)	(0.016)	(0.010)
Quoted spread	0.019^{**}	-0.018^{***}	0.018^{**}	-0.017^{**}
	(0.008)	(0.006)	(0.008)	(0.006)
Tick size	1.759^{**}	-1.102^{***}	1.777^{**}	-1.130^{***}
	(0.642)	(0.347)	(0.646)	(0.352)
Abs (delta)	0.401^{***}	-0.261^{***}	0.383^{***}	-0.249^{***}
	(0.041)	(0.018)	(0.044)	(0.021)
Gamma	-0.427^{***}	0.233^{***}	-0.432^{***}	0.238^{***}
	(0.065)	(0.036)	(0.062)	(0.035)
Vega	0.0004	-0.0003^{*}	0.0003	-0.0002
	(0.0003)	(0.0002)	(0.0002)	(0.0001)
Price (midpoint)	-0.002^{***}	0.0004^{**}	-0.002^{***}	0.0004^{*}
	(0.0004)	(0.0002)	(0.0004)	(0.0002)
Stock FE	Y	Y	Y	Y
Date FE	Y	Y	N	N
Exchange FE	N	N	Y	Y
Sample	Auction trades	Auction trades	Auction trades	Auction trades
Observations	7,267,982	7,267,982	7,267,982	7,267,982
Adjusted R^2	0.308	0.242	0.348	0.290
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5: Auction and non-auction exchanges' propensity to be at the NBBO

This table presents the propensity of auction and non-auction exchanges to be at the best bid and ask prices. Auction (non-auction) exchange at best bid (or ask) is an indicator variable that equals one if any of the auction (non-auction) exchanges is quoting at the best price. The table presents the results for the overall sample, and separately based on the number of option exchanges quoting the best price. The statistics presented below are averages of daily averages calculated across all observations during the trading day. t-statistics and p-values are based on standard errors clustered at the underlying stock level. Tests of significance are estimated each day and the average across days is presented in the table.

	At NBB					At NBO				
	Auction exchanges	**Non-auction exchanges**	**Average Difference**	**Average t-statistic**	**Average p-value**	**Auction exchanges**	**Non-auction exchanges**	**Average Difference**	**Average t-statistic**	**Average p-value**
Overall sample	75.8%	87.8%	-12.0%	-12.0	*0.00*	75.5%	87.8%	-12.3%	-13.5	*0.00*
Exchanges at best bid=1	35.4%	64.7%	-29.4%	-12.0	*0.00*	82.5%	91.4%	-8.9%	-10.4	*0.00*
2	63.4%	84.7%	-21.3%	-8.6	*0.00*	77.3%	89.0%	-11.7%	-10.5	*0.00*
3	75.9%	94.1%	-18.2%	-8.3	*0.00*	75.7%	89.0%	-13.3%	-11.5	*0.00*
4 to 6	92.6%	98.9%	-6.2%	-7.1	*0.00*	74.5%	89.5%	-14.9%	-12.3	*0.00*
>6	100.0%	100.0%	0.0%	5.7	*0.00*	71.0%	84.7%	-13.7%	-13.4	*0.00*
Exchanges at best ask=1	83.3%	91.2%	-7.9%	-8.7	*0.00*	35.0%	65.0%	-30.1%	-13.7	*0.00*
2	77.7%	88.8%	-11.2%	-9.5	*0.00*	63.1%	84.6%	-21.6%	-8.9	*0.00*
3	75.6%	88.9%	-13.3%	-10.9	*0.00*	75.1%	94.0%	-18.9%	-7.3	*0.00*
4 to 6	74.1%	89.4%	-15.3%	-11.7	*0.00*	92.1%	98.8%	-6.7%	-6.6	*0.00*
>6	71.2%	84.9%	-13.7%	-12.4	*0.00*	100.0%	100.0%	0.0%	6.3	*0.00*

Table 6: Difference between auction and non-auction exchanges' propensity to be at NBBO

This table examines the propensity of auction and non-auction exchanges to be at the best bid or offer in a regression setting. The dependent variable equals one if one or more exchanges in an exchange grouping (auction or non-auction) is at the best bid (in the first set of presented results) or best offer (the second estimation presented below). The explanatory variables include: "Auction exchange", which equals one for auction exchanges and zero for non-auction exchanges; the dollar NBBO quoted spread at the time of the trade, the tick size for the particular option series in which the trade occurs, and option series characteristics. All models include stock and date fixed effects. t-statistics and p-values are based on standard errors clustered by underlying stock and date.

	Dependent variable:			
	At NBB		At NBO	
	(1)	(2)	(3)	(4)
Auction exchange	-0.120***	-0.117***	-0.123***	-0.119***
	(0.009)	(0.008)	(0.009)	(0.007)
Quoted spread		0.055***		0.056***
		(0.005)		(0.005)
Tick size		0.688***		1.240***
		(0.073)		(0.071)
Abs (delta)		-0.049***		-0.117***
		(0.007)		(0.008)
Gamma		0.038***		0.014
		(0.010)		(0.012)
Vega		-0.0001***		-0.00003
		(0.00003)		(0.00002)
Price (midpoint)		-0.001***		-0.0005***
		(0.00004)		(0.00003)
Stock FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Observations	94,696,067	84,175,941	94,696,067	84,175,941
Adjusted R^2	0.035	0.036	0.035	0.039
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Quote competitiveness when Arca DMM is also DMM on an auction exchange

This table compares the propensity for NYSE Arca to be at the NBB when the DMM on NYSE Arca is also the DMM for the same option class on at least one auction exchange. The dependent variable is the difference between an indicator variable which equals one if NYSE Arca is at the NBB and an indicator variable which equals one if one of the other non-auction exchanges is at the NBB. Control variables include the dollar NBBO quoted spread at the time of the trade, the tick size for the particular option series in which the trade occurs, and option series characteristics Models include DMM and date fixed effects. t-statistics and p-values are based on standard errors clustered by underlying stock and date.

	Dependent variable:	
	At NBB (Arca minus non-auction)	
	(1)	(2)
DMM on auction exchange	-0.085**	-0.049*
	(0.034)	(0.027)
Quoted spread		0.050**
		(0.022)
Tick size		0.983*
		(0.524)
Abs (delta)		0.004
		(0.020)
Gamma		0.297***
		(0.075)
Vega		-0.001***
		(0.0002)
Price (midpoint)		-0.001**
		(0.0004)
Stock FE	Y	Y
Date FE	Y	Y
Observations	46,515,821	41,300,122
Adjusted R^2	0.006	0.013
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 8: Quote competitiveness when Arca DMM is also DMM on an auction exchange, by DMM

This table compares the propensity for NYSE Arca to be at the NBB when the DMM on NYSE Arca is also the DMM for the same option class on at least one auction exchange. The table presents results separately for each DMM. One DMM does not have any option classes where it serves as a DMM on auction exchanges and is excluded from this analysis. The dependent variable is the difference between an indicator variable which equals one if NYSE Arca is at the NBB and an indicator variable which equals one if one of the other non-auction exchanges is at the NBB. Model 2 includes the following control variables: the dollar NBBO quoted spread at the time of the trade, the tick size for the particular option series in which the trade occurs, and option series characteristics. Both models include date fixed effects. t-statistics and p-values are based on standard errors clustered by underlying stock and date.

Panel A: DMM on auction exchanges - frequency

	DMM 1	DMM 2	DMM 3	DMM 4	DMM 5
Options class (%)	93.6	36.0	41.4	91.1	45.3
Trades (%)	99.7	5.6	63.8	99.1	61.7

Panel B: Regression results

	DMM 1	DMM 2	DMM 3	DMM 4	DMM 5
Model 1 (no control variables)					
DMM on auction exchange	-0.139^{**}	0.062^{*}	-0.153^{***}	-0.123^{***}	0.002
	(0.055)	(0.032)	(0.05)	(0.027)	(0.022)
Model 2 (with control variables)					
DMM on auction exchange	-0.075	0.015	-0.099^{***}	-0.03	0.008
	(0.053)	(0.02)	(0.031)	(0.022)	(0.02)
Date FE	Yes	Yes	Yes	Yes	Yes

Table 9: changes in auctions and quoting behavior around 2017 rule change

This table presents a difference-in-differences analysis of changes in auctions and quoting behavior in the period surrounding rule changes prohibiting or restricting auctions when the spread equals $0.01. The rule changes were implemented on January 18, 2017. The regression models are estimated within a sample of penny-pilot options with prices below $3 where the tick-size equals $0.01 since the rule change is relevant only for these options. We divide the penny-pilot option classes into high-bind and low-bind subsamples based on the propensity of $0.01 spreads in the pre-period. "High bind" equals one for the 102 option classes in the high-bind sample and zero for the 102 options classes in the low-bind sample. "Post" equals one for the period after the change spanning January 18, 2017 to February 28, 2017, and zero for the pre-period from December 1, 2016 to January 17, 2017. The table presents results for: Stopped trades, an indicator variable that equals one if the trade is stopped and zero if it's a regular trade; "Best bid difference" which is the difference between an indicator variable for auction exchanges (as a group) at the NBB and an indicator for non-auction exchanges (as a group) at the NBBO; and "Best ask difference", which is defined similarly for NBO quotes. All models include stock and date fixed effects. Model 2 is estimated for trades on auction exchanges only. T-statistics and p-values are based on standard errors clustered by underlying stock and date.

	Stopped trade (1)	Stopped trade (2)	Best bid diff (3)	Best ask diff (4)
High bind*Post	-0.054***	-0.110***	0.051**	0.051**
	(0.007)	(0.010)	(0.021)	(0.021)
Abs (delta)	0.087***	0.174***	-0.075***	-0.098***
	(0.014)	(0.023)	(0.018)	(0.015)
Gamma	0.034***	0.022	0.033*	-0.010
	(0.012)	(0.016)	(0.018)	(0.015)
Vega	0.002***	0.003***	-0.001	0.001*
	(0.0005)	(0.001)	(0.001)	(0.001)
Price (midpoint)	-0.021***	-0.018***	-0.014*	-0.012**
	(0.004)	(0.006)	(0.008)	(0.006)
Stock FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Sample	All	Auction exchanges	All	All
Observations	13,435,210	6,834,312	13,435,210	13,435,210
Adjusted R^2	0.025	0.033	0.029	0.030
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 10: changes in spreads around 2017 rule change

This table presents a difference-in-differences analysis of changes in NBBO quoted spreads (dollar and percentage), effective spreads, (dollar and percentage) and EQ ratios in the period surrounding rule changes prohibiting or restricting auctions when the spread equals $0.01. The rule changes were implemented on January 18, 2017. The regression models are estimated within a sample of penny-pilot options with prices below $3 where the tick-size equals $0.01. We divide penny-pilot option classes into high-bind and low-bind subsamples based on the propensity of $0.01 spreads in the pre-period. "High bind" equals one for the 102 option classes in the high-bind sample and zero for the 102 options classes in the low-bind sample. "Post" equals one for the period after the change spanning January 18, 2017 to February 28, 2017, and zero for the pre-period from December 1, 2016 to January 17, 2017. All models include stock and date fixed effects. T-statistics and p-values are based on standard errors clustered by underlying stock and date. Panel A presents results for all trades in our sample. Panel B presents results for effective spreads and EQ ratios for small trades (one to five contracts).

Panel A: all trades

	Dependent variable:				
	Quoted spread ($)	Quoted spread (%)	Effective Spread ($)	Effective Spread (%)	Eff-to-quoted ratio
	(1)	(2)	(3)	(4)	(5)
High bind*Post	-0.006**	-0.009***	-0.002	-0.004**	0.018***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.005)
Abs (delta)	-0.026***	-0.276***	-0.020***	-0.225***	-0.089***
	(0.005)	(0.018)	(0.004)	(0.014)	(0.010)
Gamma	0.012**	-0.019	0.008**	-0.013	0.029***
	(0.005)	(0.015)	(0.003)	(0.012)	(0.008)
Vega	-0.001***	-0.012***	-0.001***	-0.009***	-0.001***
	(0.0003)	(0.001)	(0.0002)	(0.001)	(0.0005)
Price (midpoint)	0.026***	0.012*	0.017***	0.013**	-0.006*
	(0.003)	(0.006)	(0.002)	(0.005)	(0.003)
Stock FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Observations	13,435,210	13,435,210	13,435,210	13,435,210	13,435,210
Adjusted R^2	0.194	0.257	0.142	0.225	0.021
Pre-period mean (high bind)	0.026	0.069	0.019	0.053	0.83
Note:					*p<0.1; **p<0.05; ***p<0.01

Panel B: small trades (1 to 5 contracts)

	Dependent variable:		
	Effective Spread ($)	Effective Spread (%)	Eff-to-quoted ratio
	(1)	(2)	(3)
High bind*Post	-0.002	-0.003	0.016***
	(0.001)	(0.002)	(0.005)
Abs (delta)	-0.020***	-0.199***	-0.069***
	(0.004)	(0.015)	(0.011)
Gamma	0.010**	-0.026*	0.044***
	(0.004)	(0.014)	(0.009)
Vega	-0.001***	-0.008***	-0.001***
	(0.0002)	(0.001)	(0.0005)
Price (midpoint)	0.017***	0.008	-0.007**
	(0.002)	(0.005)	(0.003)
Stock FE	Y	Y	Y
Date FE	Y	Y	Y
Observations	8,582,899	8,582,899	8,582,899
Adjusted R^2	0.146	0.215	0.021
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 11: competition in auctions

This table presents an analysis of the effect of competition in auctions. Panel A focuses on the pre-period (December 1, 2016 to January 17, 2017) to describe competition in auctions. The subsamples used in each estimation are a subset of the sample of penny-pilot options with prices below \$3 where the tick-size equals \$0.01. Each model describes the subsample used for estimation below the results. Panel B presents a difference-in-differences analysis of changes in NBBO quoted spreads (dollar and percentage), effective spreads, (dollar and percentage) and EQ ratios in the period surrounding rule changes prohibiting or restricting auctions when the spread equals \$0.01. The rule changes were implemented on January 18, 2017. The regression models are estimated within the subsample of high-bind options. We divide penny-pilot option classes into high-bind and low-bind subsamples based on the propensity of \$0.01 spreads in the pre-period. “High bind” equals one for the 102 option classes in the high-bind sample and zero for the 102 options classes in the low-bind sample. Within the high bind sample, we further divide option classes into those with higher and lower competition in auctions during the pre-period. The competition measure only uses auctions where the combined size traded is greater than one contract. “Post” equals one for the period after the change spanning January 18, 2017 to February 28, 2017, and zero for the pre-period from December 1, 2016 to January 17, 2017. All models include stock and date fixed effects. T-statistics and p-values are based on standard errors clustered by underlying stock and date.

Panel A: Auction competition in pre-period

	Dependent variable:			
	EQ ratio	Competitive auction	Largest share	EQ ratio
Competitive auction	0.240***			0.301***
	(0.013)			(0.019)
Spread=0.01		0.119***	-0.061***	
		(0.007)	(0.003)	
Abs (delta)	-0.190***	0.022*	-0.010	0.006
	(0.019)	(0.012)	(0.007)	(0.010)
Gamma	0.094***	-0.020**	0.007	0.045***
	(0.018)	(0.008)	(0.005)	(0.013)
Vega	-0.003***	-0.001	0.001**	-0.0002
	(0.001)	(0.001)	(0.0004)	(0.001)
Price (midpoint)	-0.043***	-0.024***	0.013***	-0.018***
	(0.005)	(0.004)	(0.002)	(0.005)
Stock FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Sample	Stopped,pre, size>1	Stopped,pre, size>1	Stopped,pre, size>1	Stopped,pre, size>1,spread>.01
Observations	643,353	643,353	643,353	453,136
Adjusted R^2	0.212	0.040	0.042	0.142
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B: effect of competition on spreads

	Dependent variable:				
	Quoted spread ($)	Quoted spread(%)	Effective spread ($)	Effective spread (%)	EQ ratio
	(1)	(2)	(3)	(4)	(5)
High competition*Post	-0.003	-0.002	-0.001	-0.0003	0.002
	(0.002)	(0.003)	(0.001)	(0.002)	(0.006)
Abs (delta)	-0.011^{***}	-0.294^{***}	-0.010^{***}	-0.245^{***}	-0.098^{***}
	(0.004)	(0.016)	(0.003)	(0.013)	(0.011)
Gamma	-0.002	0.005	-0.0003	0.006	0.036^{***}
	(0.003)	(0.013)	(0.002)	(0.011)	(0.008)
Vega	-0.001^{***}	-0.013^{***}	-0.001^{***}	-0.011^{***}	-0.002^{***}
	(0.0002)	(0.001)	(0.0002)	(0.001)	(0.001)
Price (midpoint)	0.015^{***}	0.029^{***}	0.011^{***}	0.026^{***}	-0.003
	(0.002)	(0.005)	(0.002)	(0.004)	(0.003)
Stock FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Sample	High bind=1	High bind=1	High bind=1	High bind=1	High bind=1
Observations	9,887,028	9,887,028	9,887,028	9,887,028	9,887,028
Adjusted R^2	0.051	0.238	0.038	0.223	0.014
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure 1
This figure presents a broad description of the mechanisms for market makers to trade against purchased order flow. When the market maker is quoting the best price, they can choose to trade in limit order book at the quoted price or launch an auction where price improvement is possible. When the market maker is not at the best quoted price, they can choose to start an auction to trade with the order.

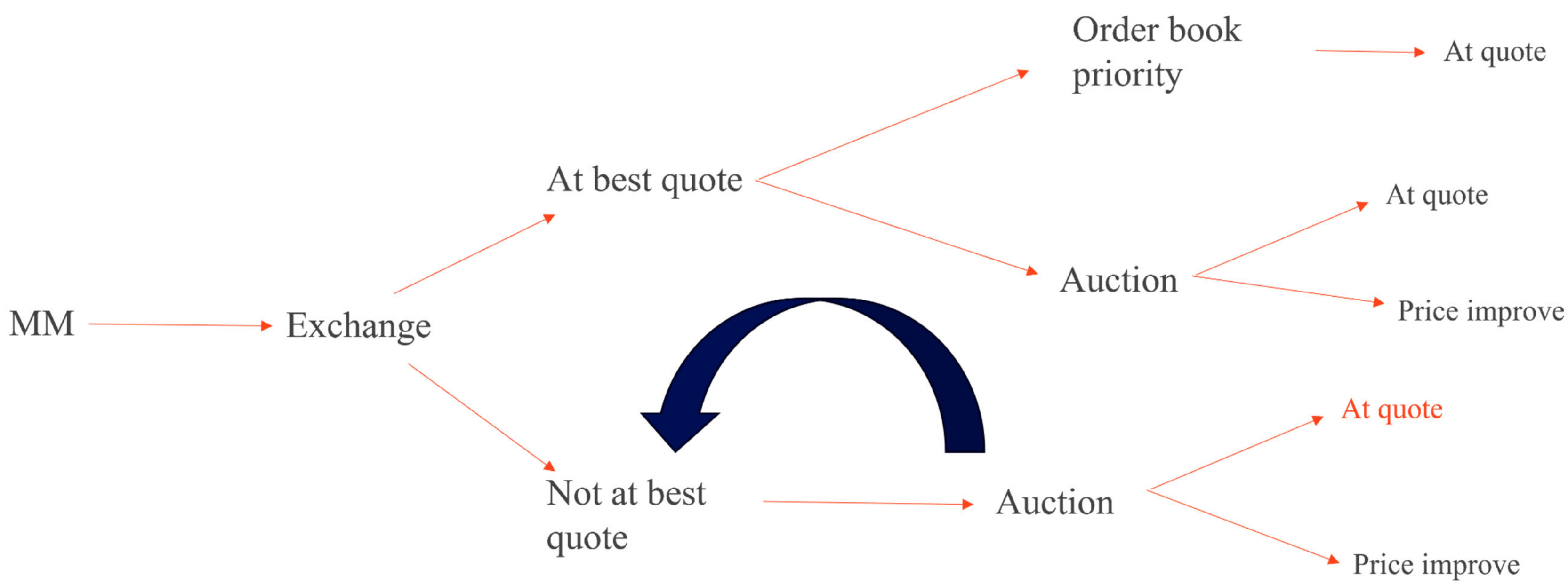


Figure 2

This figure presents the daily average percentage quoted spreads, percentage effective spreads and the proportion of single-leg trades that occur in auctions. The plots are 30 day moving averages using data from January 2011 to June 2018. Over this period, we calculate the statistics for each stock-day and then calculate an average each day weighted by the number of trades for a stock in the day. Auctions are proxied by stopped trades during this period.

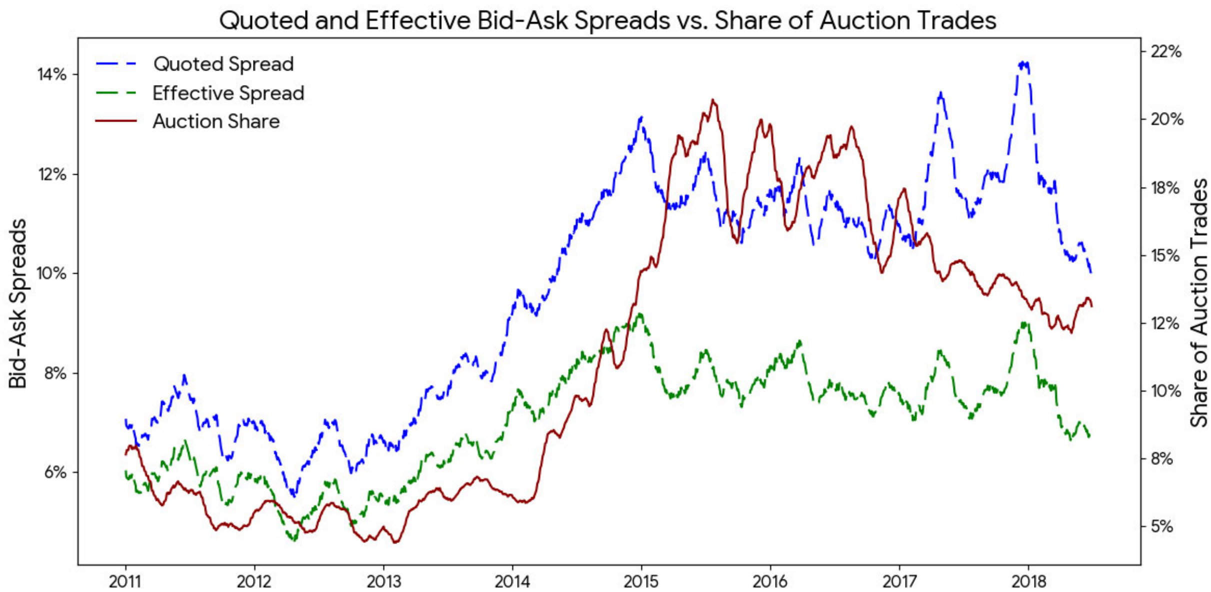
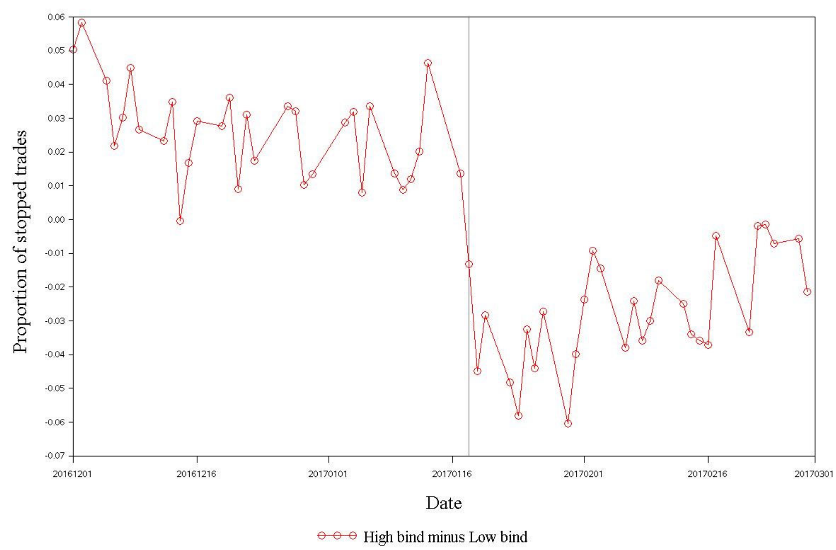
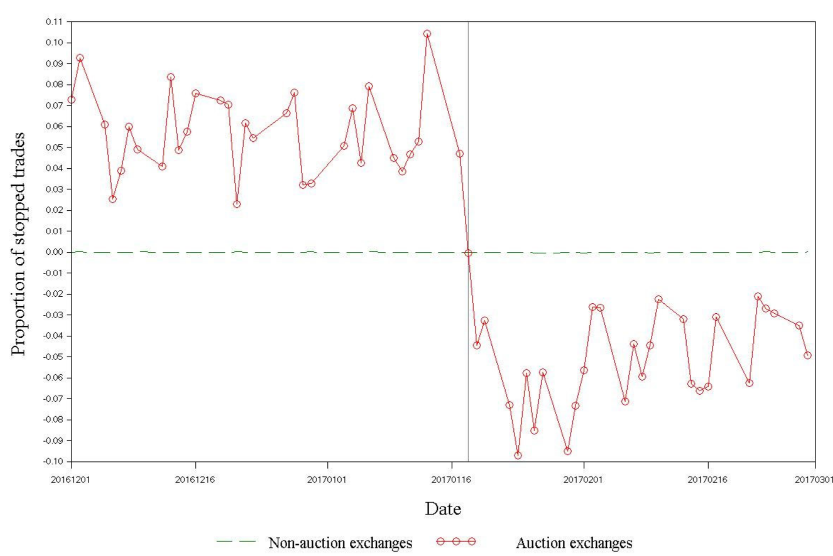


Figure 3
This figure presents the difference in the proportion of stopped trades between the high-bind and low-bind samples over our analysis period surrounding rule changes prohibiting or restricting auctions when the spread equals $0.01. The rule changes were implemented on January 18, 2017. The proportions are calculated within a sample of penny-pilot options with prices below $3 where the tick-size equals $0.01. We divide penny-pilot option classes into high-bind and low-bind subsamples based on the propensity of $0.01 spreads in the pre-period. The figure plots the series from December 1, 2016 to February 28, 2017. The vertical line on January 18, 2017 reflects the rule implementation date. Panel A presents the overall results, while Panel B presents the differences separately for auction and non-auction exchanges.

Panel A:



Panel B:



Appendix Table 1: Exchange auction shares, and propensity to be at best quotes

This table presents the percentage of trades in auctions, the propensity of the exchange to be quoting at the best price when a trade occurs at the exchange, the proportion of observations across the sample where the exchange is quoting at the NBB or the NBO, and the market share of the exchange. The statistics presented below are averages of daily averages calculated across all observations during the trading day. The 16 exchanges include 11 exchanges with auction mechanisms and five without an auction mechanism. Exchanges are sorted by the percentage of their trades in our sample that occur in auctions.

		% trades in auction							
	Exchange	Average	Minimum	Maximum	At best quote when trade	At best bid	At best ask	Market share - trades	Market share - contracts
Auction exchanges	Mercury	87.6	84.8	90.2	33.2%	21.6%	22.1%	1.8%	1.7%
	PHLX	76.3	73.7	78.6	42.2%	31.3%	31.2%	8.9%	12.9%
	Miami options	64.1	59.4	68.7	46.0%	34.8%	34.6%	5.5%	4.9%
	CBOE	40.5	35.6	52.3	44.2%	34.7%	34.8%	6.0%	6.8%
	EDGX	33.5	29.2	38.1	47.4%	38.2%	38.1%	3.3%	3.1%
	ISE	31.4	26.5	35.9	66.8%	29.7%	29.8%	0.9%	0.9%
	AMEX	30.4	27.4	37.9	82.3%	40.1%	41.0%	7.1%	6.3%
	BOX	25.0	21.3	29.3	77.3%	43.3%	42.4%	5.5%	5.3%
	GEMX	1.7	1.6	1.8	91.1%	53.9%	53.3%	10.0%	10.5%
	MIAX Emerald	0.1	0.0	0.4	98.8%	36.3%	35.5%	3.0%	2.6%
	BX	0.1	0.0	0.9	85.1%	37.9%	38.4%	1.4%	1.1%
Non auction exchanges	Nasdaq	0	0	0	87.4%	61.9%	61.7%	13.5%	13.1%
	NYSE Arca	0	0	0	99.7%	62.0%	62.1%	12.8%	10.7%
	C2	0	0	0	70.3%	44.7%	44.1%	3.7%	3.4%
	BATS	0	0	0	75.6%	63.6%	64.1%	8.3%	9.5%
	MIAX Pearl	0	0	0	98.6%	61.2%	60.7%	8.3%	7.2%
	Correlation with %auction				-0.87	-0.75	-0.75		

Appendix Table 2

This table presents the results of regression models explaining the use of the auction mechanism. The regression models are estimated within trades on auction exchanges each day. The table presents the average, min and max of the 20 estimated coefficients and t-statistics. The dependent variable equals one if the trade occurs using the auction process and zero if it is a regular trade. The explanatory variables include: "At best quote when trade" which equals one if the exchange where a trade occurs is at the best quote on the side of the trade (NBO for buy and NBB for sell) at the time of the trade, and zero otherwise. Trades with prices above the NBBO midpoint are classified as buys and those below as sells; the dollar NBBO quoted spread at the time of the trade, the tick size for the particular option series in which the trade occurs, and option series characteristics. All models include stock fixed effects. T-statistics and p-values are based on standard errors clustered by stock.

	Average estimate	**Average t-statistic**	**Average p.value**	**Min (estimate)**	**Max (estimate)**	**Min (t-statistic)**	**Max (t-statistic)**
At best quote when trade	-0.4812	-46.33	*0.00*	-0.5027	-0.4560	-92.32	-22.67
Quoted spread	0.1020	11.82	*0.00*	0.0764	0.1280	6.90	16.13
Tick size	1.0159	3.09	*0.01*	0.7716	1.2459	1.91	5.16
Abs (delta)	0.0402	2.68	*0.11*	0.0096	0.0801	0.67	5.47
Gamma	0.0106	0.26	*0.46*	-0.0438	0.0674	-2.06	2.75
Vega	-0.0002	-2.93	*0.10*	-0.0005	0.0001	-8.11	1.19
Price (midpoint)	-0.0017	-4.12	*0.00*	-0.0026	-0.0014	-7.53	-2.41

Appendix Table 3: January to June 2021

This table presents results of regression models similar to those in Table 3, 4 and 6, separately for each month from January to June 2021. The regression models are estimated within the specified subsample. In models 1 and 2, the dependent variable equals one if the trade occurs using the auction process and zero if it is a regular trade. In models 3 and 4, the dependent variable is an indicator variable that equals one if the trade occurs at a price better than the quoted price, and zero otherwise. In models 5 and 6, the dependent variable equals one if one or more exchanges in an exchange grouping (auction or non-auction) is at the best bid or best offer. The variable of interest in models 1 to 4 is "At best quote when trade" which equals one if the exchange where a trade occurs is at the best quote on the side of the trade (NBO for buy and NBB for sell) at the time of the trade, and zero otherwise. Trades with prices above the NBBO midpoint are classified as buys and those below as sells. the dollar NBBO quoted spread at the time of the trade. The variable of interest in models 5 and 6 is "Auction exchange", which equals one for auction exchanges and zero for non-auction exchanges. All models include control variables: the tick size for the particular option series in which the trade occurs, the quoted spread at the time of the trade, and option series characteristics (abs(delta), gamma, vega and option price). Models 1, 3, 5 and 6 include stock and date fixed effects. Models 2 and 4 include stock and exchange fixed effects. T-statistics and p-values are based on standard errors clustered by underlying stock and date.

		Auction trade (1)	Auction trade (2)	Trade inside quote (3)	Trade inside quote (4)	At NBB (5)	At NBO (6)
2021-01	At best quote when trade	-0.550***	-0.363***	0.164***	0.165***		
		(0.009)	(0.007)	(0.012)	(0.012)		
	Auction exchange					-0.122***	-0.122***
						(0.014)	(0.013)
2021-02	At best quote when trade	-0.526***	-0.363***	0.163***	0.164***		
		(0.011)	(0.010)	(0.011)	(0.011)		
	Auction exchange					-0.135***	-0.131***
						(0.012)	(0.010)
2021-03	At best quote when trade	-0.508***	-0.345***	0.173***	0.176***		
		(0.013)	(0.011)	(0.016)	(0.016)		
	Auction exchange					-0.136***	-0.134***
						(0.009)	(0.009)

		Auction trade	Auction trade	Trade inside quote	Trade inside quote	At NBB	At NBO
		(1)	(2)	(3)	(4)	(5)	(6)
2021-04	At best quote when trade	-0.505***	-0.308***	0.171***	0.174***		
		(0.010)	(0.008)	(0.014)	(0.016)		
	Auction exchange					-0.112***	-0.110***
						(0.009)	(0.008)
2021-05	At best quote when trade	-0.483***	-0.310***	0.170***	0.167***		
		(0.010)	(0.005)	(0.014)	(0.016)		
	Auction exchange					-0.117***	-0.119***
						(0.008)	(0.007)
2021-06	At best quote when trade	-0.456***	-0.305***	0.172***	0.176***		
		(0.005)	(0.007)	(0.011)	(0.013)		
	Auction exchange					-0.118***	-0.122***
						(0.008)	(0.007)
	Controls	Y	Y	Y	Y	Y	Y
	Stock FE	Y	Y	Y	Y	Y	Y
	Date FE	Y	N	Y	N	Y	Y
	Exchange FE	N	Y	N	Y	N	N
	Sample	Auction exchanges	Auction exchanges	Auction trades	Auction trades	All obs	All obs
	Note:						*p<0.1; **p<0.05; ***p<0.01

Appendix Table 4

This table presents a difference-in-differences analysis of changes in competition in auctions in the period surrounding rule changes prohibiting or restricting auctions when the spread equals $0.01. The rule changes were implemented on January 18, 2017. The regression models are estimated within a sample of penny-pilot options with prices below $3 where the tick-size equals $0.01 since the rule change is relevant only for these options. The specific subsample used is specified in the "Sample" row. We divide the penny-pilot option classes into high-bind and low-bind subsamples based on the propensity of $0.01 spreads in the pre-period. "High bind" equals one for the 102 option classes in the high-bind sample and zero for the 102 options classes in the low-bind sample. "Post" equals one for the period after the change spanning January 18, 2017 to February 28, 2017, and zero for the pre-period from December 1, 2016 to January 17, 2017. The table presents results for: "Competitive auction", an indicator variable that equals one if the auction is reported as more than one trade; and "Largest share" which is the proportion associated with the largest trade associated with an auction. All models include stock and date fixed effects. T-statistics and p-values are based on standard errors clustered by underlying stock and date.

	Dependent variable:	
	Competitive auction	Largest share
High bind*Post	-0.003	-0.002
	(0.008)	(0.004)
Abs (delta)	0.021^{**}	-0.011^{**}
	(0.009)	(0.005)
Gamma	0.043^{***}	-0.030^{***}
	(0.012)	(0.007)
Vega	-0.002^{***}	0.001^{***}
	(0.001)	(0.0004)
Price (midpoint)	-0.021^{***}	0.011^{***}
	(0.003)	(0.002)
Stock FE	Y	Y
Date FE	Y	Y
Sample	Stopped, size>1,spread>.01	Stopped, size>1,spread>.01
Observations	930,650	930,650
Adjusted R^2	0.020	0.023
Note:		*p<0.1; **p<0.05; ***p<0.01

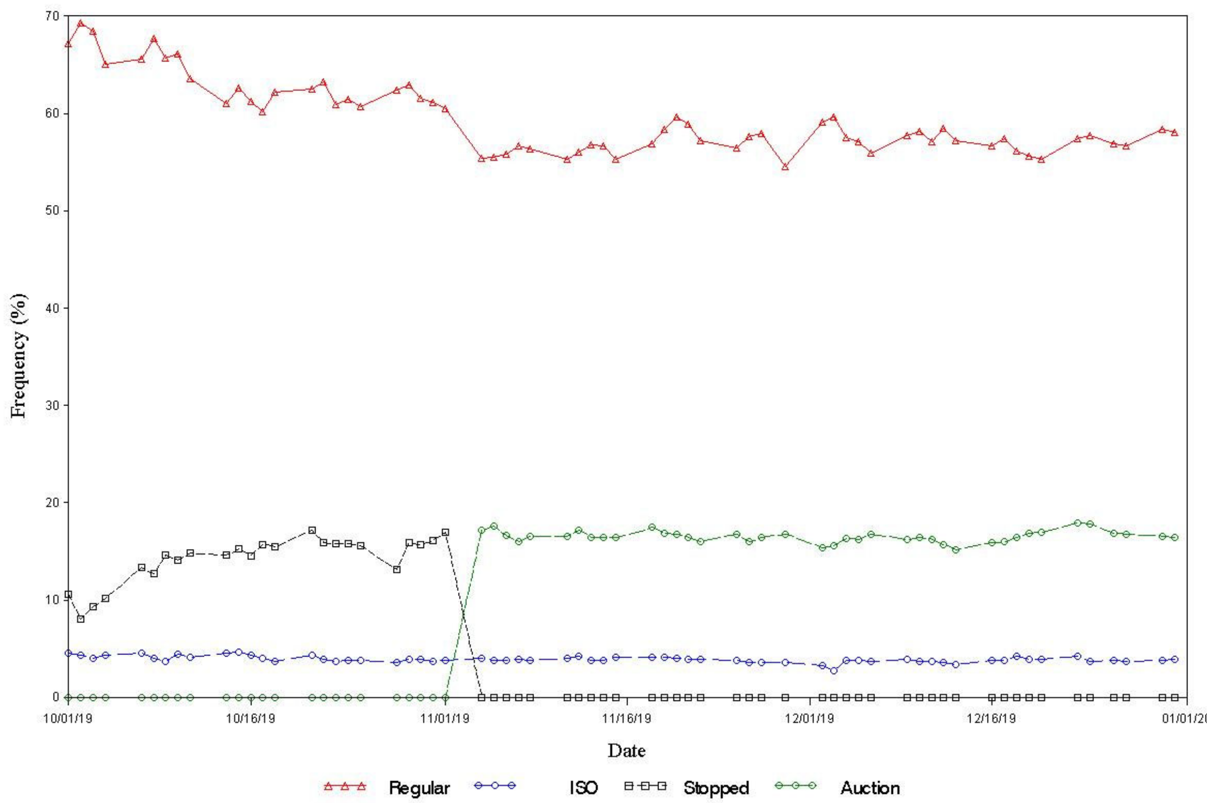
Appendix Table 5

This table is similar to Table 11, Panel B, except that it examines options classes with lower propensity to have binding spreads (*Highbind*=0), while Table 11, Panel B presents results for the *Highbind*=1 subsample. This table presents a difference-in-differences analysis of changes in NBBO quoted spreads (dollar and percentage), effective spreads, (dollar and percentage) and EQ ratios in the period surrounding rule changes prohibiting or restricting auctions when the spread equals \$0.01. The rule changes were implemented on January 18, 2017. The regression models are estimated within the subsample of low-bind options. We divide penny-pilot option classes into high-bind and low-bind subsamples based on the propensity of \$0.01 spreads in the pre-period. "High bind" equals one for the 102 option classes in the high-bind sample and zero for the 102 options classes in the low-bind sample. Within the low bind sample, we further divide option classes into those with higher and lower competition in auctions during the pre-period. The competition measure only uses auctions where the combined size traded is greater than one contract. "Post" equals one for the period after the change spanning January 18, 2017 to February 28, 2017, and zero for the pre-period from December 1, 2016 to January 17, 2017. All models include stock and date fixed effects. T-statistics and p-values are based on standard errors clustered by underlying stock and date.

	Dependent variable:				
	Quoted spread (\$)	Quoted spread(%)	Effective spread (\$)	Effective spread (%)	EQ ratio
	(1)	(2)	(3)	(4)	(5)
High competition*Post	-0.0004	0.004	0.001	0.005	0.002
	(0.005)	(0.005)	(0.003)	(0.003)	(0.008)
Abs (delta)	-0.036***	-0.276***	-0.027***	-0.203***	-0.046***
	(0.012)	(0.045)	(0.009)	(0.034)	(0.011)
Gamma	-0.012	-0.068	-0.011	-0.079*	-0.071***
	(0.013)	(0.055)	(0.009)	(0.043)	(0.022)
Vega	-0.002***	-0.010***	-0.001***	-0.007***	-0.0003
	(0.0005)	(0.002)	(0.0004)	(0.001)	(0.0004)
Price (midpoint)	0.047***	-0.015	0.030***	-0.010	-0.010**
	(0.005)	(0.010)	(0.004)	(0.008)	(0.005)
Stock FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Sample	High bind=0	High bind=0	High bind=0	High bind=0	High bind=0
Observations	3,598,054	3,598,054	3,598,054	3,598,054	3,598,054
Adjusted R^2	0.201	0.253	0.150	0.210	0.013
Note:					*p<0.1; **p<0.05; ***p<0.01

Appendix Figure 1

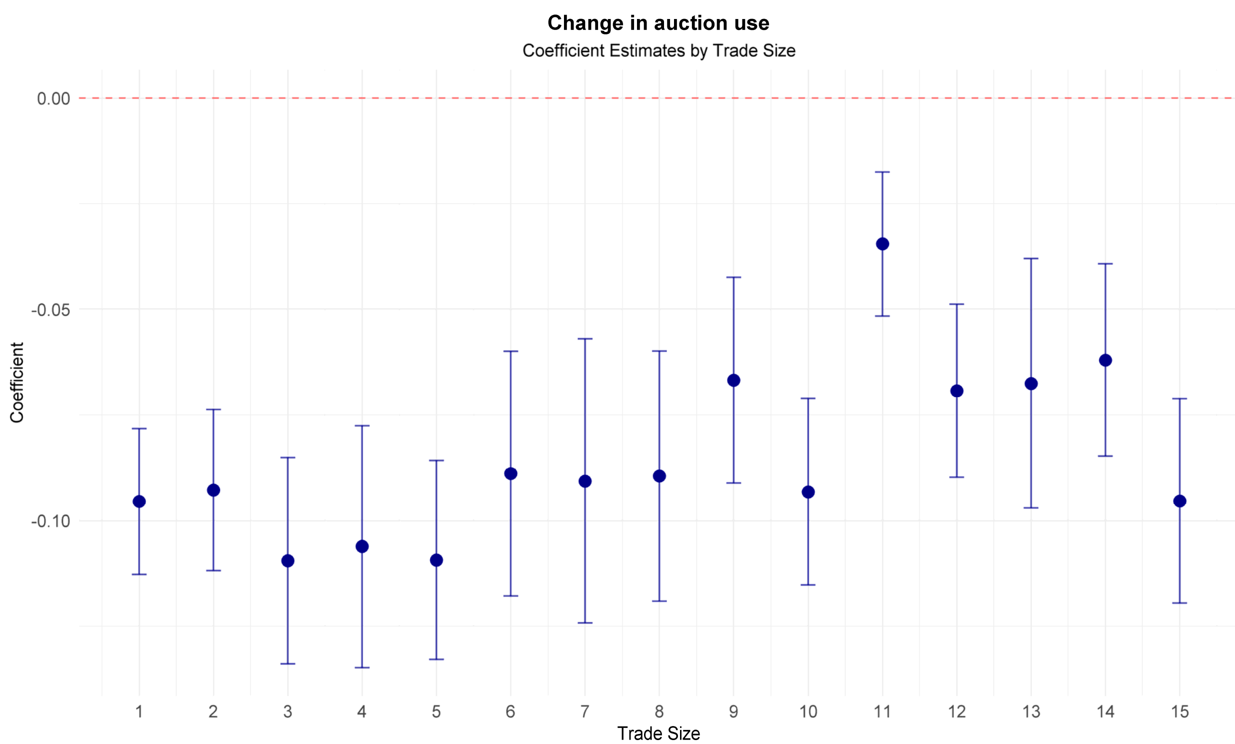
The figure plots the observed frequency of trade indicators associated with single-leg trades in equity options around November 2019 when the auction trade identifier was introduced in the OPRA data.



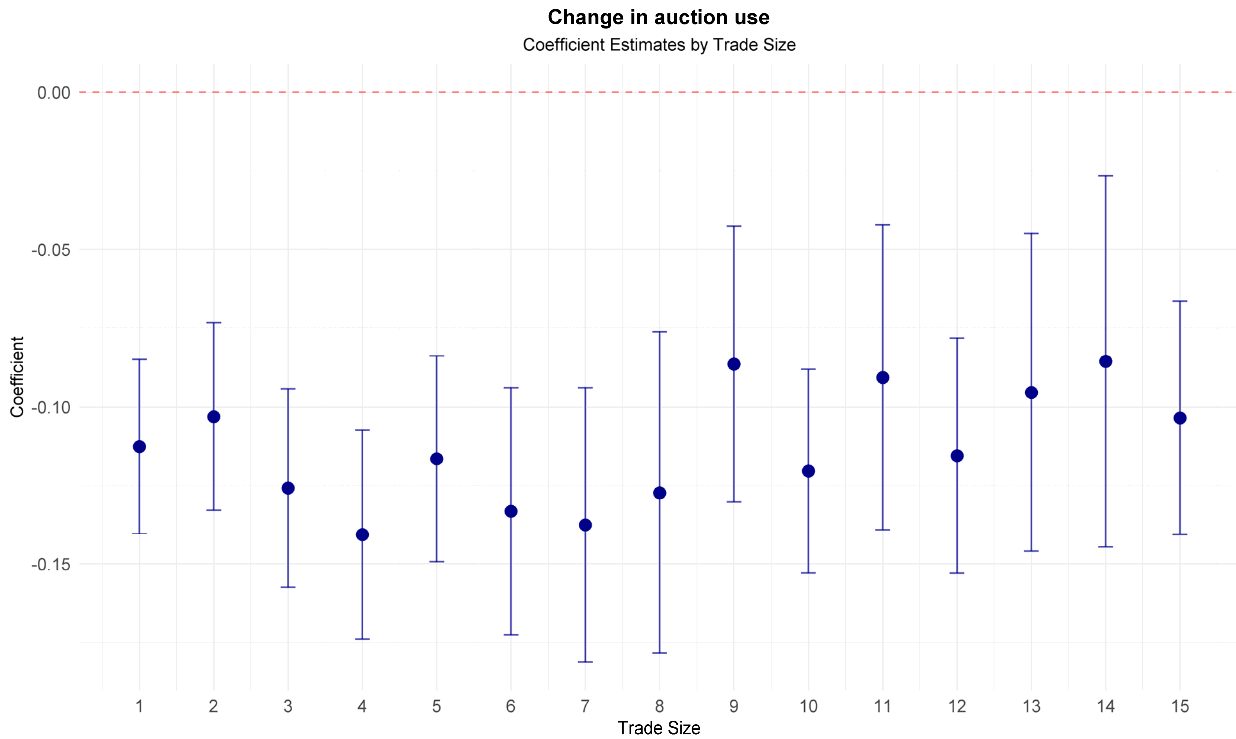
Appendix Figure 2

This table presents a difference-in-differences analysis of changes in auctions, by trade size, in the period surrounding rule changes prohibiting or restricting auctions when the spread equals $0.01. The regressions are similar to the results presented in Table 9, except that that regressions are estimated for trade sizes presented below. The figures plot the coefficient on *Highbind*Post* in equation 2. Panel A presents the results for the entire sample, Panel B for the cases where the trade occurs when the exchange executing the trade is not quoting the best price, and Panel C when the exchange is quoting the best price. The rule changes were implemented on January 18, 2017. The regression models are estimated within a sample of penny-pilot options with prices below $3 where the tick-size equals $0.01 since the rule change is relevant only for these options. We divide the penny-pilot option classes into high-bind and low-bind subsamples based on the propensity of $0.01 spreads in the pre-period. “High bind” equals one for the 102 option classes in the high-bind sample and zero for the 102 options classes in the low-bind sample. “Post” equals one for the period after the change spanning January 18, 2017 to February 28, 2017, and zero for the pre-period from December 1, 2016 to January 17, 2017. All models include stock and date fixed effects. Ranges are based on standard errors clustered by underlying stock and date.

Panel A: all trades



Panel B: Exchange not at best quote



Panel C: Exchange at best quote