Do auctions impact quote competition? [*]

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Abstract

Auctions in options markets provide price improvement for retail traders, but they also allow market makers to trade without competing on displayed bid and ask prices. We study the effects of auctions on quote competition and bid-ask spreads. We find that when an auction exchange is not at the best quote, an auction trade is significantly more likely, and these trades are less likely to receive price improvement. These results are consistent with the use of auctions to match the best price on another exchange. Auction exchanges are less likely to quote at the best prices, particularly to improve the best quoted price. When auction use is restricted due to an exogenous rule change, quoted spreads decline, while the impact on effective spreads is more muted. Overall, we show that auctions reduce quote competition.

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1. Introduction

The increase in retail trading since the Covid pandemic has brought academic and regulatory scrutiny to how retail orders are handled in the current market structure. Retail marketable orders are mostly routed by brokers to market makers, who, in turn, pay brokers for these orders. With the recent surge in options trading, the payments associated with options order flow exceed those for equities.[1] Unlike equities, where retail orders are internalized off-exchange, in options, market makers use exchange-based auctions to trade against purchased retail orders. These auctions are the primary mechanism for providing price improvement to purchased orders. Option auctions are common, accounting for 19.4% of trades in our sample. SEC (2022) proposes to introduce auctions in equity markets. While there are differences in the mechanisms, the SEC proposed structure aims to emulate option auctions in facilitating order-by-order competition.

Recent studies show that retail orders receive substantial price improvement in the US equities markets.[2] Ernst and Spatt (2024) and Hendershott, Khan and Riordan (2023) focus on the options markets and find that auction trades receive greater price improvement than those outside auctions, and that market maker profitability is higher in options than in equities. We complement these studies by examining the effects of auctions on quote competition and spreads in options markets. Similar to equities, options exchanges prohibit trade throughs, requiring a market maker to either be at the best price before order arrival, or to route the order to a better price on another exchange. Instead, a market maker, who is not quoting the best price, can match or improve the best price by initiating an auction. Figure 1 provides an illustration of the possibilities available to option market makers for trading against purchased order flow. When the market maker is quoting the best price, they can trade at the quoted price or provide price improvement in an auction. When the market maker is not at the quoted price, they can choose to trade in

[1] For example, the transaction-based net revenue for Robinhood in Q2, 2024 is $182 million from options and $40 million from equities. Ernst and Spatt (2022) provide a detailed comparison of internalization in equities and options markets.

[2] See, for example, Battalio and Jennings (2023), Brown, Johnson, Kothari and So (2024), Dyhrberg, Shkilko and Werner (2023) and Ernst and Spatt (2022).

an auction, where the rules permit matching the best quote in the market. This delinking of displayed quotes at the best price and attracting order flow raises concerns about quote competitiveness.[3]

Theoretical models support this view. Dutta and Madhavan (1997) show that routing orders to preferred dealers can increase market maker entry barriers and decrease quote competition.[4] In an experimental setting, Bloomfield and O'Hara (1998) find that payment for order flow can decrease quote competition and increase bid-ask spreads if the practice is widespread. van Kervel and Yueshen (2024) show that using the National Best Bid and Offer (NBBO) as a reference price for retail order trading disincentivizes quote competition. A related literature (see Easley, Kiefer and O'Hara (1996)) shows that the segmentation of retail order flow increases adverse selection for market makers who widen spreads in response.

Options markets provide a useful setting to explore the interplay between internalization mechanisms and market maker quotes. All trades, including internalized trades by market makers in auctions, occur on exchanges, and auction trades are clearly identified in public data.[5] Further, given the large number of distinct option series (approximately 1.5 million)[6], exchanges rely on designated market maker (DMMs) and other exchange market makers for liquidity provision. These market makers maintain

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[3] This concern has existed as long as auctions have existed in options. For example, Citadel (2005) argues against the introduction of auctions in options markets: "Participants with a guaranteed source of order flow through internalization opportunities do not need to compete for orders on the basis of their displayed quotations. As a result, they are incented not to display their best quotes to the open market. 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. Improving the market price will simply lessen the amount of money it can extract from internalized orders." More recently, Paul Jiganti, Managing Director for options business development at IMC (a market making firm), voices a similar concern: "There are many factors that have negatively impacted market makers' ability to quote and compete in today's market, but today the one that is most impactful and can be easily addressed is auction mechanisms. I am concerned about an oversized reliance on auctions diminishing the incentive for market makers to populate the screens with aggressive quotes." "Options auctions vex market makers", *Traders Magazine*, September 28, 2016. Similarly, SEC (2004) asks, "To what extent, if any, does payment for order flow in the options markets affect a specialist's or market maker's incentive to quote aggressively?"

[4] Godek (1996), Kandel and Marx (1999), Parlour and Rajan (2003) and Lescourret and Robert (2011) also find adverse effects on quote competition.

[5] Bryzgalova, Pavlova and Sikorskaya (2023) use auction trades to proxy for retail trades.

[6] https://www.nasdaq.com/articles/whats-driving-the-growth-in-options-trading

regular two-sided quotes in their assigned option classes.[7] Exchanges offer market makers the ability to do mass quote updates across option series, in addition to advantages in order allocation and fees. Due to these advantages, SEC (2021) notes: "displayed liquidity is primarily derived from market maker quotes" in options markets. These factors create an opportunity to analyze the relationship between auction trades and exchange quotes, as both can be attributed to the same market makers.

Our contributions draw on two sets of analyses. First, we examine the use of auctions in a recent period where the data clearly identify auction trades. We find that auctions are more likely, and auction trades are more likely to match the quoted price (rather than price improve), when an exchange is not quoting at the best price. These results indicate that auctions help market makers meet trade-through obligations without displaying competitive quotes. At a broader level, we find that auction exchanges are less likely to quote at the NBBO and particularly less likely to set the NBBO. Further, these quote competition effects spill over to a non-auction exchange for a market making firm.

Second, guided by the analysis above, we examine an exogenous rule change that restricts auctions to examine the effects on quoting behavior and bid-ask spreads. Using a difference-in-differences framework, we find that option classes that are more affected by the auction restriction experience an increase in quote competition from auction exchanges, a decline in NBBO quoted spreads, and a smaller decline in effective spreads. These results suggest that spreads are affected by auctions. Since quoted spreads decline more than effective spreads, the effective-to-quoted spread ratios (EQ ratio) show a significant increase indicating lower price improvement relative to quoted prices. The results suggest caution in drawing conclusions on execution quality from changes in EQ ratios in isolation. The combined results of the two analyses indicate that auctions lower quote competition and increase quoted spreads.

We briefly compare equity and option market structures. Both markets prohibit trading through better prices on other exchanges, and primarily operate through limit order books. A few large trading firms

[7] 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.

dominate as high frequency trading firms in equities and as exchange market makers in options. Trading is fragmented with 16 equities exchanges and 18 options exchanges in 2024. Options trading must occur on exchanges, and auction trades are identified in public data after November 2019. In contrast, equity internalization occurs off-exchange, and is reported with an identifier that combines internalized trades with other off-exchange trades (e.g., on Alternative Trading Systems). Equities data also do not allow a linkage between internalized trades and market maker quotes on exchanges. Our analysis reflects the evolution of the market structure and leverages unique features of options markets to extend the prior rich literature on internalization in equities, which includes Battalio, Greene and Jennings (1997), Bessembinder and Kaufman (1997), Bessembinder (1999) and Chung, Chuwonganant and McCormick (2004), among others.

Using option trades and quotes (OPRA) data from May 2021, we find that, within auction exchanges, an auction trade is 31 percentage points more likely than a limit-order-book trade when the exchange is not quoting at the best price.[8] The effect persists after controlling for quoted spreads, tick size, option price, and option Greeks (delta, gamma and vega). Auctions are often referred to as price improvement mechanisms by exchanges.[9] However, price improvement is not mandatory, as auctions can also match the best quote from another exchange to comply with the trade-through prohibition. Auction trades are 17 percentage points more likely to match the best quoted price (relative to trading inside the NBBO) when an exchange is not quoting the best price. Similarly, the EQ ratio is 0.16 larger (implying lower price improvement) for auction trades when an exchange is not at the best quote. Overall, market makers show a relative preference to trade at their quotes if they are at the best quote, and for the auction mechanism when they are not.

We examine whether auctions are associated with a broader tendency to quote less competitively. We compare the propensity of the 11 auction exchanges against the five non-auction exchanges to post at

[8] We repeat our analyses for each month between January and June 2021. The results are similar to those for May 2021 and are included in Appendix Table 3.
[9] For example, auctions are called the Price Improvement Period (PiP) on BOX, the Price Improvement XL (PIXL) mechanism on PHLX, and the Price Improvement Mechanism (PRIME) on MIAX.

the best quotes. That is, if any one exchange within each group is quoting at the National Best Bid (NBB) or Offer (NBO), we count that group as at the NBB/O. Auction exchanges (53% of sample trades) are 12 percentage points less likely to quote at the NBB/O than non-auction exchanges. We focus on cases when there is only one exchange at the NBB/O since these cases indicate a price setting exchange. When a single exchange quotes the NBB (NBO), it is more likely to be a non-auction exchange by 29.4 (30.1) percentage points. These differences suggest a lower propensity for auction exchanges to compete for order flow using displayed quotes.

We examine whether a DMM firm, with auction access on one exchange, is likely to change its trading behavior on a non-auction exchange. Options exchanges rely on similar DMMs, creating concerns about spillovers. We focus this analysis on NYSE Arca, which does not include auctions but does include DMMs. We exploit the feature that the same market making firm is frequently the assigned DMM for the same option class on multiple exchanges. We compare Arca's propensity to quote best prices in option classes with and without overlapping DMM assignments, controlling for DMM fixed effects. To account for security specific differences, we benchmark the quoting behavior on Arca against that of other non-auction exchanges in the same option class. An overlapping DMM assignment with an auction exchange is associated with a five percentage point lower propensity to quote at the best price.

We next turn to the question of the effect of auctions on quoted and effective spreads. Bloomfield and O'Hara (1998) provide experimental evidence that internalization can increase spreads, but that this effect may be mitigated by competition from non-internalizing market makers. If market maker entry is restricted due to payment for order flow arrangements as in Dutta and Madhavan (1997), or if non-internalizing market makers are less competitive in the presence of auctions since a part of order flow is unresponsive to quotes, spreads may be larger. In addition to competitive effects, cream-skimming of uninformed orders using auctions (Easley, Kiefer and O'Hara (1996)) may create higher adverse selection in the limit order book and consequently higher quoted spreads. The net effect of auctions on spreads in options is an open empirical question.

We examine the aggregate effects using an exogenous event. On January 18, 2017, auction exchanges simultaneously implemented rule changes to make it more difficult (or impossible) to initiate an auction if the prevailing NBBO spread equals $0.01 at order arrival.[10] The simultaneous rule changes across exchanges are driven by the exchanges seeking to make auctions permanent after running them under a pilot program. Exchanges were required to submit their analysis of the pilot program, which suggested that auctions did not generate discernible price improvement when the spread equaled $0.01. The coordinated event across exchanges restricting auctions suggests an active role of the SEC in implementing the rule change.

We use this market-wide exogenous event to examine changes in option classes which have a higher incidence of NBBO spreads at $0.01 relative to those with lower probability of spreads at $0.01 before the rule change. We restrict our analysis to option series below $3 within penny-pilot option classes in our sample since a tick size of $0.01 only applies for these options.[11] The analysis compares the treatment and control samples, before and after the rule change. This analysis is guided by our earlier analysis. While auctions are restricted only when spreads equal $0.01, since market makers are no longer able to make the trading decision after receiving the order, the need to be at the best quote increases; thus, we expect auction exchanges' quote competitiveness to increase.

First, we verify that auction usage drops in our treatment (relative to control) sample after the change. Consistent with our expectations, the quote competitiveness of auction exchanges increases. We then examine the implications for spreads. We find that the rule change is associated with a decline in NBBO quoted dollar and percentage spreads. The difference-in-differences coefficient suggests that dollar quoted spreads decline by 0.6 cents after the rule change. This compares to a level of 2.6 cents before the rule change. Effective spreads show smaller declines with a statistically significant decline for percentage

[10] According to the rule changes, three exchanges reject auctions, and the remaining require price improvement of at least a penny over the NBBO, if the NBBO equals $0.01.

[11] 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.

spreads but not for dollar spreads. Declines in percentage effective spreads are approximately half of the decline in percentage quoted spreads. The net effect of the two is an increase in EQ ratios. These results indicate that quoted spreads become more competitive, but price improvement declines as auctions are restricted. Overall, the results suggest that auctions may reduce the competitiveness of quoted spreads. We note that EQ ratios show a relative increase in our analysis even though other metrics do not show worsening execution quality, suggesting caution in interpreting changes in EQ ratios.

Our paper relates to recent papers examining retail trading in options. Bryzgalova et al. (2023) introduce auction trades as a proxy for retail trading. Hendershott et al. (2023) find better execution quality in option auctions than regular trades. They also find that order routing is affected by payment for order flow. Ernst and Spatt (2022) find smaller price improvement and larger market maker profits for internalized options trades compared to equities. They also examine option classes where one DMM firm serves on all 11 DMM exchanges, finding wider spreads if the sole DMM pays for order flow. In equities, Dyhrberg, Shkilko and Werner (2023), and Battalio and Jennings (2023) conclude that market makers provide valuable price improvement to retail traders.[12]

We complement these studies by showing that the auction mechanism is sometimes used by market makers to match NBBO quotes to meet trade through obligations, and reduces market makers' incentive to compete on quoted prices. Our results add important nuance to the understanding of auction mechanisms: while they improve prices for internalized trades, they may reduce quote competition.

The execution quality of internalized trades in equities is currently an area of regulatory focus. For example, SEC (2022) proposes Rule 615, which would require internalization in equities markets to occur in qualified auctions, aiming to increase price improvement. The recently adopted revisions to Rule 605 in SEC (2024) expand execution quality disclosures to broker-dealers to enhance competition. Rule 605 now also extends the price improvement metrics to include EQ ratios, which brokers use to evaluate execution

[12] Schwarz, Barber, Huang, Jorion and Odean (2023), Huang, Jorion, Lee and Schwarz (2023) and Ernst, Malenko, Spatt and Sun (2024) focus on broker monitoring of market maker price improvement.

quality. While the focus on price improvement is important for retail investors, our results highlight the added dimension of quote competition. Ernst, Spatt and Sun (2024) analyze the proposed auction structure in SEC (2022) and caution that the winner's curse in the proposed auctions would hinder their success. We suggest that the effects on quote competition should also be considered.

In the rest of the paper, we discuss the relevant details of the institutional framework around options trading in the US, describe our data and sample, present the details of our analysis and results, and conclude.

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.[13] This fee is distributed through DMMs to pay to bring order flow to the exchange. 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 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

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

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. (2023) 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).[14] Following Bryzgalova et al. (2023) and Hendershott et al. (2023), 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 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.

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

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 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, market makers can match or improve on the NBB or NBO price after receiving the order, even if the market maker was not quoting at 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 at 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.[15] 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

[15] 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.

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 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.[16]

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:

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

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

[16] 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.

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 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. (2023), 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 48.3 percentage points more likely if the exchange is not at the best quote than when it is.[17] 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.[18]

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.

[17] 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.
[18] In unreported results, we include a combined exchange-stock-day fixed effect. The results are similar to model 4.

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).[19] 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 at the best price and auction trades that occur when it is not.

The coefficient on *ExchangeBestWhenTrade* suggests that when an exchange is quoting at 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 quoting at the best price. 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.

[19] A small number of trades that occur at prices worse than the NBBO are excluded in this estimation.

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).[20] 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 "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. We use a regression framework to examine differences across auction and non-auction exchanges with 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

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

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.[21]

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

So far, our results are consistent with market makers on options exchanges using auctions to trade when they are not quoting the best prices. These auction exchange market makers are less likely to quote at the best prices, and especially in a manner which would be consistent with improving the quoted price. These 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

[21] 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.

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.[22] We present the results using bid quotes in Table 7; the results for ask quotes are similar.

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.

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,

[22] 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 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 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 (BOX, Miax, Amex), or require price improvement of at least \$0.01 over the NBBO (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 marketwide 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. 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. 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 1.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 1.A. reflects market-wide trends. Trades can be stopped for reasons other than auctions. To further associate the decline with auctions, Figure 1.B. plots the proportion of stopped trades 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. On the other hand, the plot for auction exchanges shows that the trends in Figure 1.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 last row shows that 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.

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 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.

5. Conclusion

Internalization is widespread in equities and options markets. SEC (2022) proposes auctions for internalization in equities, underlining the significance of the practice. Thus, academic attention has appropriately focused on price improvement offered in auctions. We add to the understanding of auctions by examining their effect on quote competition.

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. For one market maker, the lack of quote competitiveness spills over to an exchange which does not include auctions.

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
Proportion of trades at binding tick	28.07%
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 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 in 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
Sample	Tick=.01	Tick=.01	Tick=.01
Observations	8,582,899	8,582,899	8,582,899
Adjusted R^2	0.146	0.215	0.021
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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.

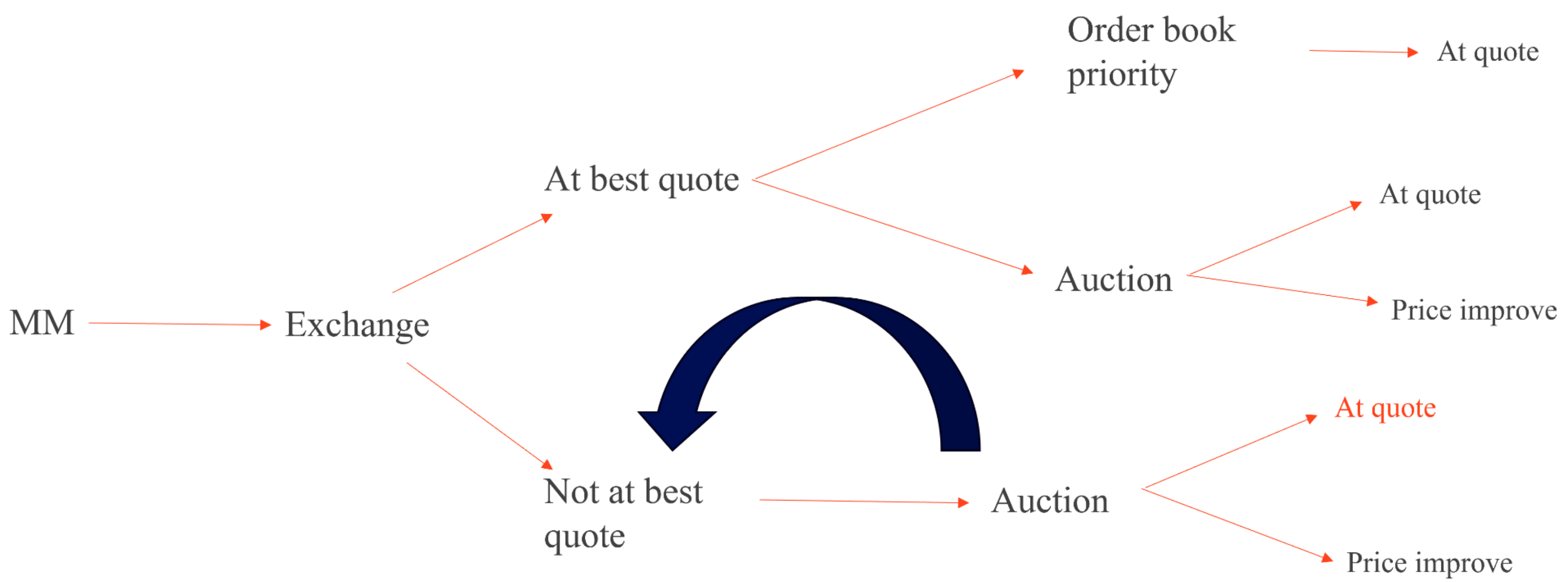
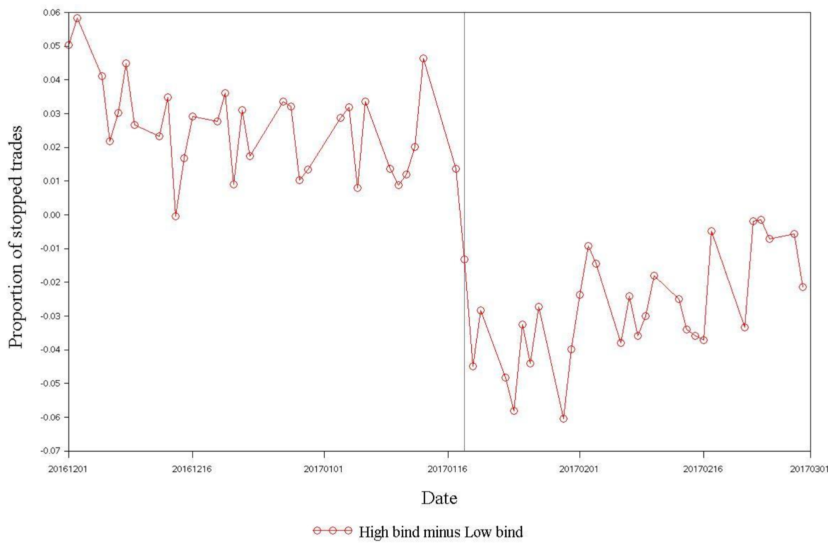
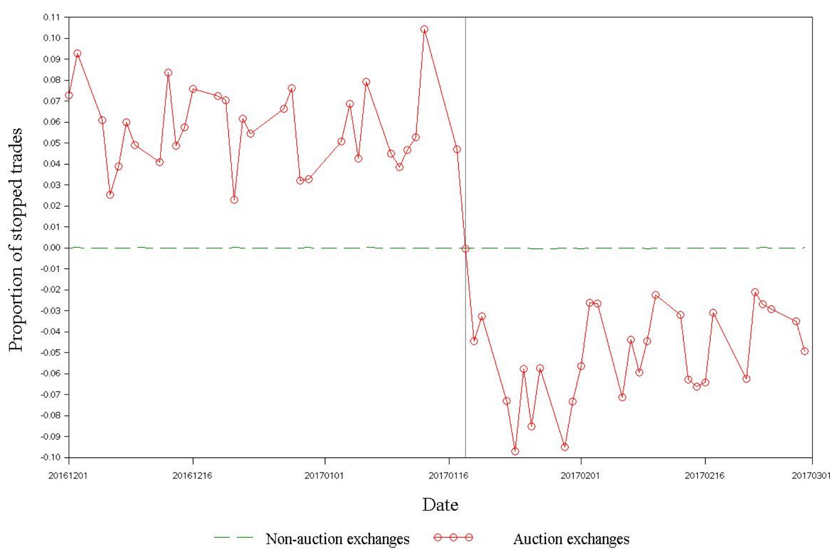


Figure 2
This figure presents the difference in the proportion of stopped trades between the high-bind and low-bind samples over our analysis period surrounding rule changes prohibiting or restricting auctions when the spread equals $0.01. The rule changes were implemented on January 18, 2017. The proportions 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 proportions 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	Auction trade	Trade inside quote	Trade inside quote	At NBB	At NBO
		(1)	(2)	(3)	(4)	(5)	(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 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.