Does internalization impact quote competition? [*]

Amber Anand, Dmitriy Muravyev

Abstract

Internalization mechanisms – like price improvement auctions in options – let market makers trade without displaying quotes. Studies in equities find little evidence that internalization reduces quote competition. Options offer a better setting because the same market makers set the best quotes and internalize retail orders. We find that market makers use auctions to match best prices when their quotes are uncompetitive: when an exchange is not posting the best price, auction trades are 31 percentage points more likely to occur, but significantly less likely to receive price improvement. Exchanges that offer auctions are less likely to compete on quotes. A market-wide change restricting auctions increased quote competition from auction exchanges and narrowed overall quoted spreads by 23%. Effective spreads declined less, as narrower quotes reduce price improvement opportunities. Long-term trends are consistent. As auction use rose sharply in 2014, quoted spreads also increased and diverged from effective spreads. While internalization may benefit individual retail orders, it reduces quote competition and widens quoted spreads.

First draft: June 2024

Current version: May 2026

---

[*] Anand (amanand@syr.edu) is at Syracuse University, Muravyev (dmuravy2@illinois.edu) is at the University of Illinois at Urbana Champaign. We thank participants at the Microstructure Exchange, the MARC conference at Villanova University, the University of Tennessee Smokey Mountain Finance Conference, Robert Battalio, Sabrina Buti, Carole Comerton-Forde, Tom Ernst, Terry Hendershott, Phil Mackintosh, Pam Moulton, Neil Pearson, Andy Puckett, Tavy Ronen, Mehrdad Samadi, Heather Seidel, Andriy Shkilko, Jonathan Sokobin, Vincent van Kervel, Kumar Venkataraman, Chaojun Wang, and Bart Yueshen for their comments.

1. Introduction

Internalization is a dominant feature of U.S. equity and options markets. Brokers route retail orders directly to market makers, who can trade with these captive orders without displaying competitive quotes. In return, brokers receive payments for order flow (PFOF). Options retail trading has surged recently, with options PFOF exceeding equity PFOF (Bryzgalova, Pavlova, and Sikorskaya, 2023). Recent research primarily evaluates price improvement for internalized orders relative to displayed quotes.[1] We ask whether internalization affects those quotes in the first place. Displayed quotes matter because they serve as the benchmark against which retail price improvement is measured. They are the primary source of information on available market liquidity, and determine the prices paid by non-internalized orders that execute at quoted prices.

We propose a simple incentive-based mechanism linking internalization to quote competition. Internalizing market makers have a weaker incentive to post aggressive quotes because internalized orders are priced relative to best quotes in the market. Thus, posting tighter quotes lowers the profit on these orders.[2] 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." Our mechanism draws on models predicting that internalization widens quoted spreads by reducing market maker competition (Bloomfield and O'Hara, 1998; Dutta and Madhavan, 1997; Battalio and Holden, 2001; van Kervel and Yueshen, 2024) and by increasing adverse selection in the remaining order flow (Easley, Kiefer, and O'Hara, 1996).

Despite these theoretical predictions, most empirical studies find that internalization does not significantly affect spreads (e.g., Battalio, 1997; Battalio, Greene, and Jennings, 1997; Battalio, Jennings,

[1] Hendershott, Khan, and Riordan (2026) and Ernst and Spatt (2026) focus on retail executions in options. Battalio and Jennings (2026), Brown, Johnson, Kothari, and So (2024), Dyhrberg, Shkilko, and Werner (2025), and Schwarz, Barber, Huang, Jorion, and Odean (2025) examine price improvement in equities.

[2] We formalize the mechanism in a stylized model of imperfect competition. The model simplifies the price-referencing framework of van Kervel and Yueshen (2024), taking order routing and internalized volume as exogenous to isolate the core mechanism. An internalizing market maker decides whether to undercut the incumbent best quote by one tick. Tightening the quote increases the probability of attracting non-internalized orders but improves the benchmark against which all internalized volume is priced.

and Selway, 2001; Bessembinder, 2003; Peterson and Sirri, 2003). These studies focus on equities, where finding the effect is difficult. Equity internalization occurs off-exchange, making it harder to observe internalized trades in public data. Linking internalization to market maker quoting behavior is also difficult because non-internalizing market makers, such as high-frequency traders, often set the best quotes. Finally, competition from these high-frequency traders mitigates the anti-competitive effects predicted by theory (Bloomfield and O'Hara, 1998).

The U.S. options market reduces these identification challenges, offering a better setting to test the theory. First, options data allow us to link market makers' internalization activity to their quoting behavior. Unlike in equities, displayed liquidity in options comes mainly from market maker quotes (SEC, 2021), and the same firms that post best quotes also internalize retail orders.[3] Second, all option trades must occur on an exchange, and market makers routinely internalize retail flow through on-exchange auctions that are identified in public data.[4] These auctions are an effective internalization mechanism because exchange fees discourage outside competition (Bryzgalova et al., 2023; Hendershott et al., 2026). As a result, market makers can trade with purchased flow without displaying competitive quotes. Finally, internalization is more prevalent and lucrative in options. Retail flow comprises about half of options volume (SEC, 2026), a proportion twice as large as in equities (Barardehi, Bogousslavsky, and Muravyev, 2025), and options PFOF is much larger. Theory predicts stronger effects under these conditions.

We examine how internalization affects quote competition and spreads using public OPRA data on equity options. We show that market makers use auctions tactically to execute trades when their quotes are uncompetitive. Using data from May 2021, we find that a trade is 31 percentage points more likely to occur in an auction when the exchange is not quoting the best price than when it is.[5] Within auctions, when the

---

[3] Customer liquidity is scarce and fragmented across numerous option contracts. For example, over 1.5 million distinct contracts trade in U.S. options markets (Nasdaq, 2024). Exchanges incentivize registered market makers to quote through benefits such as lower fees, and mass quoting and cancellation privileges.

[4] Figure 1 shows the different ways that a market maker can trade with purchased options order flow.

[5] The May 2021 sample includes over two million single-leg option trades per day across 2,444 stocks. Auctions account for 19.4% of trades. Wide bid-ask spreads averaging 9% incentivize market makers to internalize retail order flow. We also confirm the May 2021 results for each month from January to June 2021.

exchange is not quoting the best price, auction trades are 17 percentage points more likely to match the national best bid and offer (NBBO) rather than execute inside it. These results are consistent with market makers using auctions to satisfy their trade-through obligations when they are not quoting the best price.

The quote matching behavior impacts the need to compete on quotes. At the exchange level, auction exchanges (those that offer auctions) are 12 percentage points less likely to quote at the NBBO than non-auction exchanges. The gap is most pronounced when quote competition matters most. When a single exchange sets the best price, it is nearly 30 percentage points more likely to be a non-auction exchange. Because large market-making firms operate on both auction and non-auction exchanges, we explore whether auction access affects quoting beyond the auction exchange. We find that when a designated market maker (DMM) has auction access for an option contract on one exchange, it is less likely to quote the best price for that same option on a non-auction exchange. This spillover indicates that internalization can affect quoting behavior even in parts of the market making firm that do not directly internalize.

To examine whether weaker quote competition translates into broader market quality effects, we study a market-wide rule change that exogenously restricted auction usage. On January 18, 2017, the SEC approved coordinated rule changes across auction exchanges. In the new rules, exchanges either prohibit auctions when spreads are at one cent or require a minimum one-cent price improvement.[6] The event is the largest shock to auction availability in recent years with broad applicability across exchanges on a single implementation date. We use a difference-in-differences design around the event, comparing options with high versus low propensity for penny spreads. Options frequently at penny spreads are more affected by the rule change. Auction use declines by 11 percentage points in affected options after the event.[7] Auction exchanges' propensity to quote at the NBBO in the affected options increases by 5 percentage points relative to non-auction exchanges. Quoted spreads decline by 23% for the affected options, while the decline in

[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. An option class refers to all traded options on an underlying stock.

[7] Since this analysis predates public auction flags in OPRA (added in 2019), we proxy for auctions using stopped trades. Anand, Hua and Puckett (2025) provide more detail on this methodology.

effective spreads is smaller. Restricting auctions intensifies quote competition and narrows quoted spreads, but narrower spreads also reduce the scope for price improvement, limiting the effect on effective spreads.

Finally, we examine the aggregate time series of auction usage and option bid-ask spreads. Auctions were originally designed for block trades, with more restrictive exchange rules for small orders.[8] During 2013-2014, exchanges began eliminating these restrictions, converting auctions into a channel for retail internalization. The auction share increased from under 6% in 2013 to around 15% of all option trades during 2014-2015. Quoted and effective spreads closely tracked each other before 2013. The two series diverged starting in 2013: both increased, but quoted spreads rose sharply, while effective spreads rose only modestly. In contrast, the underlying stock spreads remained flat. These long-term trends are not causal evidence, since many factors affect aggregate spreads over time. However, the trends are consistent with the predicted outcomes from our earlier analyses, including the 2017 rule-change results. Aggregate trends are also useful for regulators who track them to assess the health of the market structure (e.g., SEC, 2026).

Wider quoted spreads raise costs for traders who trade at the quote. They also create hidden costs. Retail traders in auctions may receive price improvement, but it is measured against quotes widened by internalization. A commonly used execution quality metric, the Effective-to-Quoted spread (EQ) ratio, obscures this effect: holding the execution price fixed, the EQ ratio mechanically improves when quoted spreads are wider. The 2017 rule-change results illustrate this effect. EQ ratios worsen after the event, even as effective spreads experience small declines, because the quoted spread benchmark declines more. Wider spreads and PFOF can also reinforce one another (Chordia and Subrahmanyam, 1995, and Kandel and Marx, 1999). Wider spreads also create more room for discretion if brokers trade off PFOF against client execution quality (Huang, Jorion, and Schwarz, 2025).

We primarily contribute to the literature on market-wide effects of internalization. Microstructure theory (e.g., Parlour and Rajan, 2003; Easley, Kiefer and O'Hara, 1996; Dutta and Madhavan, 1997; Bloomfield and O'Hara, 1998; Kandel and Marx, 1999; Lescourret and Robert, 2011; van Kervel and

[8] For example, a common restriction was that smaller orders of less than 50 contracts would need to be price improved in auctions relative to prevailing quotes, while larger orders could match these quotes.

Yueshen, 2024) predicts that internalization can widen spreads. However, empirical studies in equities find little effect, whether using exogenous changes to internalization (Battalio, 1997; Battalio, Greene, and Jennings, 1997) or cross-sectional variation in internalization levels (Bessembinder and Kaufman, 1997; Bessembinder, 2003; Peterson and Sirri, 2003; Hansch, Naik, and Viswanathan, 1999), with rare exceptions such as Chung, Chuwonganant, and McCormick (2004).[9] To our knowledge, we are the first to study this question outside equities. We show that internalization reduces quote competition and widens quoted spreads in options, where internalization is observable, economically large, and conducted by the same market makers who set best quotes.

We also extend recent work on retail options trading. Bryzgalova et al. (2023) introduce auctions as a retail proxy; Hendershott et al. (2025) find better execution quality in auctions and recommend expanding their use; Ernst and Spatt (2026) show how DMM assignments facilitate internalization.[10] While auctions may benefit individual retail orders, we show that they reduce overall quote competition. Our findings inform policy debates around internalization, including the SEC Proposed Rule 615, which would have introduced auctions for equity internalization (SEC, 2022). Without a requirement to post competitive quotes, such mechanisms may widen displayed spreads.

Exchange pricing also shapes options market competition (Battalio, Shkilko, and Van Ness, 2016; Anand, Hua, and McCormick, 2016). Anand et al. (2016) show that make-take pricing strengthens incentives to improve the NBBO. Their sample, however, largely predates the growth of auctions. During that period, internalization primarily occurred at displayed quotes, and quoted and effective spreads were closely related.[11] Our setting differs because auctions allow market makers to internalize without first

[9] O'Hara and Ye (2011) find that dark trading (combining internalized retail and institutional non-exchange volume) reduces costs in U.S. equities, while Hatheway, Kwan, and Zheng (2017) find the opposite. Farley, Kelley, and Puckett (2025) find no effect of a dark trading shock on U.S. equity spreads. Comerton-Forde, Malinova, and Park (2018) find that restricting dark trading in Canada shifts order flow and increases lit-market depth but does not change spreads.

[10] In equities, Dyhrberg, Shkilko and Werner (2025) and Battalio and Jennings (2026) find valuable price improvement for retail traders. Schwarz, Barber, Huang, Jorion, and Odean (2025), Huang, Jorion, Lee, and Schwarz (2023), and Ernst, Malenko, Spatt, and Sun (2024) describe broker monitoring of price improvement.

[11] Anand et al. (2016) note that purchased orders "…typically trade against the best available quotes. Thus, market makers on traditional option exchanges are frequently at the market-wide best bid and offer quotes."

displaying competitive quotes. Moreover, our 2017 event restricts auctions without any changes to exchange pricing, and much of our other analysis compares behavior within exchanges. Thus, make-take pricing is unlikely to explain our evidence on auctions and quote competition.

The paper proceeds as follows. Section 2 describes the institutional setting. Section 3 presents data and sample construction. Section 4 documents tactical auction use and quote competition effects. Section 5 analyzes the 2017 rule change. Section 6 examines long-term trends. Section 7 concludes.

2. Internalization in options markets

Unlike equity markets, where market makers internalize trades off-exchange, all option trades occur on exchanges. In this section, we briefly describe how internalization works in options markets.

Exchanges that facilitate internalization charge a marketing fee to executing market makers, including DMMs. This fee compensates brokers for routing order flow to the exchange. Market makers typically supplement these fees with additional PFOF payments to brokers. Once a market maker has purchased order flow, there are two primary mechanisms for trading with it. The first applies to small orders of fewer than five contracts. If the DMM is quoting at the best price when the order arrives, the DMM receives priority over other market makers and can trade with the entire order. However, quoting the best price increases quote competition and exposes the market maker to trading with less preferred counterparties, such as professional traders.

Auctions provide the second mechanism for internalizing order flow. Unlike the small order allocation described above, auctions do not require the market maker to be quoting at the best price. Figure 1 describes the two internalization mechanisms available to market makers and their interaction with the market maker’s quotes when an order arrives. The market maker who brings the order to the exchange initiates the auction with an associated limit price at which it is willing to trade. This 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 an auction message to other participants, providing details on the option contract, trade direction, and order size. Exchanges differ on whether the initiating market maker's starting limit price is included. Auctions typically run for 100 milliseconds. The initiating market maker's allocation depends on responses received: 100% if no other market maker matches the price, 50% with one other market maker, or 40% with additional competition.

Although auctions allow competition from multiple market makers, exchange rules and fees favor the initiating market maker, discouraging competition from other participants (Bryzgalova et al., 2023). Hendershott et al. (2026) estimate that the initiating market maker faces no competition in over 90% of auctions. Auctions allow market makers to provide price improvement, which brokers monitor using metrics such as the EQ ratio.

Auctions were originally permitted under a pilot program that required exchanges to report statistics on price improvement. These statistics revealed that price improvement was rare when the NBBO spread was at its minimum of one penny. This finding led exchanges to adopt rule changes when making the pilot program permanent. Some exchanges eliminated auctions when arrival-time spreads equal $0.01 (Miax, Amex, and BOX), while others required a minimum price improvement of $0.01 (Phlx, BX, EDGX, ISE, BATS, GEMX, and MRX). Essentially, these exchanges, which matched the NBBO in auctions when the spread was at a penny, could no longer do so. We study this 2017 rule change as an exogenous shock to the ability to internalize without quoting the best price.

The SEC approved these exchange proposals on January 18, 2017, which we use as our event date. The simultaneous, market-wide implementation is notable: auction exchanges adopted similar rules restricting auction use on the same date, suggesting active coordination with the SEC. This coordinated timing makes the 2017 rule change useful for studying how auction availability affects quote competition.

3. Data and sample

We use publicly available data from the Options Price Reporting Authority (OPRA), processed by the CBOE (formerly Livevol). This dataset includes comprehensive trade information: price, 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 Livevol consolidated trade-quote dataset provides a manageable alternative to processing the massive raw OPRA quote feed. Following Bryzgalova et al. (2023) and Hendershott et al. (2026), we focus on single-leg trades executed as either regular (auto-executed) or auction trades.

We use these data across different periods for our analysis. We examine May 2021, a recent period when auction trades are explicitly identified in OPRA, for the granular analysis of the linkages in our proposed mechanism in how auctions are used and the effects on quote competition. We confirm the May 2021 results for each month from January to June 2021. This analysis period is influenced by the availability of Livevol data with exchange quotes. CBOE has retrospectively removed exchange-specific quotes, leaving only NBBO quotes in the data. We use data from December 2016 to February 2017 for the analysis of the 2017 event described above. Finally, we use data from January 2011 to December 2016 to plot long-term trends in the use of auctions and quoted and effective spreads.

We apply several filters to the data. We exclude observations where either the trade price, NBB or the NBO equals zero, the NBB is greater than or equal to the NBO, the quoted spread exceeds $20, or the effective spread exceeds three times the quoted spread. We drop cancelled trades, those reported with zero contracts or those reported outside trading hours. We combine the Livevol data with Optionmetrics and CRSP. We restrict the sample to options on common stocks (CRSP share codes 10 and 11) with a price of at least $1, option series with less than 365 days to maturity, and options with standard settlement in Optionmetrics.

Table 1 describes the May 2021 sample. We calculate daily averages and then average across days in the month. On an average day, the sample includes approximately 2,444 option classes and 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 on an average day. Consistent with previous studies of single-leg trades, most trades are in call options.

Bid-ask spreads are large in options markets (e.g., Muravyev and Pearson, 2020). The average quoted spread in our sample is close to 9% on an average day; effective spreads are smaller at 6.87%. The EQ ratio, which measures price improvement, with lower values indicating larger improvement, averages 0.82. On an average day, 19.4% of trades occur in auctions. Eleven of the 16 exchanges offer auctions, and these auction exchanges account for 53.3% of trades.

Table 2 disaggregates the sample by exchange type and trade type. 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 scope for price improvement. The difference in EQ ratios between auction and regular trades is large: auction trades have an average EQ ratio of 0.49, indicating that orders executed in auctions pay effective spreads roughly half of quoted spreads, while regular trades show an average EQ ratio of 0.90. Thus, auctions frequently occur at prices that are not displayed to the market.

4. Results

4.1 Conceptual framework

Internalization allows market makers to trade without posting quotes and creates a disincentive to compete on quotes. Competing through quotes reduces the profits on internalized volume, since these executions are benchmarked to the prevailing best prices. Brokers' use of EQ ratios to evaluate execution quality reinforces this disincentive. At identical execution prices, the EQ ratio appears more favorable when quoted spreads are wider. Two forces encourage quote competition in options, but are partially mitigated in practice. First, the small-trade priority mechanism described in Section 2 rewards market makers who quote at the best price with execution priority, though limited competition in auctions reduces the need to quote aggressively. Second, market makers who do not quote competitively risk losing non-internalized orders, though this flow is likely to be more informed and therefore less attractive.

Bloomfield and O'Hara (1998) show that reduced quoting by internalizing market makers widens the NBBO, but only if non-internalizing market makers do not compete aggressively to narrow quotes.

Several features of options markets may limit such competition. Exchange rules favor registered market makers over outside liquidity providers. Non-internalizers may also be able to undercut auction exchange spreads without narrowing them to competitive levels. Whether non-internalizing market makers provide sufficient competitive discipline on quotes in options markets is an open empirical question.

We formalize this core framework in a model presented in Appendix A, building on the price-referencing framework of van Kervel and Yueshen (2024). Two market makers supply liquidity: a non-internalizer who quotes on the exchange only, and an internalizer who also quotes but executes order flow at prices benchmarked to the NBBO. When the internalizer considers tightening the displayed quote by one tick, she faces a trade-off. Improving the quote captures more public exchange flow but reduces the per-unit profit on benchmarked internalized volume. In equilibrium, the non-internalizer sets the widest spread that the internalizer will not undercut, and the resulting NBBO spread increases in the ratio of internalized to public volume. Since retail flow constitutes a larger proportion of volume in options than in equities, the model suggests that wider spreads are more likely in options. The model is deliberately stylized to isolate the price-referencing channel, while taking order routing and internalized volume as given rather than modeling entry, inventory, or endogenous flow.

The anti-competitive effect operates through this price-referencing channel and holds even if all order flow is equally uninformed. This distinguishes it from adverse selection theories (Easley, Kiefer, and O'Hara, 1996), where internalizers cream-skim uninformed flow. The two channels are complementary. The price-referencing mechanism also requires imperfect quote competition, consistent with the high profitability and concentration of options market making (Hu, Kirilova, Muravyev, and Ryu, 2023).

4.2 The use of the auction mechanism

We examine whether market makers use auctions tactically to internalize order flow when they are not quoting the best price. 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/O 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.[12] 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 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. Indeed, 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, exchanges with more auction trading are less likely to be at the best quotes at the time of the trade. The average daily correlation between the two variables for the 16 exchanges is -0.87.[13]

We examine 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

---

[12] 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. For midpoint trades, if either the exchange's bid equals the NBB or its ask equals the NBO, we set the measure equal to one. Results remain similar.

[13] Outside of auctions, trades can occur at exchanges not displaying the best price through hidden liquidity in price improvement orders (Nasdaq, C2, BATS) or order flashing (CBOE, AMEX, PHLX, ISE, Miax). Order flashing allows market makers to match or improve the NBBO when the exchange is not at the best price. However, flashing is not effective for internalization since the market maker bringing the order has no priority in trading with it.

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. A vector of control variables **X** includes the NBBO quoted spread at the time of the trade, the NBBO quote midpoint at the time of the trade, the tick size, and the delta, gamma, and vega of the option series (drawn from Optionmetrics). Models 1 and 2 include underlying stock and date fixed effects, while models 3 and 4 include underlying stock and exchange fixed effects. Standard errors are clustered at the stock and date level.

The first model sets the baseline and is estimated without our variable of interest. Consistent with Hendershott et al. (2026), auctions are more likely when quoted spreads are wider, likely because there are greater opportunities for price improvement. The second model adds *ExchangeBestWhenTrade* and shows 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.[14] Models 3 and 4 include 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. We also estimate a model with a combined exchange-stock-day fixed effect with similar results.

In Table 4, we examine whether price improvement for auction trades differs based on whether the exchange is quoting the best price or not. Table 3 shows that auction trades are more likely when the

[14] 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.

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 are used tactically to 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 includes 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, this analysis compares auction trades that occur when the exchange is quoting the best price and auction trades that occur when it is not.

The coefficient on *ExchangeBestWhenTrade* shows that when an exchange is quoting the best price, there is a 17 percentage point greater likelihood of the trade executing inside the NBBO. That is, 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 being used by market makers to execute trades when their quotes are not at the best prices available in the market. These 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.

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

4.3 Quote competition

We examine whether the results discussed above 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 one 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.[16] We create a similar indicator for the five non-auction exchanges and calculate the difference (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 for the same option series. Since there is no structural impediment for either set of exchanges to quote the best price, the univariate differences provide a meaningful result without additional controls. We average these variables each day and report 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 tests of significance are based on standard errors 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, relevant for both liquidity and price discovery. Our data do not allow us to directly observe which exchanges improve on the NBBO prices. To work within this limitation, 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 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

[16] The variable construction adjusts for exchange level heterogeneity. For example, an average across exchanges may be affected by a small, less competitive exchange.

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, see, e.g., page 261 of CBOE (C1) Exchange rule book). At the other extreme, many exchanges at the NBB/O likely reflect easier quoting conditions, where the marginal value of each individual quote is lower.

Table 5 disaggregates results by the number of exchanges at the NBB and NBO, grouped into five buckets: one, two, three, four to six, and seven to 16 exchanges. Focusing on the NBB, when only one exchange is at the best bid, it is a non-auction exchange 64.7% of the time versus 35.4% for auction exchanges. 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 an 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 moment that affect quoting propensity affect both auction and non-auction exchanges. The regression includes stock and date fixed effects. We also present a specification with the control variables used in the previous tables. Standard errors are clustered by stock and date. The results are almost identical to the univariate results in Table 5. Across specifications, auction exchanges are approximately 12 percentage points less likely to be at the NBB/O than non-auction exchanges.[17]

[17] Appendix Table 1 reports exchange-level quoting statistics, sorting exchanges by auction volume share. Exchanges with higher auction shares are less likely to quote at the NBB or NBO: the average daily correlation is −0.75 on both sides. Thus, the auction/non-auction contrast is not driven by any single exchange.

Anand et al. (2016) find that make-take pricing creates incentives to improve the NBBO. Our auction/non-auction exchange classification overlaps with the exchange pricing mechanisms they study. However, quote competition differed during their sample because retail internalization occurred through order-book priority and auctions were not widely used for retail flow. Consistent with this difference, PFOF exchanges are at the best quote for 93% of the volume they trade in Anand et al. (2016), compared with 66% for all auction-exchange trades and 34% for auction trades in our sample. While Anand et al. (2016) show that NYSE Arca's switch to make-take increased its tendency to set the NBBO, PFOF exchanges still dominated NYSE Arca in quote competitiveness after the switch. In Section 5, we strengthen the link between auctions and quote competitiveness by examining an exogenous event that affects auctions but not exchange pricing.

We examine whether the results from May 2021 extend 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 consistent with those for May 2021. We note that these are the last months for which exchange-specific quotes are available to us, as CBOE has retrospectively removed exchange-level identification from the data.

4.4 Auction market maker behavior on a non-auction exchange

The mechanism we propose involves internalizing market makers pulling back from aggressive quoting, while non-internalizers may undercut their quotes. Our results so far show that market makers on auction exchanges do not compete aggressively on quotes. As Bryzgalova et al. (2023) and Ernst and Spatt (2026) emphasize, options markets are dominated by large firms that operate across exchanges. A firm that internalizes on an auction exchange may also make markets on a non-auction exchange. This structure creates an overlap between non-auction market making and auction access elsewhere within the same firm. In this section, we examine how a firm's access to auctions on one exchange affects its 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 that helps us in this analysis is that since only a few large firms serve as DMMs across all option exchanges, the same firm is frequently the DMM for a given option class on multiple exchanges. In our Arca sample, 79.5% of option classes (representing 84.2% of observations) are handled by an Arca DMM who also serves as DMM for the same option class on at least one other exchange. Since all other exchanges that use DMMs are auction exchanges, these overlapping assignments give the Arca DMM access to an auction mechanism on another exchange. At the same time, some option classes have Arca DMMs with no such overlapping assignments. This within-DMM variation (across option classes with and without access to auctions) allows us to examine whether our quote competitiveness results spill over to non-auction exchanges.

Comparing across option classes within a DMM's portfolio raises the concern that option-class characteristics may affect an exchange's propensity to quote at the best price. To address this, we construct a within-observation difference measure for each Arca-listed option. This difference is between an indicator variable for Arca quoting at the NBB (or NBO) and an indicator for any of the four other non-auction exchanges quoting at the NBB (or NBO). Because this difference is calculated at the same moment for the same option series, it nets out option-class characteristics and isolates variation specific to quoting characteristics of non-auction exchanges. Table 7 presents regressions with this difference as the dependent variable. The key explanatory variable is "*DMM on Auction Exchange*," an indicator equal to one if the Arca DMM for a given option class also serves as DMM for that class on at least one auction exchange.[18]

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 are based on standard errors clustered by underlying stock and date. Models 3 and 4 present results for NBO.

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 for both the NBB and the NBO. Model 2 coefficients on control variables are suppressed in the table. Both models include date fixed effects, and standard errors are clustered by underlying stock and date.

We find a negative coefficient on *DMM on Auction Exchange* for three of the five DMM firms. However, two of the five firms (DMM1 and DMM4), have samples that tilt overwhelmingly toward option classes with overlapping auction exchange assignments, limiting meaningful comparison. 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 involve an overlapping DMM assignment. DMM2 tilts the other way with only 5.6% of observations with overlapping DMM assignments. Given the lack of variation, we do not draw conclusions from the analysis for DMM1, DMM2, or DMM4. DMM3, by contrast, has a reasonable split between option

[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.

classes with and without overlapping assignments. We find that DMM3 is 9.9 percentage points less likely to be at the NBB and 8.9 percentage points less likely to be at the NBO when it also serves as DMM on an auction exchange, relative to option classes where it does not have an overlapping 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.

5. Auctions and spreads

We examine the implications of auctions on quoted and effective 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.

5.1 Auction restrictions and their effect on spreads

On January 18, 2017, the SEC simultaneously 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. As discussed earlier, 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.

The event has unique advantages for our analysis. It is the largest shock to auction availability in U.S. options markets in recent years and has a precise implementation date, making it well suited for a difference-in-differences design. Unlike events that introduce new features, which are usually adopted gradually, this change prohibits an action, forcing immediate compliance on the effective date. The event speaks directly to our mechanism of auctions disconnecting quoting and trading. Specifically, the rule change makes auctions infeasible when quoted spreads equal one cent. Market makers can still internalize these orders, but only through the limit order book, which requires them to be at the best quote before order arrival. The change therefore restores the link between displayed quote competition and trade execution. This allows us to revisit our earlier results using an exogenous shock and to extend the analysis to spreads.

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. Anand, Hua and Puckett (2025) describe and validate this approach. 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 a reasonable proxy for auctions.

Figure 3 plots the difference in the proportion of stopped trades 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 stay flat at zero. For auction exchanges, the difference is positive in the pre-period, 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, indicating 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 on auction exchanges 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 on auction exchanges decline by 11 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 3. The pre-period average for the treatment sample is 38%. Thus, the decline is economically significant.[19,20]

Model 2 shows that, as auction use is restricted, auction exchanges are more likely to be at the best quote when they trade. 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. We note that this analysis focuses on change in auction exchanges' quote competitiveness related only to a restriction on auction use, and controls for other market structure features, including the pricing structure (PFOF or make-take) used by exchanges.

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 (from a pre-period average of 2.6 cents) for the high-bind sample after the rule change. 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 only percentage spreads declining statistically significantly. The expectations for effective spreads are also less clear. Narrowing quoted spreads would narrow effective spreads for trades that occur at the quote,

[19] Appendix Figure 2.A shows weekly coefficients for our estimation. Week -1 (ending on January 17, 2017) is the reference period. Week +1 starts on the event date of January 18, 2017. The figure plots the coefficients for *Highbind*RelativeWeek* indicating the difference between treatment and control sample in the weeks surrounding the event. The figure shows a sharp drop in stopped trades for the high bind sample after the event date.

[20] Auction incentives vary with trade size. One-contract orders cannot be split with a competing market maker, so the initiating market maker can trade the full order even if another participant matches the auction price. For one- to five-contract orders, exchange rules also allow DMMs to internalize when they are quoting the best price at order arrival, potentially reducing auction use relative to larger trades. Following Ernst and Spatt (2026), Appendix Figure 3 examines auction changes by trade size around the 2017 rule change. The effects are similar across size groups.

but may also lower opportunities for price improvement. The magnitude of the effective percentage spread reduction is about half of the quoted spread reduction. Because quoted spreads fall more than effective spreads, the EQ ratio increases (Model 5).[21]

Panel A of Table 10 reports outcomes for all trades, including non-retail trades. Because internalized retail trades are difficult to identify outside auctions, Panel B uses small trades of one to five contracts as a proxy for retail activity. Although this subsample may still include non-retail trades, it likely better captures retail executions. The results are similar to Panel A: effective spreads decline insignificantly, while EQ ratios increase significantly. We omit quoted spreads here because Panel A uses the larger quote sample, which better captures market maker quoting behavior before trade arrival.

These results also 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 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.

5.2 Competition in auctions

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, their results 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.

[21] Appendix Figures 2. E through 2.I plot weekly coefficients for the Table 10 outcomes. Figures 2.E and 2.F show discontinuous declines in dollar and percentage quoted spreads, while effective-spread changes are smaller, consistent with Table 10. Although many weekly coefficients are not statistically significant, likely reflecting lower power, their patterns align with the main results.

We follow Hendershott, et al. (2026) 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 cases where no other market maker responded to trade in the auction.[22] 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.

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 motivated by the observation that price improvement is extremely rare when the spreads are binding at a penny. Thus, these situations are the ones where competing market makers are likely to match the quoted price, and no market maker offers price improvement. Column 2 shows that a competitive auction is 11.9 percentage points more likely when the spreads are binding at one cent. Column

[22] One-trade cases may include auctions with competition when one market maker strictly dominates on price. Some exchanges may also report consolidated trades, making competitive auctions harder to identify. Because we focus on how competition interacts with spread changes rather than on its exact level, these reporting differences are unlikely to drive our results.

3 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. This is consistent with the winner's curse in auctions predicted by Ernst, Spatt and Sun (2025). We separately examine whether our measures of competition change in the post period using the same difference in differences specification as in Tables 9 and 10. We do not find a significant change (Appendix Table 4).

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 is different from that conceived in Bloomfield and O'Hara (1998). However, it may be that market makers compete more aggressively on quoted prices outside of auctions. 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. For example, we divide option 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. 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. We report similar results for *Highbind* equals zero subsample in Appendix Table 5.

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.

6. Aggregate trends in auctions and spreads

In this section, we examine longer-term trends in spreads and the use of auctions in options markets. While market-wide trends cannot isolate causal mechanisms, they provide useful context on how auctions and spreads have evolved together, and regulators and market participants routinely use such trends to assess the health of the market structure (see, e.g., SEC, 2026).

Auctions in options were originally designed to facilitate larger orders, with early auction mechanisms explicitly emphasizing block trades. To support this objective, exchange rules placed greater restrictions on auctions for orders smaller than 50 contracts than for larger orders. For example, several exchanges required price improvement in auctions for smaller orders, while larger orders could be priced to match the prevailing quotes. Exchanges started to eliminate the differential treatment in the 2013-2014 period (see, for example, SR-PHLX-2013-76, SR-MIAX-2014-56, SR-ISE-2014-35).[23] During this period, MIAX significantly expanded its market share by capitalizing on auctions for sub-50-contract orders. These changes helped convert auctions from a block-trading utility into a channel for retail internalization, but the gradual adoption does not provide a clean discontinuity amenable to an event study analysis.

We plot three market-wide series in Figure 2: percentage quoted and effective spreads for single-leg trades, and the share of single-leg trades that execute in auctions (on the right scale) over January 2011 through December 2016. 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 similar to the

[23] Exchanges that created auction mechanisms after this period adopted similar rules allowing auctions to match the quoted prices regardless of order size.

tests in Section 5. We build each day's statistics at the option-class level and then average across option classes using contract-volume weights and plot 30-day moving averages to smooth noise.

Figure 2 shows that the auction share rises quickly in 2014, from about 6% early in the sample to over 15% after 2015, with peaks approaching one-fifth of trades. Around the same time, quoted spreads increased much more than effective spreads. For example, quoted spreads increased from an average of about 6.3% in January 2013 to 11.8% in December 2014, while effective spreads increased from 5.3% to 8.5% over the same period. The gap between quoted and effective spreads increases from around 100 basis points early in the sample to about 300 basis points by the end of 2014 and stabilizes at that level thereafter. This increasing divergence between quoted and effective spreads as auctions become more prevalent is consistent with the implications from our earlier quote competition and 2017 event analyses.

The divergence between quoted and effective spreads matters even if effective spreads rise by less. As the two series diverge, quoted spreads become less useful as an ex-ante measure of expected transaction costs and available liquidity. Wider quoted spreads also raise the immediacy cost for orders taking displayed liquidity and are less useful as a benchmark for execution quality. Price improvement statistics, such as EQ ratios, mechanically improve when quoted spreads widen, even if effective spreads do not fall. In 2013-14, the larger increase in quoted spreads relative to effective spreads reduced the EQ ratio from 0.87 to 0.78, which we attribute to greater market maker discretion rather than improved execution quality. Wider quotes also create more room for broker-market maker bargaining over PFOF and execution quality. Consistent with this view, Huang et al. (2025) report large differences in PFOF and price improvement across brokers, and Hendershott et al. (2026) show that auctions are more likely when quoted spreads are larger.

The trends in Figure 2 do not appear to be a simple byproduct of changes in volatility or underlying stock quoted spreads. Appendix Figure 4 shows that underlying stock spreads are flat to modestly declining over the period. Market-wide volatility, proxied by the VIX index, also shows no sustained trends. We are also mindful of composition effects that can influence long term analyses. Appendix Figure 5 replicates Figure 2 for a subsample of options on S&P 500 stocks that are at the money (moneyness between 0.8 and 1.2), have more than 10 days to expiration, and are standard monthly options (i.e., it drops all weekly options). This subsample shows similar trends to Figure 2. Furthermore, we focus on the divergence between quoted and effective spreads, which requires explanations beyond factors that affect both series.

Overall, our detailed analysis in previous sections predicts a positive association between internalization via auctions and aggregate quoted spreads. Consistent with this prediction, we find that as auction usage more than doubled, quoted spreads increased substantially and diverged from effective spreads. We acknowledge that cleanly isolating the effect of internalization on spreads in long-term time series is difficult because these trends may also reflect other changes in market conditions, product composition, technology, and exchange pricing.

7. Conclusion

Whether internalization weakens quote competition is a longstanding question in market microstructure. Theory predicts that it should, because internalization lowers quote competition and increases adverse selection. Yet empirical studies in equities have generally found limited evidence that internalization widens spreads or weakens quote competition. Options provide a better laboratory. Internalization is salient for market makers and brokers because it constitutes a large proportion of the market. Further, internalization is observable through on-exchange auctions, and the same market makers that internalize retail orders are also central to quote setting. We are the first to test whether internalization reduces quote competition in options markets.

We first show that auctions weaken quote competition. Auction trades are disproportionately more likely when the auction exchange is not quoting the best price, and these trades are more likely to match, rather than improve on, NBBO prices. This pattern suggests that auctions allow market makers to trade at NBBO prices without first displaying competitive quotes. Consistent with this mechanism, auction exchanges are less likely to quote at the NBBO and especially less likely to set the best price. We also find spillovers across exchanges: when a market maker has auction access for an option on one exchange, it quotes less competitively for the same option on non-auction exchanges.

We then examine whether weaker quote competition affects aggregate market quality. A 2017 rule change that restricted auctions when spreads were at one cent reduces auction use, increases auction exchanges' propensity to quote at the NBBO, and narrows quoted spreads. Effective spreads decline less, because narrower quoted spreads also reduce the room for price improvement. Long-run aggregate patterns are consistent with this evidence. As auctions expanded from a block-trading mechanism into a retail internalization channel during 2013–2014, auction usage more than doubled, and quoted spreads increased sharply while diverging from effective spreads.

These findings qualify the interpretation of price improvement in options auctions. Retail traders may receive price improvement on individual orders, but that improvement is measured relative to quotes that internalization itself may widen. As a result, execution-quality metrics such as the effective-to-quoted spread ratio can improve mechanically when quoted spreads widen, even if actual trading costs do not fall. More broadly, our results show that internalization can reduce quote competition when market makers can access order flow without first displaying competitive prices. This tradeoff is central to policy debates over auctions, PFOF, and market design in both options and equities.

1 Appendix A: Conceptual Framework

This appendix presents a simple model that formalizes a specific channel through which internalization can widen *quoted* spreads. The mechanism is simple: internalized executions are typically benchmarked to NBBO. When a market maker tightens the public quote, it improves the benchmark and thereby reduces the profit it earns on all internalized volume priced off that NBBO. This creates an opportunity cost of quote improvement that can decrease competition.

The model simplifies van Kervel and Yueshen (2024) to focus on a single channel. It takes the volume of public exchange flow and benchmarked internalized flow as given, then derives how the equilibrium the NBBO spread depends on these quantities. The goal is not to build a complete model of market making with entry, inventory, and endogenous order routing. Rather, the model isolates the price-referencing mechanism and provides a transparent mapping from internalization intensity to quoted spreads.

The model is agnostic about whether internalized flow is informed. The mechanism operates through the opportunity cost of quote improvement. In adverse-selection theories, internalizers cream-skim uninformed flow, leaving exchanges with more toxic order flow and forcing wider spreads to protect against informed traders. The two mechanisms are complementary as the price-referencing channel would operate even if all order flow were equally uninformed. Internalized executions benchmark to the NBBO which creates an incentive to keep spreads wide, independent of information asymmetry.

1.1 Setup

Consider a single quoting period around a fixed fundamental value, normalized to zero. A symmetric bid-ask spread $S \geq 0$ is quoted with a bid at $-S/2$ and an ask at $+S/2$. With equally likely buys and sells, expected gross revenue per executed unit equals the half-spread $S/2$. We abstract from inventory risk and adverse selection; these can be added as a per-unit cost c without changing the comparative statics.[1]

There are two liquidity suppliers. A *pure* market maker P quotes only on the exchange. An *internalizing* market maker I also quotes on the exchange but additionally receives order flow that it executes through internalization or auction mechanisms at prices benchmarked to the prevailing NBBO. The parameter θ below captures the internalizer's share of public exchange flow when it matches the incumbent quote.

[1] With per-unit cost $c \geq 0$ (capturing adverse selection, inventory, or fees), replace each $S/2$ below with $S/2 - c$. The equilibrium spread shifts up by $2c$, but the effect of internalization on spreads is unchanged.

Order flow is exogenous. A mass $Q_{Pub} > 0$ of public orders routes to the exchange and executes against the best displayed quote. The internalizer also receives a mass $K \geq 0$ of benchmarked internalized orders that it executes at the prevailing NBBO. The parameter K measures internalization intensity, and larger K means more of the internalizer's volume is priced off the public quote.

Two institutional features are important. First, prices are discrete. Feasible spreads lie on the tick grid $S \in \{\Delta, 2\Delta, 3\Delta, \dots\}$ where $\Delta > 0$ is the tick size. This discreteness is economically important in options markets, where a typical tick is five cents, while many actively traded options have prices around two dollars, so one-tick quote improvement is a nontrivial price concession. Second, execution at the best quote depends on the exchange's allocation rule, such as price-time priority, pro-rata allocation, or a hybrid. We summarize this with a parameter $\theta \in [0, 1)$: if I matches the incumbent best spread, it captures a fraction θ of public exchange flow; the remainder goes to the incumbent. If I improves the quote by at least one tick, it becomes the new NBBO and captures the public exchange flow.[2]

Finally, the model focuses on the internalizer's incentive to step ahead of the incumbent public quote. The public side is represented by the marginal public quoter currently setting or disciplining the NBBO.[3] This keeps the mechanism transparent while allowing the internalizer's share of exchange flow when matching the quote to vary with market design.

1.2 Equilibrium spread

We characterize the spread that can be sustained when the internalizer can step ahead of the public quote. Take as given an incumbent best quote with spread $S_P \in \{\Delta, 2\Delta, \dots\}$ posted by the marginal public quoter. The internalizer then decides whether to step ahead. I can retreat and does not improve the quote; it may match S_P and share public flow according to θ, but the NBBO remains S_P. I can also compete by improving the displayed quote by one tick to $S_I = S_P - \Delta$, becoming the new NBBO and capturing the public exchange flow. Compete action is feasible only if $S_P \geq 2\Delta$; if the incumbent spread is already at the tick floor, it cannot be improved further.

[2]Under strict price-time priority with the incumbent having queue priority, $\theta \approx 0$. Under pro-rata allocation, $\theta > 0$ reflects the possibility of winning executions by matching rather than improving. Allowing $\theta > 0$ strengthens the mechanism, but the key channel is the benchmarked internalized flow K.

[3]The two-player formulation can be interpreted as a reduced form for a market with multiple public market makers. If m public market makers and the internalizer share public exchange flow at a common quote, the parameter θ can be interpreted as the internalizer's equilibrium allocation share when it matches the best quote; under equal sharing, $\theta = 1/(m+1)$. The spread characterization continues to apply provided that the marginal public quote is itself stable, meaning that no public market maker has a profitable one-tick step-ahead deviation at the candidate spread. This condition holds, for example, if public market makers face offsetting quoting costs or capacity or queue-position constraints.

The spread sustained in this incumbent-internalizer game is the maximal incumbent spread at which the internalizer does not profit from stepping ahead. We describe the internalizer's incentive to undercut by one tick, and the same logic applies whenever I considers quote improvement in a dynamic environment.

Restricting attention to one-tick improvements is without loss. Any action that increases execution probability on public flow must tighten the NBBO by at least Δ, and tightening by more than Δ is strictly dominated because it reduces per-unit revenue on both public and internalized executions.

If I retreats, the NBBO spread remains S_P. The incumbent P executes fraction $1-\theta$ of public exchange flow at half-spread $S_P/2$, while the internalizer executes fraction θ of public exchange flow plus its benchmarked internalized flow K, all priced at the NBBO:

$$\pi_P^R(S_P) = \frac{S_P}{2}(1-\theta)Q_{Pub}, \qquad \pi_I^R(S_P) = \frac{S_P}{2}\big(K+\theta Q_{Pub}\big). \tag{1}$$

If instead I improves the quote by one tick, the NBBO tightens to $S_P - \Delta$. The internalizer captures public exchange flow and continues to internalize flow, but now at the tighter benchmark:

$$\pi_P^C(S_P) = 0, \qquad \pi_I^C(S_P) = \frac{S_P-\Delta}{2}(Q_{Pub}+K). \tag{2}$$

The comparison between (1) and (2) illustrates the mechanism. Quote improvement gives the internalizer the public exchange flow that would otherwise be executed by the incumbent. But it also reduces the per-unit margin on all volume executed at the NBBO, including internalized flow. The incremental cost relative to standard quote competition is the margin lost on internalized volume K.

We solve the model by backward induction, assuming ties are broken in favor of retreat. Fix S_P and compare the internalizer's profits from retreating versus competing. Using (1) and (2), I retreats if retreat yields weakly higher profit:

$$\begin{aligned} \pi_I^R(S_P) \geq \pi_I^C(S_P) \quad &\iff \quad \frac{S_P}{2}\big(K+\theta Q_{Pub}\big) \geq \frac{S_P-\Delta}{2}(Q_{Pub}+K) \\ &\iff \quad S_P \leq \Delta\frac{Q_{Pub}+K}{(1-\theta)Q_{Pub}} = \frac{\Delta}{1-\theta}\left(1+\frac{K}{Q_{Pub}}\right). \end{aligned} \tag{3}$$

Larger benchmarked internalized volume K makes undercutting less attractive because quote improvement lowers the margin on more internalized executions. A larger matching share θ also makes undercutting less attractive because the internalizer already receives more public exchange flow when it matches the incumbent quote.

Anticipating (3), the incumbent quote can be sustained only if S_P is at or below the threshold. Above the threshold, the internalizer steps ahead and the incumbent loses public exchange flow. At or below the threshold, the internalizer is willing to retreat. Since the incumbent's profit from a sustained quote is increasing in S_P, the equilibrium public spread is the largest feasible tick spread that keeps the internalizer willing to retreat.

Writing $S_P = \ell\Delta$ for integer $\ell \geq 1$, the retreat condition becomes

$$\ell \leq \frac{1 + K/Q_{Pub}}{1-\theta}. \tag{4}$$

The equilibrium spread is therefore

$$S^* = \Delta \left\lfloor \frac{1 + K/Q_{Pub}}{1-\theta} \right\rfloor. \tag{5}$$

Comparative statics. Equation (5) implies that S^* is weakly increasing in internalized volume K and weakly increasing in the internalizer's matching share θ. Because quotes lie on a tick grid, the mapping is stepwise. S^* is constant over ranges of K and θ, and changes by one tick when the continuous threshold crosses an integer. To consider the continuous relaxation, we define

$$S^c(\theta) = \Delta \frac{Q_{Pub} + K}{(1-\theta)Q_{Pub}} = \frac{\Delta}{1-\theta}\left(1 + \frac{K}{Q_{Pub}}\right), \tag{6}$$

which is the spread that makes the internalizer exactly indifferent. The equilibrium spread (5) is the largest feasible tick multiple at or below $S^c(\theta)$. Since empirically measured spreads are typically averaged over time (e.g., time-weighted NBBO spreads), averaging across discrete quote states yields an approximately smooth relationship. Equation (6) provides an approximation. The spread increases in internalization intensity K and in the internalizer's matching share θ.

We re-write $K = \alpha\bar{K}$, where $\bar{K}$ is a baseline mass of internalized retail flow and $\alpha \in [0,1]$ captures the effective ability to internalize it (for example, because of eligibility rules). Substituting into (6):

$$S^c(\theta, \alpha) = \frac{\Delta}{1-\theta}\left(1 + \alpha\frac{\bar{K}}{Q_{Pub}}\right). \tag{7}$$

Changes that reduce effective internalization capacity (lower α) tighten quoted spreads.

Context. The model is inspired by van Kervel and Yueshen (2024), who show that price referencing softens competition when execution prices in one segment are tied to quotes posted in another. The present setup adopts their framework to the U.S. equity options setting, focusing on the public NBBO spread. As in their model, a liquidity supplier earns rents on a segment whose execution prices reference the public quote; here this is the benchmarked internalized volume K executed at the NBBO.

Relative to van Kervel and Yueshen (2024), we simplify the environment to obtain a transparent characterization of the quoted spread. We take Q_{Pub} and K as exogenous. We also introduce a tick grid and a reduced-form sharing parameter θ that captures how much public exchange flow the internalizer receives when it matches the incumbent quote. These simplifications remove additional channels while preserving the core incentive: when internalized executions benchmark to the NBBO, quote improvement reduces profits on benchmarked volume and weakens the incentive to compete for public exchange order flow.

References

Anand, A., Hua, J., and McCormick, T., 2016, Make-Take Structure and Market Quality: Evidence from the U.S. Options Markets, Management Science 62, 3271-3290.

Anand, A., Hua, J., and Puckett, A., 2025, Has retail trader sophistication declined in options markets?, Working paper, Syracuse University.

Barardehi, Y., Bogousslavsky, V., and Muravyev, D., 2025, Unpacking Retail Trading Costs: the Role of Options Trading and Limit Order Usage, Working paper, Chapman University.

Battalio, R. H., 1997, “Third Market Broker-Dealers: Cost Competitors or Cream Skimmers?” Journal of Finance 52(1), 341-352

Battalio, R., Greene, J., and Jennings, R., 1997, Do Competing Specialists and Preferencing Dealers Affect Market Quality?, Review of Financial Studies, 10, 969-993.

Battalio, R. and Holden, C.W., 2001. A simple model of payment for order flow, internalization, and total trading cost. Journal of Financial Markets, 4(1), pp.33-71.

Battalio, R. H., and Jennings, R. H., 2026, Wholesaler execution quality, Management Science 72, 4163–4182.

Battalio, R., Jennings, R., and Selway, J., 2001, The Relationship Among Market-Making Revenue, Payment for Order Flow, and Trading Costs for Market Orders. Journal of Financial Services Research 19, 39–56.

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

Bessembinder, H., 2003, “Issues in Assessing Trade Execution Costs,” Journal of Financial Markets 6, 233–257

Bessembinder, H. and Kaufman, H.M., 1997. A cross-exchange comparison of execution costs and information flow for NYSE-listed stocks. Journal of Financial Economics, 46(3), pp.293-319.

Bloomfield, R., and O'Hara, M., 1998, Does Order Preferencing Matter?, Journal of Financial Economics, 50, 3–38.

Brown, T., Johnson, T., Kothari, S.P., and So, E., 2024, Anatomy of Trading Costs for Retail Investors: Savings from Off-Exchange Execution, Working paper, University of Texas, Austin.

Bryzgalova, S., Pavlova, A., and Sikorskaya, T., 2023, Retail Trading in Options and the Rise of the Big Three Wholesalers, *The Journal of Finance*, 78, 3465-3514.

Chordia, T., and A. Subrahmanyam, 1995, “Market Making, the Tick Size, and Payment-for-Order Flow: Theory and Evidence,” Journal of Business 68(4), 543-575.

Chung, K., Chuwonganant, C., and McCormick, T., 2004, Order preferencing and market quality on NASDAQ before and after decimalization, Journal of Financial Economics, 71(3), 581–612.

Citadel, 2005, Comment letter Re: Chicago Board Options Exchange Automated Improvement Mechanism Proposal (SR-CBOE-2005-60) and American Stock Exchange Price Improvement Auction Proposal (SRAMEX-2004-107), November 8, 2005.

Comerton-Forde, C., K. Malinova, and A. Park, 2018, "Regulating Dark Trading: Order Flow Segmentation and Market Quality," Journal of Financial Economics 130(2), 347–366.

Dutta, K., and Madhavan, A., 1997, "Competition and Collusion in Dealer Markets." Journal of Finance, 52, 245–276.

Dyhrberg, A., Shkilko, A., and Werner, I., 2025, The retail execution quality landscape, Journal of Financial Economics 168, 104051.

Easley, D., Kiefer, N., and O'Hara, M., 1996, Cream Skimming or Profit Sharing? The Curious Role of Purchased Order Flow, Journal of Finance, 51, 811–834.

Ernst, T., Malenko, A., Spatt, C., and Sun, J., 2024, What Does Best Execution Look Like?, Working paper, University of Maryland.

Ernst, T., and Spatt, C., 2026, Payment for order flow and option internalization, Review of Financial Studies, hhaf108.

Ernst, T., Spatt, C., and Sun, J., 2025, Would Order-By-Order Auctions Be Competitive? Journal of Finance, 80, 1879-1927.

Farley, R., Kelley, E. and Puckett, A., 2025, Dark trading volume and market quality: A natural experiment, Journal of Corporate Finance, 91, 102742

Hansch, O., N. Y. Naik, and S. Viswanathan, 1999, "Preferencing, Internalization, Best Execution, and Dealer Profits," Journal of Finance 54(5), 1799-1828.

Hatheway, F., A. Kwan, and H. Zheng, 2017, "An Empirical Analysis of Market Segmentation on U.S. Equity Markets," Journal of Financial and Quantitative Analysis 52(5).

Hendershott, T., Khan, S. A., and Riordan, R., 2026, Option auctions, Review of Financial Studies 39, 783–834.

Hu, J., Kirilova, A., Muravyev, D. and Ryu, D., 2023. Options market makers. Available at SSRN 4633451.

Huang, X., Jorion, P., Lee, J., and Schwarz, C., 2023, Who Is Minding the Store? Order Routing and Competition in Retail Trade Execution, Working paper, Washington University in St. Louis.

Huang, X., Jorion, P., and C. Schwarz, 2025, Some Anonymous Options Trades Are More Equal than Others, Working paper, Cornell SC Johnson College of Business.

Kandel, E., & Marx, L., 1999, Payments for order flow on Nasdaq, Journal of Finance, 54, 35-66.

Lescourret, L., and Robert, C., 2011, Transparency matters: Price formation in the presence of order preferencing, Journal of Financial Markets,14, 227–258.

Muravyev, D., and Pearson, N., 2020, Options Trading Costs Are Lower than You Think, The Review of Financial Studies, 33, 4973–5014.

O'Hara, M., and M. Ye, 2011, "Is Market Fragmentation Harming Market Quality?" Journal of Financial Economics 100(3), 459–474.

Parlour, C., and Rajan, U., 2003, Payment for order flow, Journal of Financial Economics, 68, 379-411.

Peterson, M., and Sirri, E., 2003, Order Preferencing and Market Quality on U.S. Equity Exchanges, The Review of Financial Studies, 16, 385–415.

Schwarz, C., Barber, B. M., Huang, X., Jorion, P., and Odean, T., 2025, The actual retail price of equity trades, Journal of Finance 80, 2507–2541

Securities and Exchange Commission (SEC), 2004, Competitive Developments in the Options Markets, Proposed Rule, 17 CFR 240, Release No. 34-49175, File No. S7-07-04.

Securities and Exchange Commission (SEC), 2013, "Order Granting Approval to Proposed Rule Change Relating to the Discontinuation of the Differentiation of Price Improvement XL Orders of Less Than 50 Contracts," Release No. 34-70654, File No. SR-Phlx-2013-76.

Securities and Exchange Commission (SEC), 2021, Staff Report on Equity and Options Market Structure Conditions in Early 2021, October 14, 2021.

Securities and Exchange Commission (SEC), 2022, Order Competition Rule, 17 CFR Parts 240 and 242, Release No. 34-96495, File No. S7-31-22.

Securities and Exchange Commission (SEC), 2026, Roundtable on Options Market Structure, Supporting Data, April 9, 2026.

van Kervel, V. and Yueshen, B., 2024, Anticompetitive Price Referencing, Working paper, Pontificia Universidad Católica de Chile.

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 in May 2021, 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, with lower values indicating larger improvement.

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

.

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 auction trades. 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 and NBO 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 (NBO) and an indicator variable which equals one if one of the other non-auction exchanges is at the NBB (NBO). 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)		At NBO (Arca minus non-auction)	
	(1)	(2)	(3)	(4)
DMM on auction exchange	-0.085**	-0.049*	-0.068**	-0.040
	(0.034)	(0.027)	(0.028)	(0.023)
Quoted spread		0.050**		0.046**
		(0.022)		(0.018)
Tick size		0.983*		1.130**
		(0.524)		(0.421)
Abs (delta)		0.004		-0.010
		(0.020)		(0.019)
Gamma		0.297***		0.255***
		(0.075)		(0.069)
Vega		-0.001***		-0.001***
		(0.0002)		(0.0002)
Price (midpoint)		-0.001**		-0.001***
		(0.0004)		(0.0004)
DMM FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Observations	46,515,821	41,300,122	46,515,821	41,300,122
Adjusted R^2	0.006	0.013	0.005	0.011
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 and NBO 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 that equals one if NYSE Arca is at the NBB (NBO) and an indicator variable that equals one if one of the other non-auction exchanges is at the NBB (NBO). 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

	DMM1	DMM2	DMM3	DMM4	DMM5
At NBB (Arca minus non-auction)					
Model 1 (no control variables)					
DMM on auction exchange	-0.139**	0.062*	-0.153***	-0.123***	0.002
	(0.055)	(0.032)	(0.050)	(0.027)	(0.022)
Model 2 (with control variables)					
DMM on auction exchange	-0.075	0.015	-0.099***	-0.030	0.008
	(0.053)	(0.020)	(0.031)	(0.022)	(0.020)
At NBO (Arca minus non-auction)					
Model 1 (no control variables)					
DMM on auction exchange	-0.128**	0.051	-0.123***	-0.113***	0.004
	(0.049)	(0.032)	(0.040)	(0.025)	(0.022)
Model 2 (with control variables)					
DMM on auction exchange	-0.056	-0.004	-0.089***	-0.027	0.011
	(0.047)	(0.022)	(0.026)	(0.017)	(0.021)
Date FE	Yes	Yes	Yes	Yes	Yes
Note:					*p<0.1; **p<0.05; ***p<0.01

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; "Exchange at best" 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; "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 1 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	Exchange at best	Best bid diff	Best ask diff
	(1)	(2)	(3)	(4)
High bind*Post	-0.110***	0.078***	0.051**	0.051**
	(0.010)	(0.014)	(0.021)	(0.021)
Abs (delta)	0.174***	-0.043**	-0.075***	-0.098***
	(0.023)	(0.018)	(0.018)	(0.015)
Gamma	0.022	-0.107***	0.033*	-0.010
	(0.016)	(0.015)	(0.018)	(0.015)
Vega	0.003***	0.002***	-0.001	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Price (midpoint)	-0.018***	0.016***	-0.014*	-0.012**
	(0.006)	(0.006)	(0.008)	(0.006)
Stock FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Sample	Auction exchanges	Auction exchanges	All	All
Observations	6,834,312	6,452,672	13,435,210	13,435,210
Adjusted R^2	0.033	0.027	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
Competitive auction	0.240***		
	(0.013)		
Spread=0.01		0.119***	-0.061***
		(0.007)	(0.003)
Abs (delta)	-0.190***	0.022*	-0.010
	(0.019)	(0.012)	(0.007)
Gamma	0.094***	-0.020**	0.007
	(0.018)	(0.008)	(0.005)
Vega	-0.003***	-0.001	0.001**
	(0.001)	(0.001)	(0.0004)
Price (midpoint)	-0.043***	-0.024***	0.013***
	(0.005)	(0.004)	(0.002)
Stock FE	Y	Y	Y
Date FE	Y	Y	Y
Sample	Stopped,pre, size>1	Stopped,pre, size>1	Stopped,pre, size>1
Observations	643,353	643,353	643,353
Adjusted R^2	0.212	0.040	0.042
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 describes the mechanisms available to market makers to internalize 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.

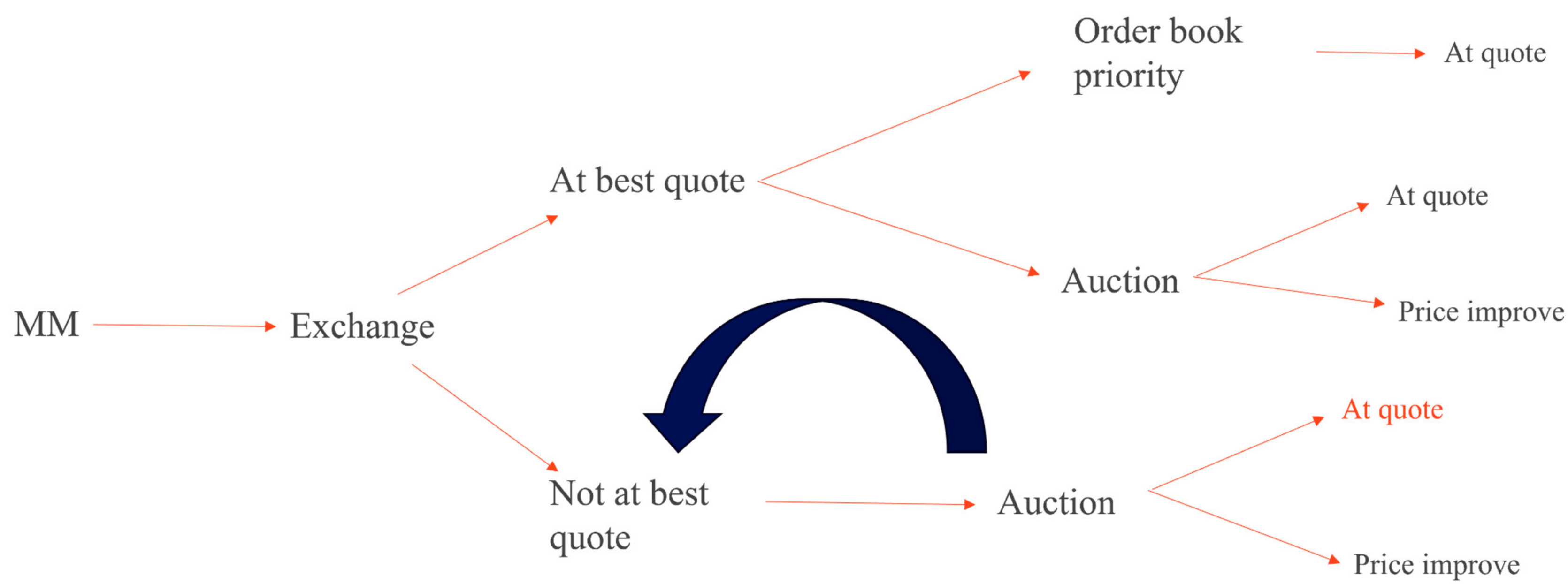


Figure 2

This figure presents the daily average percentage quoted and effective spreads for single-leg trades, and the proportion of single-leg trades that occur in auctions. Spreads are winsorized at the 99.5th percentile by date. The plots are 30-day moving averages from January 2011 to December 2016. Over this period, we calculate the statistics for each stock-day weighted by number of trades in a series 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.

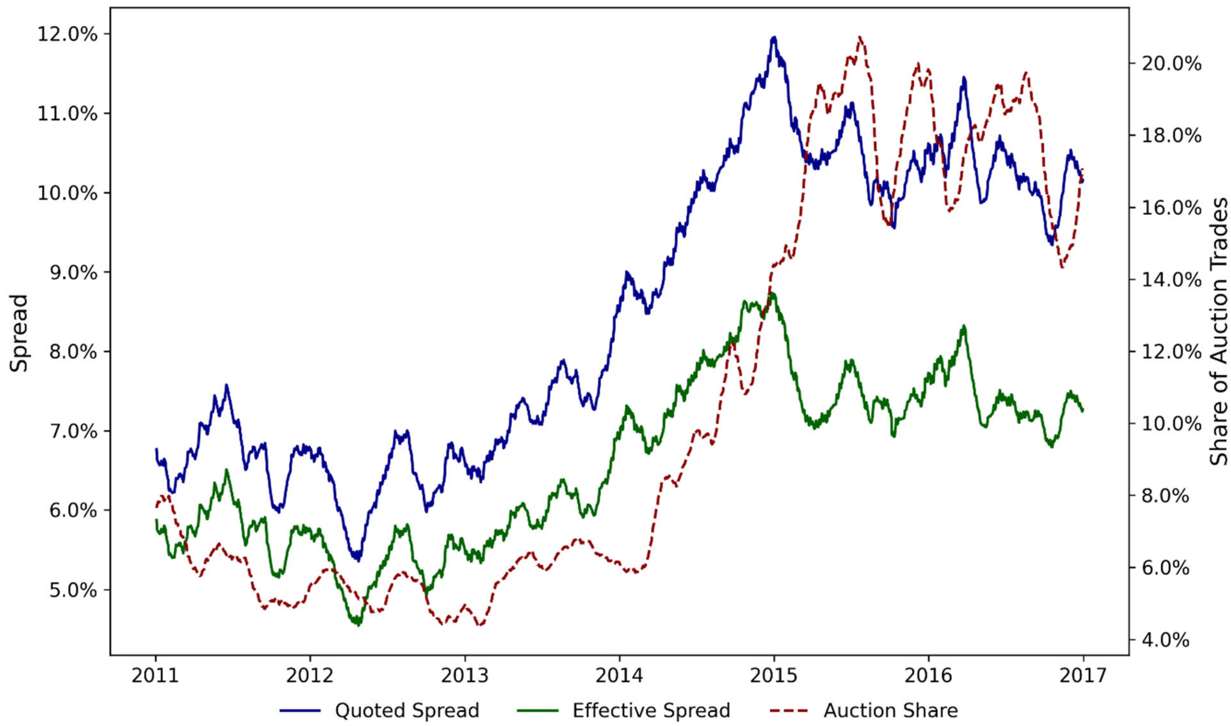
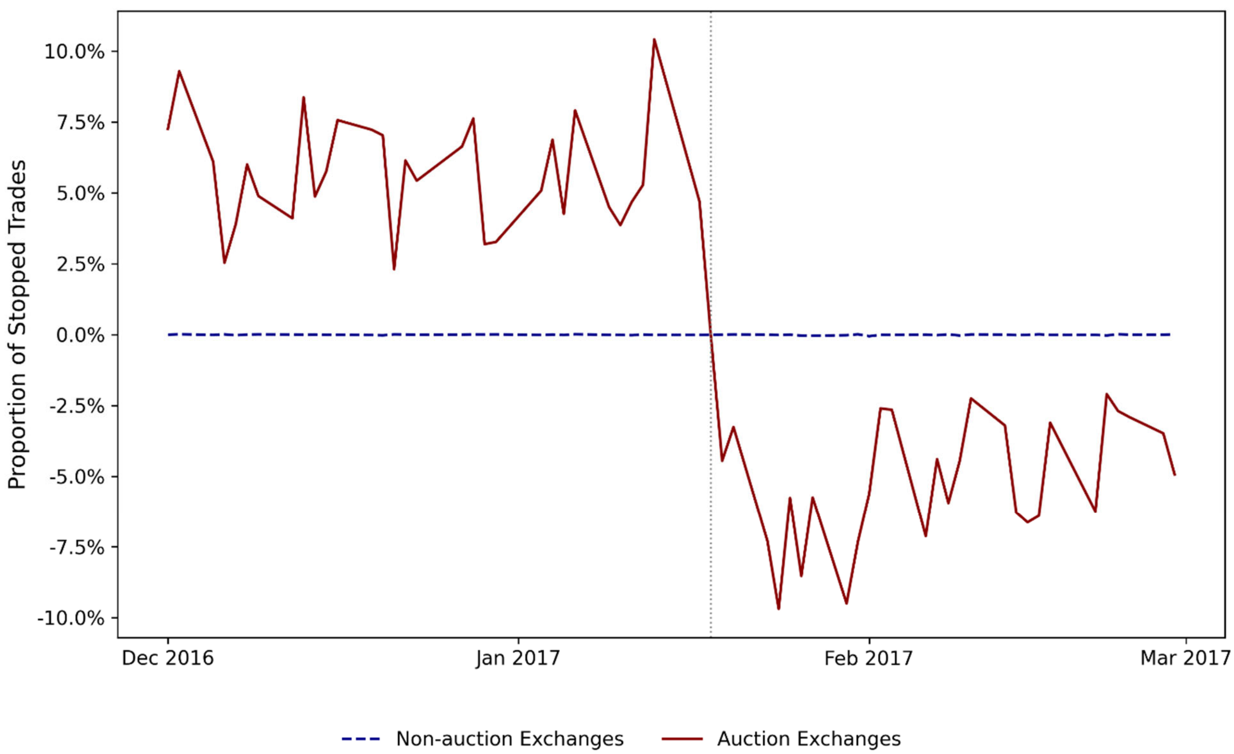


Figure 3

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. The figure presents the differences separately for auction and non-auction exchanges.



Internet Appendix

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 in May 2021. 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: Extended sample January to June 2021

This table presents results of regression models similar to those in Tables 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 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.

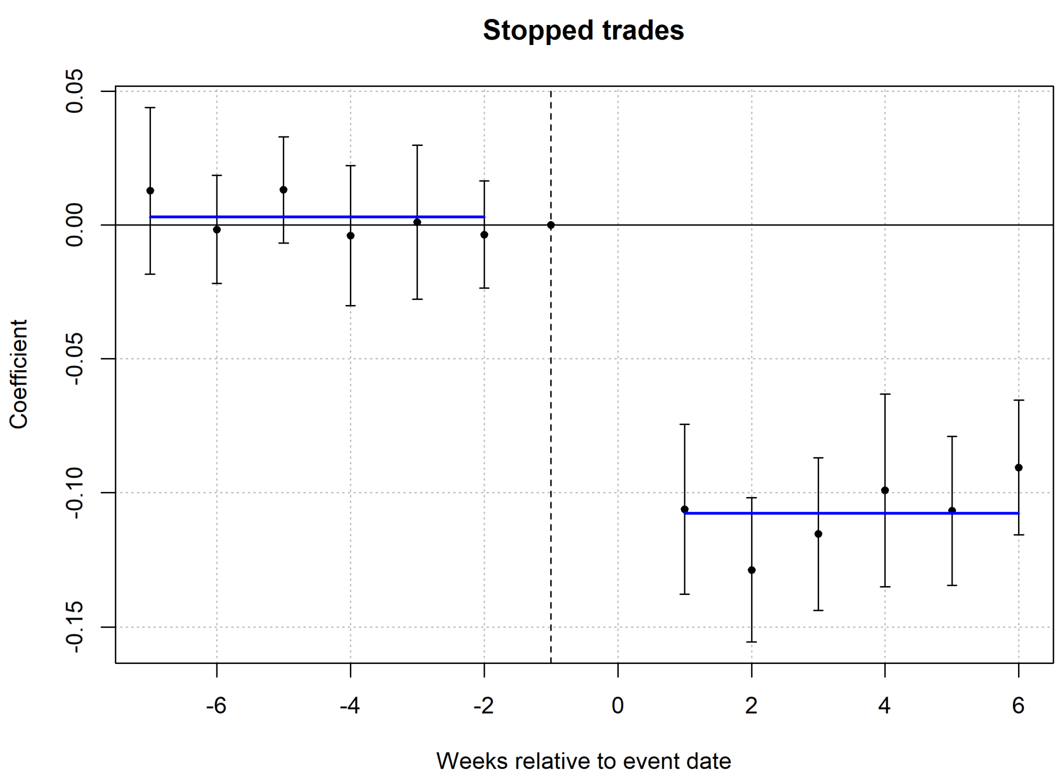
Appendix Figure 2

This figure presents weekly coefficients corresponding to the difference-in-differences analysis in Tables 9 and 10. We define relative time in weekly bins, with the week immediately preceding treatment (week −1) as the reference period. The coefficients presented correspond to β_k in the model:

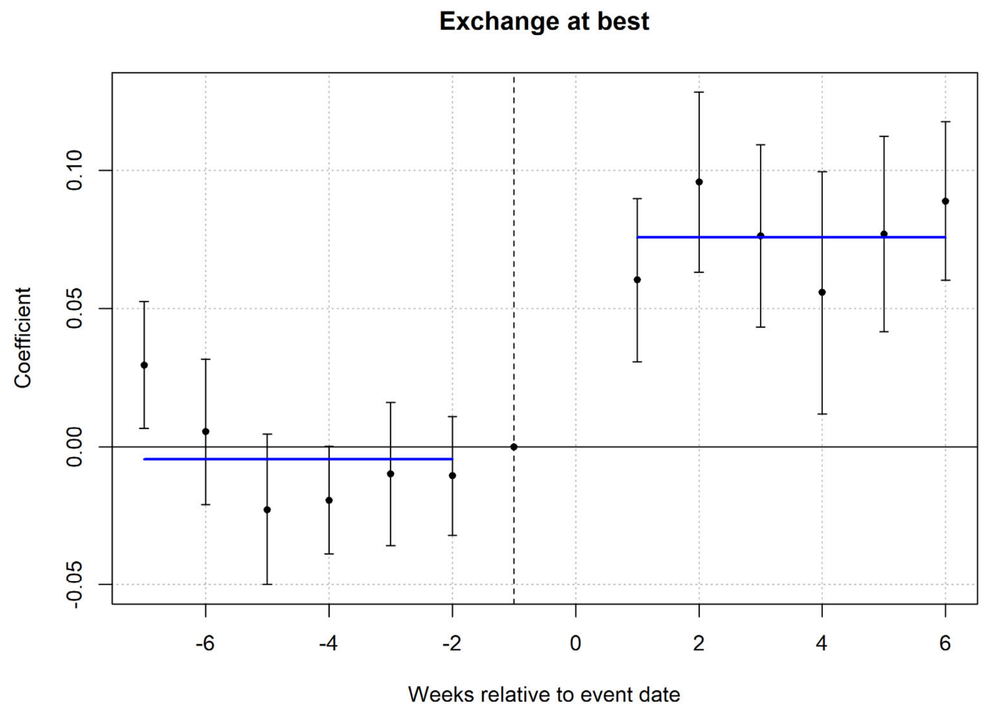
$$DepVar_{i,t} = \sum_{k \neq -1} \beta_k \; Week_k * Highbind_i + \beta'\mathbf{X} + FE + \epsilon_{i,t}$$

where $DepVar$ is the relevant dependent variable in the estimation. $Week_k$ are indicator variables for each weekly bin relative to the treatment date. $Highbind$ 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. **X** is a vector of control variables: the absolute delta, gamma, vega, and the NBBO quote midpoint. FE includes underlying stock and date fixed effects. Standard errors are clustered by underlying stock and date. The figure plots the estimated coefficients and 95% confidence intervals.

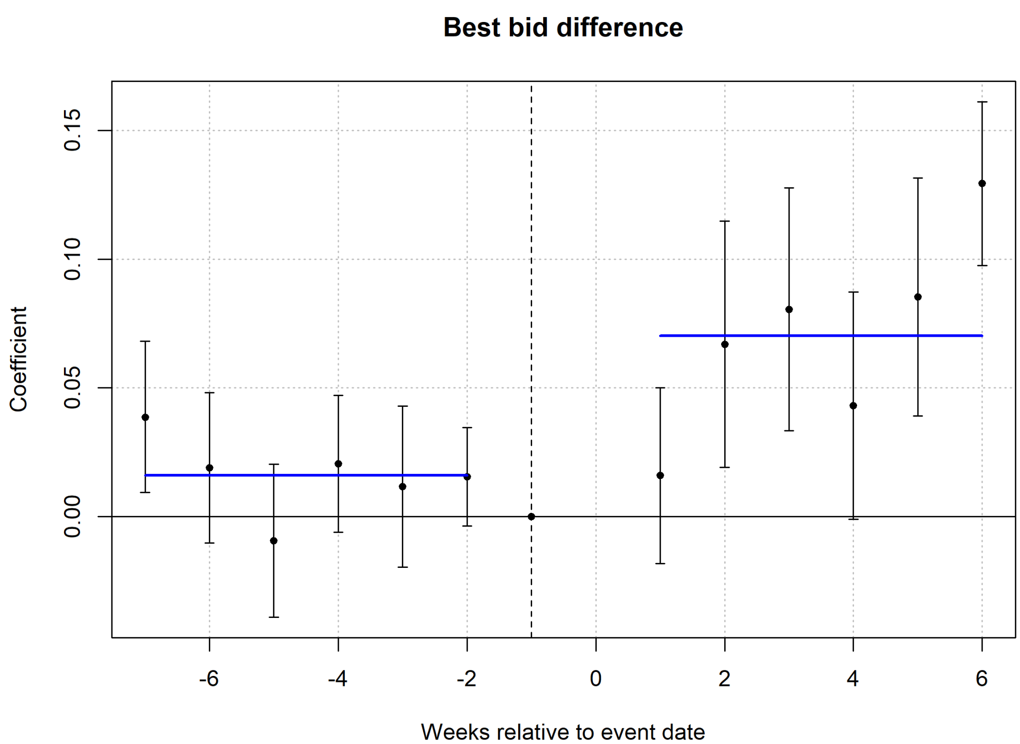
Panel A: Stopped trades



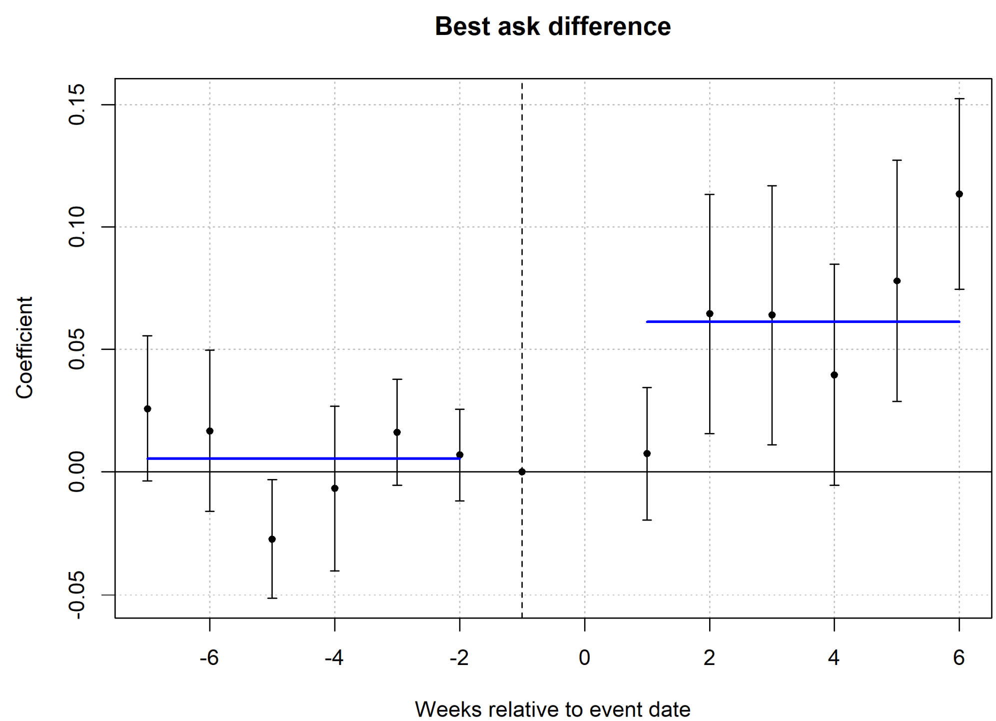
Panel B: Exchange at best



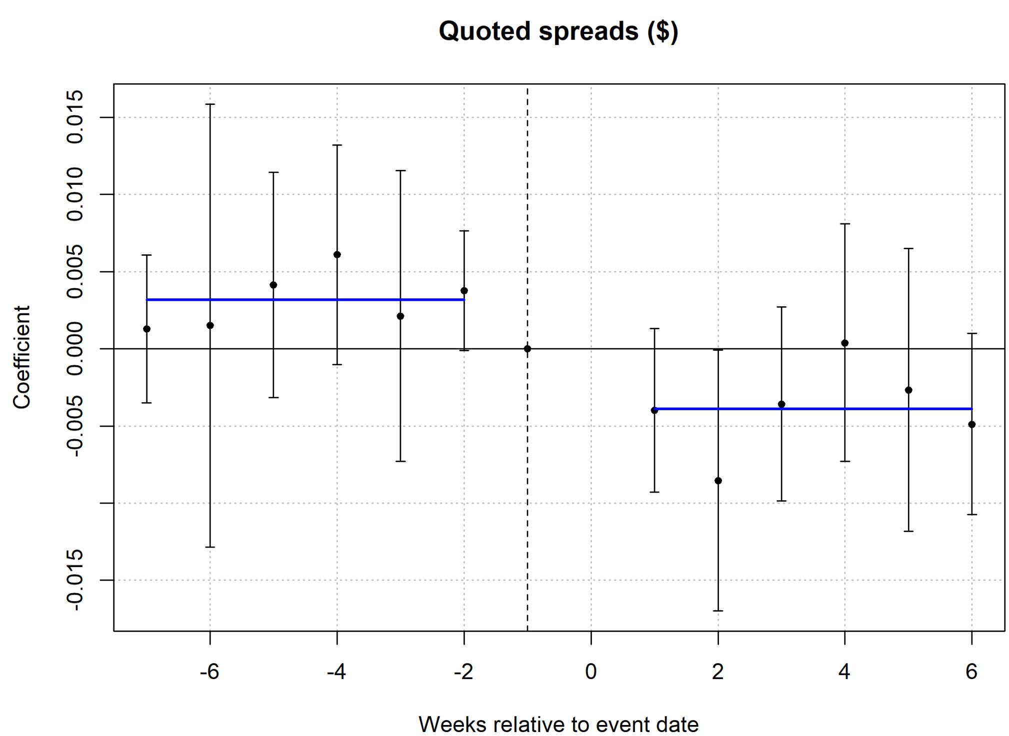
Panel C: Best bid difference



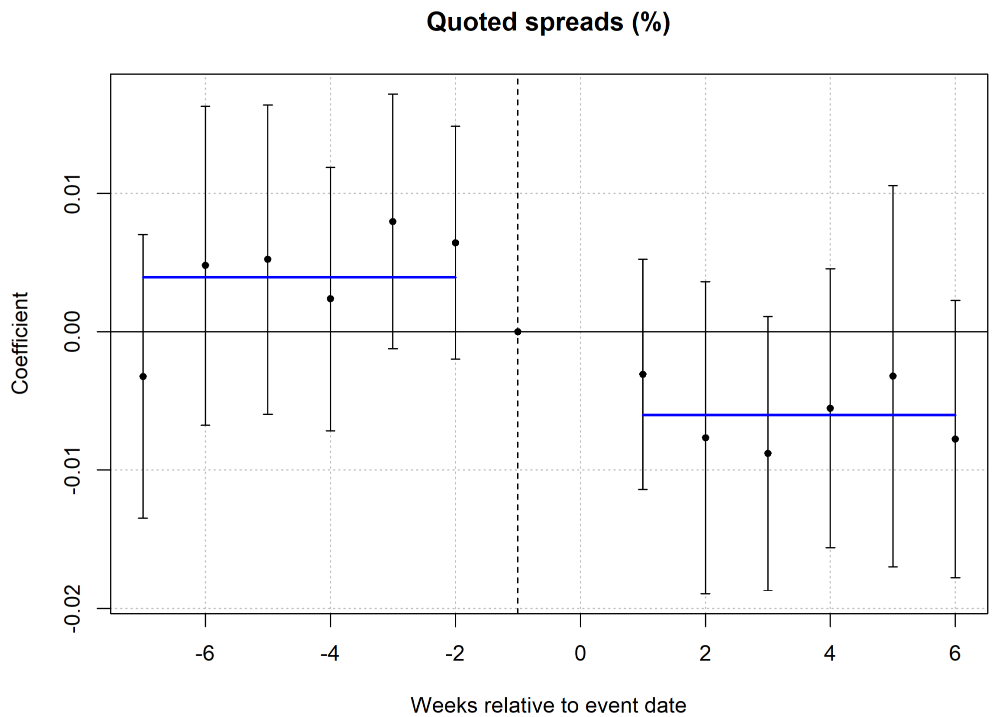
Panel D: Best ask difference:



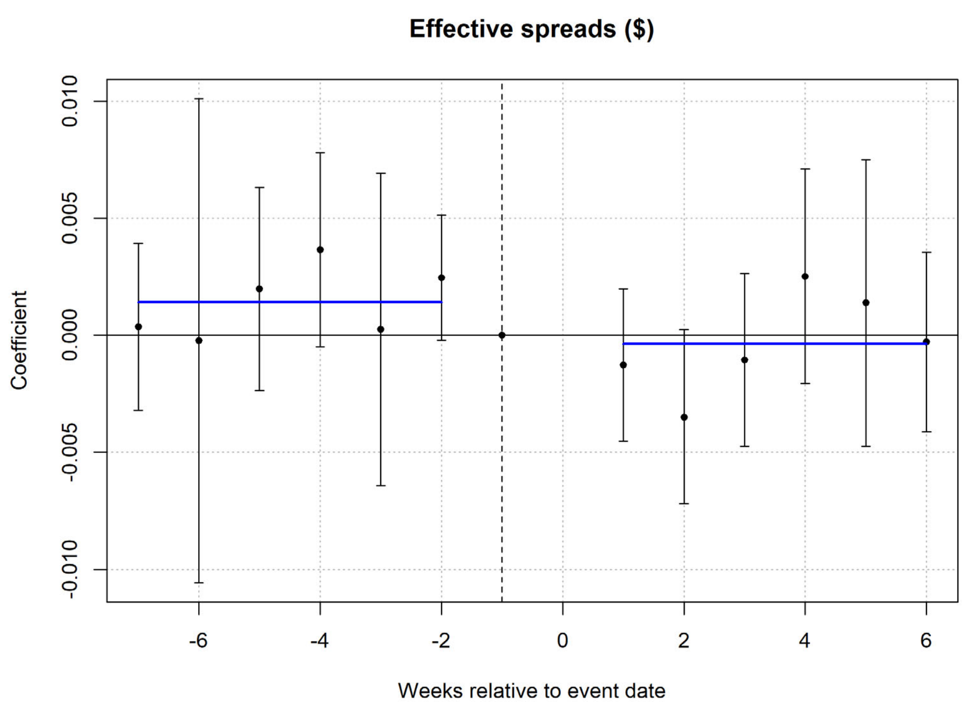
Panel E: Quoted spread ($):



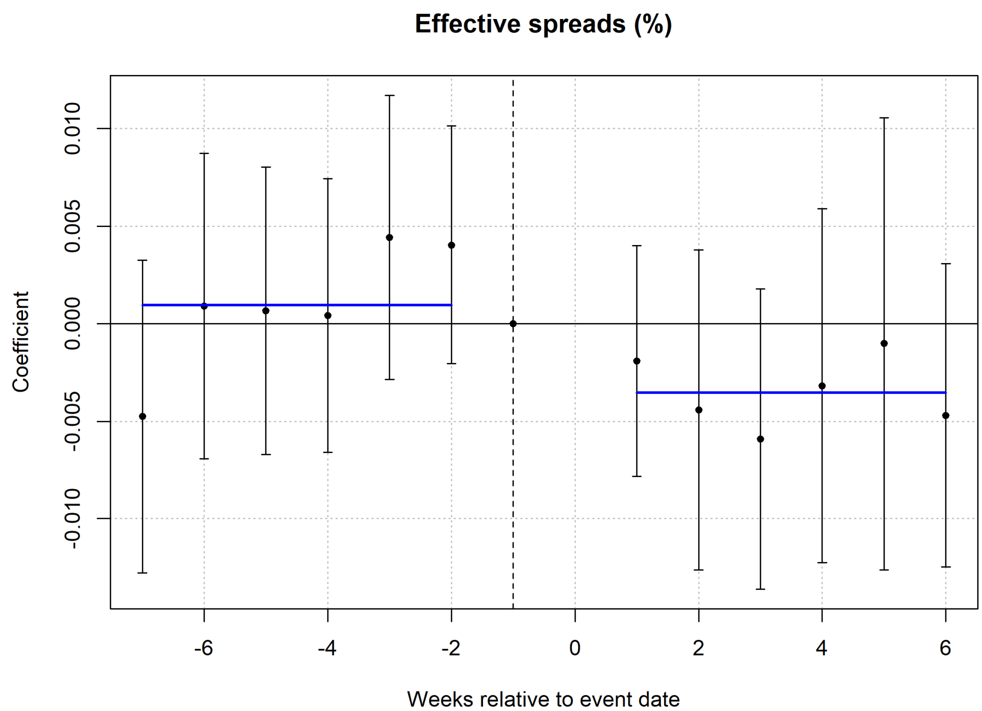
Panel F: Quoted spread (%)



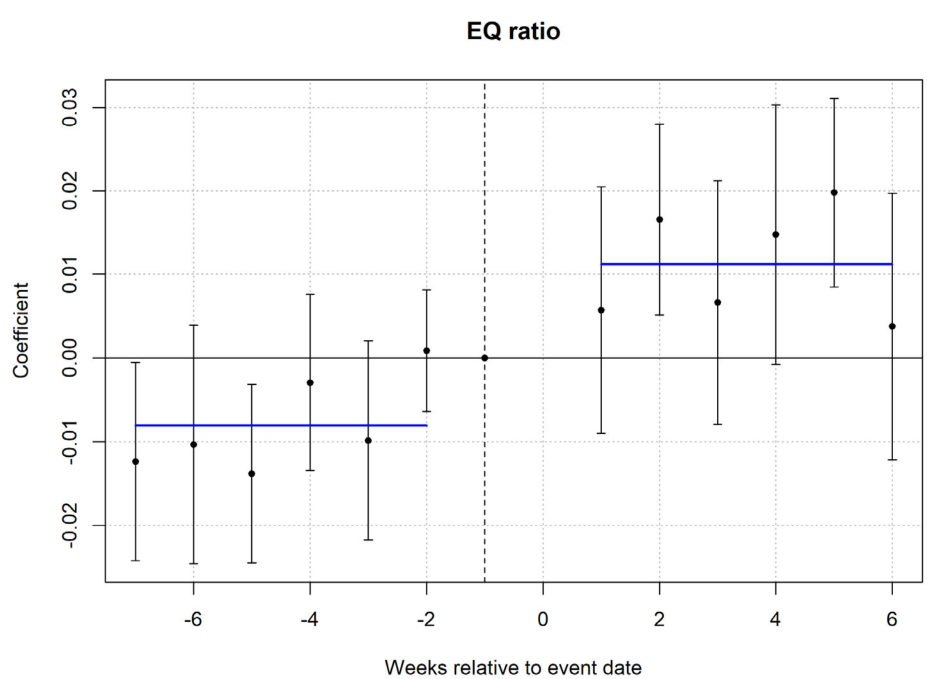
Panel G: Effective spreads ($)



Panel H: Effective spreads (%)



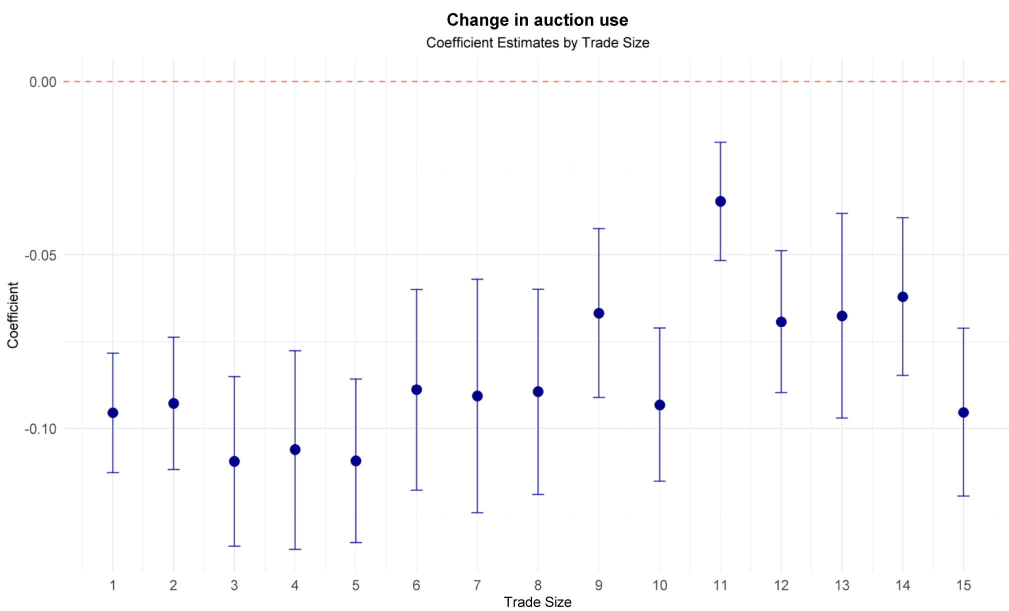
Panel I: EQ ratio



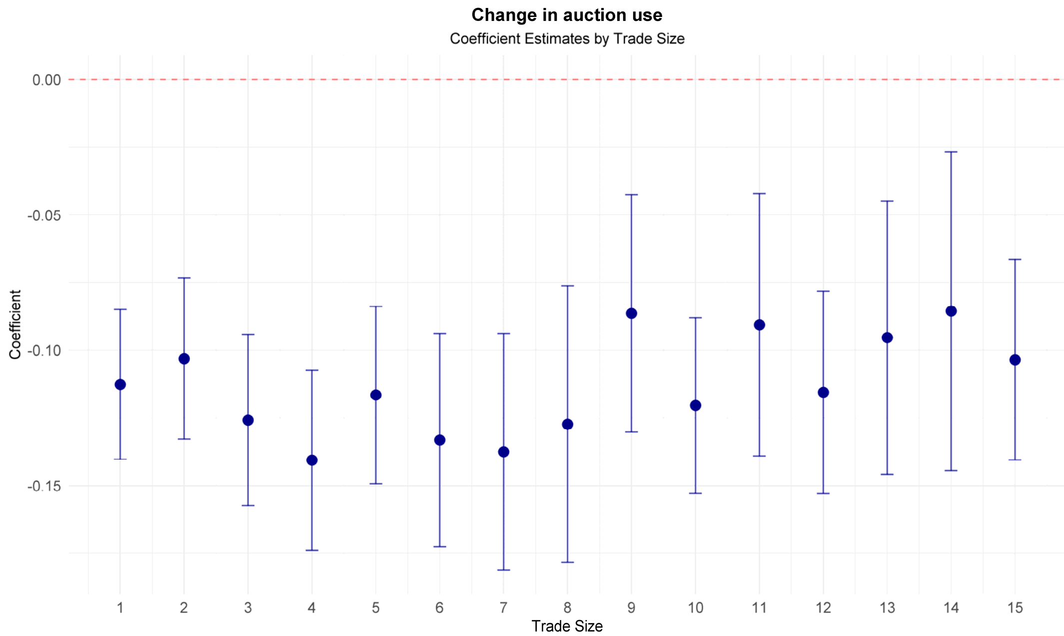
Appendix Figure 3

This figure presents a difference-in-differences analysis of changes in the use of 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 of trades on auction exchanges, 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.

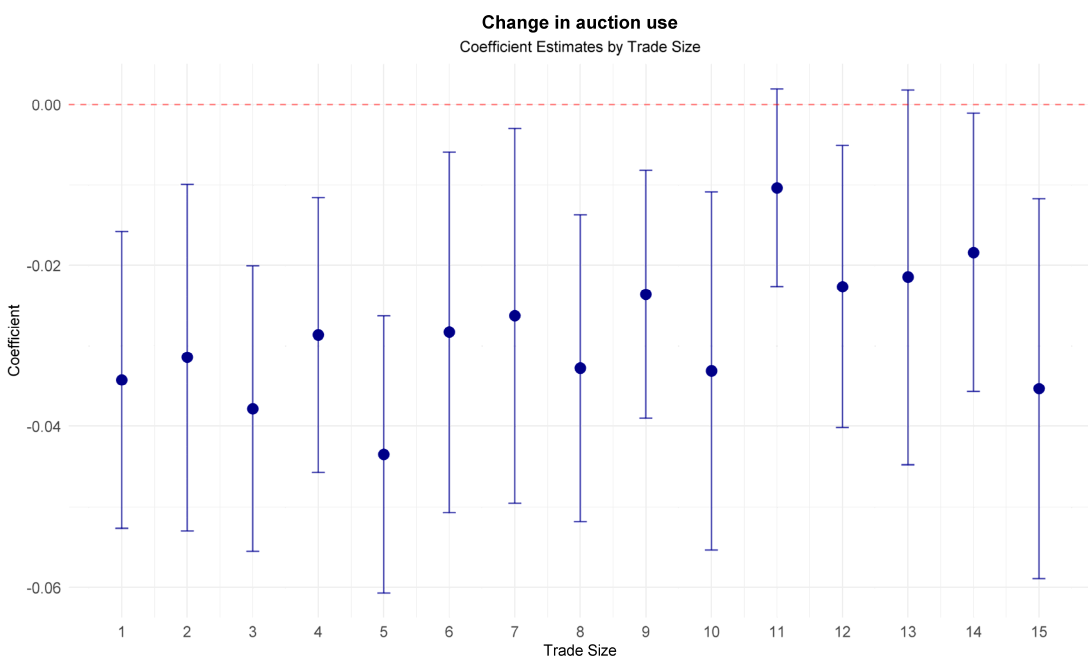
Panel A: All trades



Panel B: Exchange not at best quote

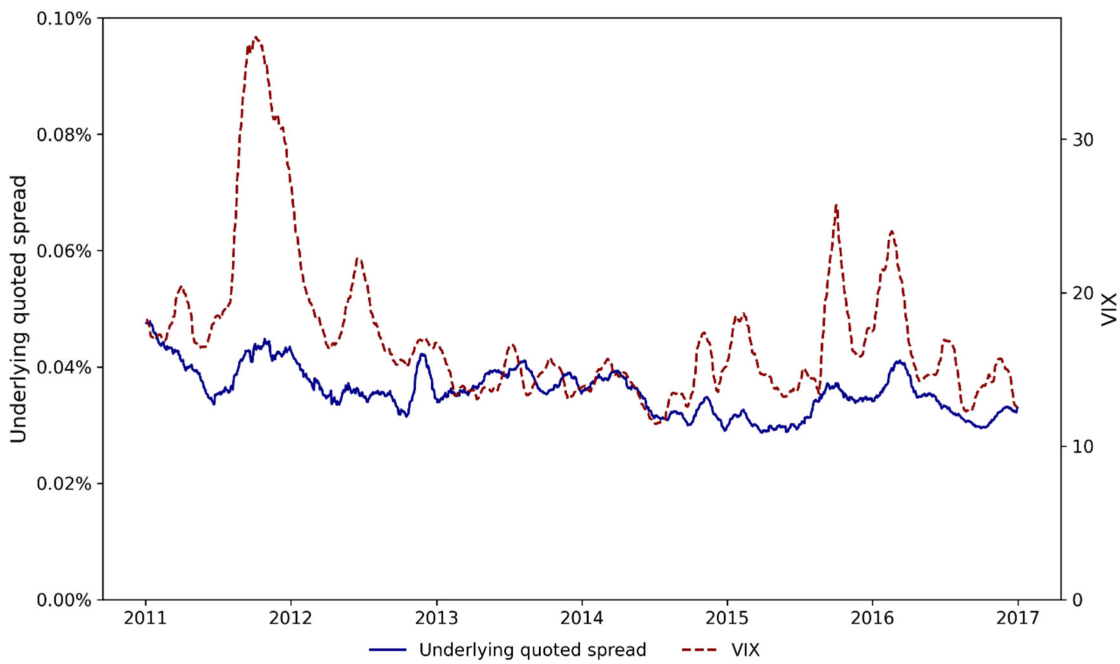


Panel C: Exchange at best quote



Appendix Figure 4

This figure plots the daily average percentage quoted spread of the underlying stocks and the VIX from January 2011 to December 2016. It provides a comparison to Figure 2 and helps assess whether the increase in option quoted spreads reflects changes in underlying stock liquidity or market-wide volatility. The underlying quoted spread is computed from CRSP daily closing bid and ask prices and is winsorized at the 99.5th percentile by date. For each day, we calculate the average underlying quoted spread across all optionable common stocks in our sample. To stay consistent with Figure 2, the averages are weighted by the number of option trades for each stock in the day.. Both series are shown as 30-day moving averages. The underlying stock spread is plotted on the left axis, and the VIX is plotted on the right axis.



Appendix Figure 5

This figure replicates Figure 2 for a subsample that is restricted to options on S&P 500 stocks, with moneyness between 0.8 and 1.2 and time to maturity exceeding 10 days to control for changing composition of options over time. The figure presents average percentage quoted and effective spreads for single-leg trades, and the proportion of single-leg trades that occur in auctions. Spreads are winsorized at the 99.5th percentile by date. The plots are 30-day moving averages from January 2011 to December 2016. Over this period, we calculate the statistics for each stock-day weighted by number of trades in a series 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.