Tick size and price discovery: Futures-options evidence*

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Abstract

The tick size, representing the minimum price increment in a financial market, can lead to market price inefficiencies when large. We examine the role of the tick size in price discovery between futures and options in the Chicago Mercantile Exchange corn and soybean markets. Futures contracts, which have a tick size twice as large as that of options, typically exhibit one-tick quoted spreads due to their binding tick sizes, while options allow for price-improving quotes given their less binding tick size. We find that despite thin and costly trading, options are as informative as futures. Price-improving quotes offered by options traders enhance information impounded into prices, suggesting that relaxing the binding tick size can enhance price discovery.

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JEL Classification Numbers: G12, G13, G14, Q02, Q13

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1 Introduction

Most financial markets currently feature public limit order books, which introduce transparency into the price discovery process. This process involves incorporation of new information into market prices (O'Hara 2003) and is influenced by market microstructure characteristics such as the tick size. The tick size establishes the minimum price increments at which traders can post orders and thus defines the market pricing grid. The literature has shown that informed traders may use price-improving limit orders, along with market orders, to reveal information in the market (e.g., Brogaard, Hendershott, and Riordan 2019; Chaboud, Hjalmarsson, and Zikes 2021). The tick size may influence the costs of revealing information by conditioning the market bid-ask spread. While limit orders enable traders to capture the bid-ask spread if executed, but face execution uncertainty, market orders guarantee execution but incur the spread cost (e.g., Kaniel and Liu 2006; Collin-Dufresne and Fos 2015).

This paper focuses on the relevance of the tick size in the context of price discovery when an asset or its derivatives are traded with different tick sizes. In this context, informed traders face the decision on where to reveal information (Narayan and Smyth 2015), in addition to choosing between market and limit orders. Markets with smaller tick sizes allow for a finer pricing grid, enabling traders to gain price priority more easily by quoting at more competitive price levels compared to large-tick markets, possibly enhancing market quality (Foley, Meling, and Ødegaard 2023). We show that the price improvements resulting from smaller tick sizes help enhance the informativeness of a market relative to markets with larger tick sizes.

When the tick size exceeds the bid-ask spread suggested by market conditions (McInish and Wood 1992), the bid-ask spread is constrained to one tick, making the tick size binding (Dyhrberg, Foley, and Svec 2023). Price discovery studies usually consider the midpoint price as a proxy of the market fundamental price (e.g., Blume and Stambaugh 1983; Lee 1993; Han and Lesmond 2011; Hagströmer and Menkveld 2019) as it represents the "conventional view of equilibrium price" (Demsetz 1968) and is straightforward to compute (Hagströmer 2021). In tick size binding markets (tick-constrained markets), depths may heavily cluster at the best-bid-offer (BBO) (Werner et al. 2023), making information incorporation very costly as informed traders may need to initiate relatively large and costly trades to adjust the midpoint price ("walk-up" the limit order book), eventually influencing price discovery.[1]

Yao and Ye (2018) suggest that in markets with binding tick sizes, it is difficult to offer

[1] Figure A1 of Appendix A provides two hypothetical limit order books in both tick-unconstrained and tick-constrained markets.

price-improving quotes, and the price priority diminishes, favoring fast liquidity providers over slow ones.[2] Conversely, in markets with less binding tick sizes (tick-unconstrained markets), there may be more opportunities for price-improving quotes (Werner et al. 2023), which could lead to more updates of the midpoint price.

We study the effect of different tick sizes on price discovery in the Chicago Mercantile Exchange (CME) agricultural futures and options markets. The futures markets are highly tick-constrained but highly traded, while the options markets are tick-unconstrained with a tick size half of the underlying futures, and lightly traded compared to futures. Leveraging these characteristics, we investigate whether price-improving quotes in the options markets help explain price discovery between futures and options in CME corn and soybean markets from January 2019 to June 2020.

Regulation National Market System (Reg NMS) mandates a tick size of one cent for U.S. stocks priced above one dollar. This uniform tick size setting prevents us assessing how tick size affects price discovery. Moreover, a stock can be traded in more than 100 lit exchanges and off-exchange venues, rendering our price discovery exercise computationally infeasible. Finally, the U.S. stocks have a more complicated market microstructure, such as various exchange fee structures (e.g., Chao, Yao, and Ye 2019), market fragmentation (e.g., Baldauf and Mollner 2021), and payment for order flow (e.g., Parlour and Rajan 2003), which could potentially confound our results. For example, informed traders who use limit orders are more willing to reveal their information in maker-taker exchanges due to rebates for providing liquidity, instead of tick size. However, agricultural options and futures are both traded in the CME with different tick sizes, which provides a unique and purer setting to investigate the impacts of the tick size on price discovery.

We define price-improving quotes as those that improve the best bid/ask price by at least one tick. To compare futures and options prices, we use the put-call parity to derive options-implied futures midpoint prices. We estimate Putniņš (2013)'s information leadership shares (ILSs) based on a bivariate vector error correction model (VECM) between the midpoint futures and the options-implied futures midpoint prices. This measure provides price discovery shares that are robust to differences in the degree of price noise across markets. For the first time, we assess how the binding nature of the tick size, approximated through the ability of traders to place price-improving quotes, affects price discovery. We use a two-stage least squares instrumental variable (2SLS-IV) regression to address potential endogeneity between price-improving quotes and price discovery.

[2] The literature may use other terms like undercutting orders (Dyhrberg, Foley, and Svec 2023; Werner, Rindi, Buti, and Wen 2023) or improving submissions (Brogaard, Hendershott, and Riordan 2019) to refer to limit orders that improve the bid or the ask prices.

Our proxy for the binding tick-size nature based on price-improving quoting differs from previous literature, which often uses the difference between actual and predicted quoted spread (Kwan, Masulis, and McInish 2015), the frequency of one-tick quoted spreads (Yao and Ye 2018; Fleming, Mizrach, and Nguyen 2018), the number of empty ticks within BBO (Dyhrberg, Foley, and Svec 2023), and the ratio of quoted spread to tick size (Foley, Meling, and Ødegaard 2023). Our approach focuses on how the tick size affects the movements of the midpoint price through price-improving quotes, which offers a more nuanced understanding of the effect of the tick size on price discovery. Specifically, we use the ratio of the number of price-improving quotes to the total number of BBO updates, reflecting liquidity providers' ability to enhance the best bid or ask price. This measure is particularly valuable in evaluating price discovery in markets characterized by low trade activity, such as the CME agricultural options markets, as it acknowledges the ability of market participants to convey information through price-improving limit orders.

Our results show that quoted spreads are wider, and trading activities significantly lower in options compared to their underlying futures. However, options exhibit substantially more frequent quote updates than trades, indicating that options are essentially driven by quotes instead of trades. Consistent with Bohmann, Michayluk, and Patel (2019), we find that average options ILSs are significantly larger than those of futures, suggesting that options are more informative. Although options are thinly traded, their less binding tick size enables timely incorporation of information through increased price-improving quoting. This ultimately leads to options dominating price discovery over futures. We find the heightened informativeness of options is particularly notable when public reports are released.

We explain options ILS by regressing it against our proxy for the binding nature of the tick size, while controlling for option market characteristics. However, tick size binding may be endogenous as enhanced price discovery in options may attract informed traders to reveal their information by posting more price-improving quotes. This may in turn affect the binding nature of tick size in options and a reverse causality may occur. To facilitate causal interpretation, we use the exogenous options floor trading closure in March 2020 due to the COVID-19 pandemic and the lagged value of price-improving quoting as a set of instrumental variables for the endogenous variable. Drawing from Gousgounis and Onur (2024) and conversations with market participants, floor traders are deemed as informed as electronic traders. When the floor venue closes, they transition to the electronic venue where they compete with high-frequency traders (HFTs). Given their slower pace compared to HFTs, floor traders in the electronic venue likely prioritize price-improving quotes to gain price priority over time priority (Yao and Ye 2018). Hence, liquidity provision by floor traders in the electronic venue is likely to alter the proportion of price-improving quotes submitted after the closure of the floor venue. Since options markets rely heavily on quotes rather than trades (e.g., Chakrabarty, Cox, and Upson 2021), the closure of the floor trading is unlikely to impact price discovery by altering the futures-option trading volume ratio thereby satisfying the exclusion restriction. Our instrument is rooted on market structure changes that are exogenous to price discovery, aligning with studies like Comerton-Forde and Putniņš (2015) and Foley and Putniņš (2016). We find that a one-standard-deviation (3.71%) increase in the options percentage price-improving quotes is expected to increase options ILS by 3.10% of its mean, thus showing evidence of the relevance of the tick size for price discovery.

We validate our results through a heterogeneous analysis. Since price-improving quotes can only be placed when the quoted spread is larger than one tick, we divide our sample of put-call pairs into different subsamples based on the frequency of one-tick quoted spreads for the put and the call. We then study the relationship between price-improving quotes and changes in options' price discovery across these different subsamples. We find that price-improving quotes enhance price discovery in put-call pairs when either the put and call options are not tick-constrained. However, they do not contribute to the price discovery in pairs where both put and call options are tick-constrained. We perform several robustness checks to further validate our findings. Our results are robust to a simpler instrumental variable, alternative fixed effects, proxy of binding tick size, alternative independent variables, and estimation methods.

Empirical evidence on the price discovery provided by options is inconclusive. In stock-options studies, findings usually suggest that options do not lead price discovery. Chakravarty, Gulen, and Mayhew (2004) suggest that options contribute about 17% to price discovery, while Muravyev, Pearson, and Broussard (2013) find their contribution to be less than 5%. Patel et al. (2020) accommodate substantial noise differences between stocks and options and find that options contribute up to 30% to price discovery. In the futures-options case, results are mixed: Boyd and Locke (2014) suggest that options contribute to price discovery up to 10% in the natural gas market, while Hsieh, Lee, and Yuan (2008) find that index options contribute about 34% to price discovery in Taiwan. Bohmann, Michayluk, and Patel (2019) focus on commodities and find that most options markets lead price discovery during 2016-2017.

Our contribution to the literature lies in evaluating the role of the tick size in determining price discovery. Our findings align with previous research (e.g., Foley, Meling, and Ødegaard 2023) and suggest that switching to a finer pricing grid can enhance informational efficiency through price-improving quotes in tick-constrained markets. We complement Foley, Meling, and Ødegaard (2023) by showing an additional informational role of price-improving quotes. Price improvements induced by the finer pricing grid are likely to improve the informativeness of markets with smaller tick sizes. Our work further helps to interpret the enhanced price discovery observed in the U.S. Treasury spot market after a tick size reduction, as reported by Fleming, Nguyen, and Ruela (2024). While they acknowledge a decline in the frequency of one-tick quoted spreads by 7% after the tick size decline, they do not empirically relate it to price discovery. Our analyses also complement research exploring the role of limit orders in price discovery within a single market (e.g., Fleming, Mizrach, and Nguyen 2018; Brogaard, Hendershott, and Riordan 2019; Chaboud, Hjalmarsson, and Zikes 2021) by linking it to the tick size. These studies find limit orders are jointly more informative than trades, suggesting that informed traders may reveal information through such orders. We find that limit orders can also affect price discovery between markets through the relative availability of price-improving quotes under different tick constraints. Finally, we extend Bohmann, Michayluk, and Patel (2019) and provide microstructure evidence on options informativeness. Our findings suggest that a more granular pricing grid in options helps explain price discovery between futures and options.

Our findings also contribute to the existing policy debate on setting the appropriate tick size. The literature suggests that a "one size fits all" approach is not suitable, with smaller tick sizes likely benefiting tick-constrained markets (Foley, Meling, and Ødegaard 2023), while larger tick sizes may be more appropriate for tick-unconstrained markets (Dyhrberg, Foley, and Svec 2023). Most CME commodity futures markets are tick-constrained with heavy clustered depths at the top of the book. This work coincides with the CME's initiative to gather feedback from market participants regarding a potential reduction of the tick size in the corn futures calendar spread market by half.[3] While currently the initiative only affects calendar spreads, if implemented, it may also require a corresponding tick size reduction in the corn outright market. The alignment of tick sizes in the spread and outright markets is crucial, as the implied functionality relies on both markets sharing identical pricing grids. Without this consistency, quotes offering better prices cannot be routed to the outright market. Our results indicate that this market reform may be promising in (outright) futures markets since it enhances the price priority in the quoting and may incentivize the submission of price-improving quotes, thus bolstering price discovery – a cornerstone function of the futures markets.

2 Data

We use the CME Market Depth data for both futures and options in corn and soybean markets. We focus on the most-traded futures contracts from January 7, 2019, to June 26, 2020.

[3]See `https://www.cmegroup.com/notices/ser/2024/03/SER-9345.html`.

We select the most-traded futures by rolling over to the next most-traded contract when the latter has higher trading volume than the former for three consecutive trading days.[4] Following Bohmann, Michayluk, and Patel (2019), we concentrate on standard American-style options whose underlying contracts are the selected nearby futures contracts. We consider all put and call options. Table B1 of Appendix B.1 shows how option contracts are paired with their underlying futures. To get daily options information, we use the CME End-of-Market-Summary-Standard data, which includes options daily trading volume, expiration date, delta, and implied volatility, etc. All data are obtained from the CME Datamine. Both futures and options prices are quoted in cents/bushel. The quoted quantity is expressed in number of contracts, where each contract is for 5,000 bushels. The tick size in futures (options) is 0.25 (0.125) cents/bushel. CME options and futures are traded electronically at Globex and share the same trading schedule. The day (night) continuous trading session is 8:30-13:20 (19:00-7:45), U.S. Central Time. Pre-open auctions start before the two continuous trading sessions. Figure B1 of Appendix B.2 shows the details of the trading sessions.

CME Market Depth data record incremental updates in both trades and quotes with nanosecond timestamps. Each update has a unique sequence number to sort updates that are recorded with identical timestamps. Tables B2 and B3 of Appendices B.3 and B.4 show examples of option and futures Market Depth data, respectively. Unlike the futures markets, CME options markets do not support implied functionality.[5] Hence, quotes in the option calendar spread markets are not allowed to be routed to the outright markets to provide liquidity and thus, all option quotes are trader-initiated. To reflect the real futures liquidity, we reconstruct the consolidated limit order book that aggregates outright quotes initiated by traders and implied quotes generated by the Globex system (see details in Figure B2 of Appendix B.5). We pre-process both the futures and options data to remove potentially erroneous observations.[6]

Table C1 of Appendix C reports descriptive statistics for options markets. The average corn options prices are lower than those of soybeans. Absolute options delta indicates that when the corn (soybean) futures price increases by 1 cent, the corn (soybean) options price changes by 0.37 (0.32) cents on average. Following Patel et al. (2020), we calculate options omega, defined as the absolute options delta multiplied by the ratio of the futures price to options price, as a proxy for leverage in options. Results show that the soybean market has

[4]By doing so, the September corn futures contract and the August and September soybean futures contracts are not selected.

[5]See more details about implied functionality in `https://cmegroupclientsite.atlassian.net/wiki/spaces/EPICSANDBOX/pages/46465350/Implied+Orders`.

[6]Our data cleaning follows Easley, de Prado, and O'Hara (2016). We delete observations with zero quoted prices and non-positive bid-ask spreads during continuous trading sessions in both the futures and options markets.

greater leverage than the corn market, as evidenced by the soybean option omega being 1.5 times larger than that of corn. We calculate options omega-adjusted trading volume and open interests and express them in million dollars, which allows comparison with futures markets. We find that options volume and open interest are substantially lower than that of futures on average for both corn and soybean. Higher leverage (i.e., larger omega) implies a relatively lower option price, which in turn should reduce the options implied volatility. Consistently, soybean, with higher leverage than corn, displays lower implied volatility.

3 Empirical design and results

3.1 *Market liquidity in option and futures markets*

We select valid individual options based on two criteria: 1) we use options with positive daily total daily trading volume on the CME, and 2) presence of BBO quoting activities, with option prices at the top of the book being positive for a trading session. In Table 1, we provide summary statistics that characterize liquidity in futures (Panel A) and options (Panel B) markets. We calculate all liquidity measures per session-day and summarize them across all futures/options-day observations. Detailed variable descriptions are shown in Table D1 of Appendix D.[7]

We compare trading costs between options and futures by analyzing dollar quoted spreads. Options typically exhibit spreads 1.5 to 3.1 times larger than futures across all commodities. We use $\%OneTick$ metric from previous studies (e.g., Yao and Ye 2018; Fleming, Mizrach, and Nguyen 2018) measured as the percentage of time when the quoted spread equals one tick, to as one proxy of the binding nature of the tick size. Consistent with smaller quoted spreads, futures markets witness more binding tick sizes compared to options, with the $\%OneTick$ being from 3.4 to 8.2 times larger. A binding tick size restricts price-improving quoting, so we report the number of price-improving quotes for each market, along with the number of trades to reflect the quoting and trading intensities. Options experience few trades (from 3 to 17 over a trading session) and a relatively larger number of best quote updates (from 4.92 thousand to 30.95 thousand), implying options markets are driven by quotes instead of trades. Futures markets witness substantially more trades (from 2.47 thousand to 13.07 thousand) and best quote updates (from 37.73 thousand to 271.00 thousand). Futures markets also exhibit higher volatility than options. Night trading sessions are generally less

[7]We do not consider trade-related spread measures (e.g., effective spread, realized spread, and price impacts) given the very low number of trades in the option markets. We do not compare relative quoted spreads (dollar quoted spread over midpoint price) between options and futures because their midpoint prices are substantially different.

liquid across all markets, with wider spreads and fewer trades/quotes. The tick size becomes less constraining during the night trading, particularly in options markets. These findings align with Boyd and Locke (2014), who observed a significantly lower number of trades in options compared to the nearby and first-deferred futures in the CME natural gas market during 2005-2007.

Our market liquidity results have implications for price discovery between futures and options. Since trading costs are higher in options, informed traders are incentivized to use limit orders to capture the spread, aligning with the observation that options markets are primarily driven by quotes. Goettler, Parlour, and Rajan (2009) suggest that best quotes are relatively more informative than trades if informed traders submit a relatively high proportion of limit orders to provide liquidity. Thus, new information is likely to be incorporated through price-improving quotes that can change the midpoint price.

3.2 *Price discovery between futures and options*

3.2.1 *Options-implied futures price*

Since options contracts are traded on their premium instead of their notional value like futures, we calculate the options-implied futures price to conduct our price discovery analyses. Following Muravyev, Pearson, and Broussard (2013) and Bohmann, Michayluk, and Patel (2019), we use put-call pairs instead of individual options. The options-implied futures price for a given put-call pair according to the European put-call parity is[8]

$$F_t e^{-r(T-t)} = C_t(K,T) - P_t(K,T) + Ke^{-r(T-t)}, \tag{1}$$

where F_t is the futures price at time t, $C_t(K,T)$ and $P_t(K,T)$ are the call and put options prices with strike price K and expiration date T, r is the continuously compounded risk-free interest rate per annum, and $T-t$ is the time to maturity. We use the 1-year Treasury bill yield as a proxy for the risk-free interest rate. Since the CME agricultural options are American style, we adjust Equation 1 to capture the early exercise premium $v_t(K,T)$. Hence,

$$F_t e^{-r(T-t)} + v_t(K,T) = C_t(K,T) - P_t(K,T) + Ke^{-r(T-t)}. \tag{2}$$

The calculation of $v_t(K,T)$ is based on the estimation of the error term from the put-call parity relationship at every bid or ask quote update for either the call, the put, or the futures.

[8] One can also use the Black-Scholes or binomial tree model to calculate the option-implied futures price (e.g., Chakravarty et al. 2004). Hsieh, Lee, and Yuan (2008) suggest that the information contained in the options-implied futures price by the put-call parity encompasses that by the Black-Scholes model.

We use the midpoint prices to estimate the error term:[9]

$$\varepsilon_t(K,T) = C_t(K,T) - P_t(K,T) + Ke^{-r(T-t)} - F_t e^{-r(T-t)}. \tag{3}$$

The early exercise premium is then calculated as the average error term for each put-call-pair-day:

$$v_t(K,T) = \frac{1}{N}\sum_{j=1}^{N} \varepsilon_j, \tag{4}$$

where N denotes the total number of quote updates. We can rewrite Equation 2 in terms of the options-implied bid price and options-implied ask price at time t:

$$Implied\ Bid = e^{r(T-t)}\left[C_t^{Bid}(K,T) - P_t^{Ask}(K,T) + Ke^{-r(T-t)} - v_t(K,T)\right], \tag{5}$$

$$Implied\ Ask = e^{r(T-t)}\left[C_t^{Ask}(K,T) - P_t^{Bid}(K,T) + Ke^{-r(T-t)} - v_t(K,T)\right]. \tag{6}$$

where $C_t^{Bid}(\cdot)$ ($C_t^{Ask}(\cdot)$) denotes the best bid (ask) price of the call options and $P_t^{Bid}(\cdot)$ ($P_t^{Ask}(\cdot)$) denotes the best bid (ask) price of the put options. We define the options-implied futures midpoint price as the arithmetic mean of implied bid and ask prices:

$$Implied\ midpoint = \frac{Implied\ Bid + Implied\ Ask}{2}. \tag{7}$$

We select the put-call pairs that meet the following criteria for our price discovery analyses: 1) Daily CME Globex trading volume and quoting activities are positive; 2) The options-implied futures midpoint prices are positive; 3) Information leadership share metrics (discussed in section 3.2.2) for each futures and put-call pair can be calculated for both day and night trading sessions in a trading day and for at least 5 days.[10] We obtain 51,954 put-call-pair-day observations in total after these filtering procedures.[11]

Table E1 of Appendix E.1 shows that the options-implied futures midpoint price is more volatile than the futures midpoint price (Table 1), which is also consistent with a wider quoted spread between implied best bid and ask prices, also reported in Table E1. The table shows summary statistics of the difference between options-implied futures and actual

[9]Our estimation of the error term is robust to using the weighted midpoint prices (Hagströmer 2021) of the futures, the put, and the call, as discussed in section 4.1.

[10]The first two criteria exclude some inactive option markets with no quoting activities or those with abnormal quoted prices, generating 52,650 observations in total. The last criterion ameliorates the effect of singleton observations in our regression analyses, resulting in the removal of about 1.32% ($= 1 - 51,954/52,650$) of observations.

[11]Hereafter, we use "option price" and "options-implied futures midpoint price" interchangeably as well as "option" and "put-call pair."

futures midpoint price, with mean differences being smaller than the options tick size (0.125 cents).

3.2.2 *Model*

Our futures-options price discovery analyses follow Hasbrouck (1995)'s one-security-many-markets context based on a standard vector error correction model (VECM). Price discovery across markets occurs when market prices are cointegrated, sharing a common stochastic trend which is the (common) *efficient* price. Hasbrouck (1995) decomposes the random-walk innovation variance into components that are attributed to innovations in each price (futures and options in our context). Each component corresponds to the respective market's information share.

Specifically, for each put-call-pair day, we estimate a VECM of the log futures midpoint prices (p_t^{fut}) and the log options-implied futures midpoint prices (p_t^{opt}). All price series are resampled at one-second level represented by the last observation in each one-second interval.[12] The VECM is defined as follows (e.g., Hasbrouck 2003):

$$\Delta \boldsymbol{p}_t = \boldsymbol{\alpha}(\boldsymbol{\beta}' \boldsymbol{p}_{t-1} - \mu) + \sum_{j=1}^{J} \boldsymbol{\Gamma}_j \Delta \boldsymbol{p}_{t-j} + \boldsymbol{\varepsilon}_t, \tag{8}$$

where $\boldsymbol{p}_t = \left[p_t^{fut}, p_t^{opt}\right]'$ and $\boldsymbol{\beta} \in \mathbb{R}^2$ denotes a (normalized) cointegrating vector $[1, -\beta]'$ that allows a constant term μ in the long-run equilibrium relationship,[13] representing known differences between the two prices, such as the cost of carry that originates from differences between the maturity date of the put-call pair and that of the underlying futures (Hsieh, Lee, and Yuan 2008).[14] $\boldsymbol{\alpha} = [\alpha_1, \alpha_2]'$ is the vector of adjustment coefficients and $\boldsymbol{\Gamma}_j$ matrices are the autoregressive coefficients. The number of lags (J) is selected based on the Schwarz Information Criterion (SIC) with a maximum lag of 60 and the VECM is estimated using

[12] One-second sampling frequency has also been used by previous research (e.g., Hasbrouck 2003; Chakravarty, Gulen, and Mayhew 2004; Anand and Chakravarty 2007).

[13] Notice that a put-call pair is matched with a futures contract based on Table B1. Hence, different costs of carry can arise from matching different contract months, or even from matching the same contract month since options expire a month before the futures. We conduct the Johansen (1991) test to assess whether cointegration exists between two price series and we remove those that are not cointegrated. A total of 8.62% (10.70%) and 5.94% (9.57%) of put-call-pair-day observations are removed at day (night) trading session in corn and soybean markets, respectively.

[14] We test whether the estimated $\boldsymbol{\beta}'$ is statistically different from $[1, -1]'$. The χ^2 statistics suggest the estimated $\boldsymbol{\beta}'$s are statistically different from $[1, -1]'$ for 91.37% of our pooled sample. Thus, we do not restrict the cointegrating vector to be $[1, -1]'$, a usual practice in the literature. Our unreported results show that estimated β is within $[0, 1]$ for 98.47% (95.37%) and 99.16% (96.47%) of put-call-pair-day observations at day (night) trading sessions in corn and soybean markets with absolute means of 0.59 (0.64) and 0.57 (0.63), respectively.

maximum likelihood (ML) (Grammig and Peter 2013).[15]

Following Baillie et al. (2002), we first calculate Gonzalo and Granger (1995)'s component share (CS) and Hasbrouck (1995)'s information share (IS). CS is obtained from the normalized orthogonal to the vector of error correction coefficients, $\boldsymbol{\alpha}_{\perp} = [\gamma_1, \gamma_2]'$, hence:

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1},\ CS_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2}. \tag{9}$$

Given the covariance matrix of the reduced form VECM error terms and its Cholesky factorization $\boldsymbol{\Omega} = \boldsymbol{M}\boldsymbol{M}'$, we have

$$\boldsymbol{\Omega} = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}, \boldsymbol{M} = \begin{bmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{bmatrix} = \begin{bmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2\sqrt{1-\rho^2} \end{bmatrix}. \tag{10}$$

IS is calculated using

$$IS_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2},\ IS_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}. \tag{11}$$

Hasbrouck (1995)'s IS is not unique and depends on the ordering of markets (prices) in the VECM. We thus calculate IS under each of the two possible orderings and then take the simple average of the upper and lower IS bounds.[16] The upper (lower) bound is obtained when the options price is placed first (last) in the VECM. This approach has been widely used in empirical studies (e.g., Baillie et al. (2002); Putniņš (2013); Bohmann, Michayluk, and Patel (2019); Patel et al. (2020)).[17]

Yan and Zivot (2010) show that both CS and IS measures capture not only the changes in the common efficient price (permanent price component), but also the relative level of noise (temporary price component) across markets. This biases the two measures towards the market with less noise (Putniņš 2013). In other words, both IS and CS are only adequate for capturing price discovery when markets display similar noise levels. Putniņš (2013) proposes an information leadership share (ILS) based on Yan and Zivot (2010) which

[15] The choice of a maximum lag of 60 assumes that the price discovery process is completed in 60 seconds (Comerton-Forde and Putniņš 2015). This is generally not a binding constraint on the lag length. In our pooled sample, 80.25% of the put-call-pair-day observations have less than 60 lags.

[16] Market price innovations may be contemporaneously correlated and Hasbrouck (1995) uses a Cholesky factorization to decompose the efficient price variance. However, the Cholesky factorization implicitly assumes the contemporaneous causality runs from the first through the last price (Patel et al. 2020) and one needs to permute the ordering of markets, resulting in upper and lower bounds of IS (Grammig and Peter 2013).

[17] We calculate the spread between the upper and lower bounds of our IS estimates. Our unreported results show a relatively narrow spread, with the average spread for options being 17.59% with standard deviation 14.29%, compared to at most 50% in Hupperets and Menkveld (2002) and about 80% in Booth et al. (2002).

mitigates the dependence on noise, providing an unbiased measure to capture the permanent price component:[18]

$$ILS_1 = \frac{\mid \frac{IS_1}{IS_2}\frac{CS_2}{CS_1} \mid}{\mid \frac{IS_1}{IS_2}\frac{CS_2}{CS_1} \mid + \mid \frac{IS_2}{IS_1}\frac{CS_1}{CS_2} \mid}, \; ILS_2 = \frac{\mid \frac{IS_2}{IS_1}\frac{CS_1}{CS_2} \mid}{\mid \frac{IS_1}{IS_2}\frac{CS_2}{CS_1} \mid + \mid \frac{IS_2}{IS_1}\frac{CS_1}{CS_2} \mid}. \tag{12}$$

Each ILS falls within the range $[0, 1]$ and together they sum to one. The market whose ILS value is above 0.5 impounds new information faster than the other price series and thus price discovery.

3.2.3 *Results*

Table 2 reports the estimated ILSs and ISs. We focus on ILSs, as they allow for noise differences across options and futures prices. Mean ILSs in the day trading session for the corn (soybean) market suggest that options are 10.92% (6.14%) more informative than futures (Panel A of Table 2). Median ILSs suggest a more even distribution of price discovery, with options still dominating (up to 3.82%) over futures. However, overnight futures play a more significant role, with mean ILSs suggesting nearly equal contributions to price discovery between corn futures (49.13%) and options (50.87%). For soybean, mean ILSs suggest that futures lead price discovery by 9.7% overnight.[19] Compared to the day trading session with around 16-17 trades, the overnight session in the options market experiences approximately 3-4 trades. This reduction is likely prompted by the relevant increase in quoted spreads from 0.38 to 0.62 cents in the corn options market and from 0.41 to 0.85 cents in the soybean options market (Table 1). Summary statistics from the pooled sample (Panel C) reveal that options dominate price discovery by 2.46%, as indicated by mean ILSs. Paired t-tests confirm statistically significant differences at 1% level in ILSs between futures and options for both corn and soybean.

ISs differ significantly from ILSs, likely due to differences in price noise levels between futures and options. We show noise ratios of futures and options in Table E2 of Appendix E.2. Noise is defined as the mean absolute difference between each price series and the estimated common efficient price. Following Gonzalo and Granger (1995), we estimate the common efficient price as the weighted average of options-implied futures and actual fu-

[18] Patel et al. (2020) proposes the information leadership indicator (ILI) under a multivariate VECM setting. However, we do not employ this measure for two reasons: 1) Estimating price discovery across numerous put-call pairs is computationally difficult due to the need to consider all permutations of variable orderings as discussed in Patel et al. (2020). 2) Since ILI is a binary variable, it would require a nonlinear regression model (e.g., logit and probit), which is computationally cumbersome, especially when introducing multiple fixed effects.

[19] We obtain more consistent results between means and medians by using the weighted midpoint prices proposed by Hagströmer (2021), as discussed in section 4.1.

tures prices, with their respective CSs as weights. We find that option prices exhibit higher noise than futures prices, with average option noise ratios being at least 3 times higher than those of futures across both day and night trading sessions, a finding supported by our pooled sample. Accordingly, all ISs indicate that futures markets are significantly more informative than options markets. This underscores that disregarding the substantial noise differences between options and futures may generate biased results. Our findings indicate that the options are faster and noisier than futures. Price-improving quoting may increase both undesirable (noise) and desirable quote volatility, with the latter responding faster to new information and thus improving price discovery (Boehmer, Fong, and Wu 2021).

Our results are consistent with Bohmann, Michayluk, and Patel (2019) who assess price discovery between futures and options in 6 commodity markets in 2016-2017. They find that the average options ILS for corn (soybean) is 6% (6.4%) higher than futures. However, our findings differ from previous studies that focus on price discovery between stocks and options. Muravyev, Pearson, and Broussard (2013) find that options contribute less than 5% to price discovery based on ISs. Despite allowing for substantial noise differences between stocks and options, Patel et al. (2020) find options ILS to be between 30 and 50%.[20]

Figure 1 displays the average ILSs of futures and options as options approach maturity for the day and night trading sessions, and for corn and soybean markets. Options expiring within 100 days display ILSs that are around 90%, yet their informativeness diminishes to about 20% around maturity. Options and futures ILSs intersect approximately 40 days prior to option maturity, indicating an equal contribution to price discovery from both contracts at that point.[21]

We also examine how price discovery changes when monthly WASDE reports are released by the USDA at 11:00 Central Time during the day trading session,[22] and the results are reported in Table E3 of Appendix E.3. On announcement days, we observe a notable increase in the informativeness of options. On average, ILSs suggest that options contribute 26.66% (10.9%) more to price discovery compared to futures in the corn (soybean) market, with mean differences in ILSs between options and futures being statistically significant at 1%. On non-announcement days, option leadership in price discovery declines, with options ILS being 10.16% (5.92%) larger than futures ILSs in the corn (soybean) market. Qualitatively

[20]Although previous studies do not use information leadership shares that adjust noise difference between stocks and options, it is worth noting that most U.S. stock options are also tick-constrained, which may help explain the why our findings differ from theirs. Patel et al. (2020) focus on 35 large U.S. stocks listed on the NYSE and NASDAQ and show that the time-weighted average (median) quoted dollar spread is \$0.07 (\$0.06), which is close to the tick size of \$0.05 for stock options priced below \$3.

[21]CME agricultural options are typically expired two weeks prior to the CME agricultural futures.

[22]WASDE announcement days are available at https://usda.library.cornell.edu/concern/publications/3t945q76s?locale=en.

similar results are also obtained from the pooled sample. Our findings add a new dimension to the literature on price discovery during WASDE announcements by showing options incorporate new information faster than futures. Previous studies mainly focus on futures price behavior (e.g., Adjemian and Irwin 2018) and trading strategies (Huang, Serra, and Garcia (2022), Ma and Serra (forthcoming)) in futures markets during WASDE announcements. Our results suggest that monitoring options markets alongside futures may be crucial for traders when reacting to public information releases.

3.3 *Price discovery and price-improving quotes*

3.3.1 *Proxy for tick size binding*

In this section, we approximate the binding nature of the tick size to investigate its role in price discovery between options and futures. In our descriptive analysis, we used $\%OneTick$ variable, measuring the frequency of one-tick quoted spreads. We improve this measure to better assess the impact of tick size on price discovery. A binding tick size restricts the placement of limit orders improving the best bid or ask prices and consequently the midpoint price. This limitation is particularly significant in low-trading activity markets where information is primarily conveyed through limit orders, such as our sample options markets.

We define our proxy as the ratio of the number of price-improving quotes to the total number of BBO updates, reflecting liquidity providers' ability to enhance best bid/ask prices. A higher ratio suggests a less binding tick size, allowing for adjustments to the options-implied futures midpoint price, which can eventually influence price discovery between futures and options markets. Unlike the traditional $\%OneTick$ measure, our proxy allows a more nuanced understanding of how the binding nature of the tick size affects price discovery through the analysis of the price-improving quotes.

For each put-call pair, trading session, day, and market, we calculate the percentage of price-improving quotes ($\%PriceImprove^{OPT}$) as the sum of put and call price-improving quotes relative to the sum of put and call BBO updates, on a scale of 0-100. We calculate this percentage using event-time data which allows us to include all possible quote updates that affect the options-implied futures midpoint price. We apply the same strategy to calculate the percentage of price-improving quotes in futures. Table 3 reports summary statistics of the percentages for options and futures. On average, options witness a percentage of price-improving quotes five times larger than futures (8.59% vs 1.72%), along with a larger variation, as indicated by the standard deviation. This aligns with the results reported in Table 1, which indicate that futures markets are constrained more than 90% of the time across markets and trading sessions.

3.3.2 *Baseline OLS regression*

To assess the effect of the binding nature of the tick size in the options market on price discovery, we regress options ILS against the percent of options price-improving quotes, while controlling for option market characteristics. The regression specification is

$$ILS_{ijmt}^{OPT} = \beta \times \%PriceImprove_{ijmt}^{OPT} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt}, \tag{13}$$

where ILS_{ijmt}^{OPT} denotes the information leadership share (on a scale of 0-100) of put-call pair i at trading session j in market m on day t. $\%PriceImprove_{ijmt}^{OPT}$ represents the percentage of options price-improving quotes. Parameters λ_i, γ_j, and δ_m denote put-call pair, trading session, and market fixed effects, respectively. We double cluster the standard errors by put-call pair and day.

We rely on previous research when choosing our control variables ($\boldsymbol{Controls}$) representing options market characteristics. We estimate different regressions with different controls, to test the robustness of our results. We control for the potential informativeness of daily options volume ($Volume_{imt}^{OPT}$), which is measured as the sum of call and put omega-adjusted volume.[23] We consider options time-to-maturity ($TimeMaturity_{imt}^{OPT}$), as suggested by Figure 1, is expected to be positively correlated with options ILS. We also consider the percent of price-improving quotes in the futures market ($\%PriceImprove_{jmt}^{FUT}$) which is expected to reduce the informativeness of options. We follow Patel et al. (2020) and control for options leverage. We develop a measure of leverage that is applicable to put-call pairs by considering whether a put or call option is more likely to be used by informed traders:

$$Leverage_{imt} = Leverage_{imt}^{call}\mathbf{1}\left\{r < 0\right\} + Leverage_{imt}^{put}\mathbf{1}\left\{r > 0\right\}, \tag{14}$$

where $Leverage_{imt}^{call}$ and $Leverage_{imt}^{put}$ are the call and the put option omega, respectively. $\mathbf{1}\left\{r > 0\right\}$ ($\mathbf{1}\left\{r < 0\right\}$) is an indicator function that equals 1 if the daily futures return at $t+1$ is positive (negative).[24] Following Patel et al. (2020), we also consider alternative mea-

[23]Our unreported results show that daily futures volume (measured in million dollars) does not have a statistically significant effect on options ILS and the coefficients of options percentage price-improving quotes are almost identical to those reported in our main results in both OLS and 2SLS-IV regressions for all specifications.

[24]The definition of leverage for put-call pairs is supported by the fact that informed traders with good (bad) news are likely to sell put (call) options rather than buy call (put) options. To verify this, we calculate the best quote updates at bid/ask relative to BBO updates for put and call options during the WASDE announcements. Our unreported paired t-test results show that the average proportion of best quote updates at ask (bid) for put options is significantly higher (lower) than that at bid (ask) for call options when market surprises are positive (negative) at 1% level. Market surprises are measured as the difference between the actual value of the release and its median estimate from Bloomberg analysts, following Chordia, Green, and Kottimukkalur (2018). This indicates that informed traders intend to sell put (call) options when good (bad)

sures to represent options leverage, including options implied volatility ($Impvolatility_{imt}$) from the Black-Scholes model, which affects options leverage through its price level. We also measure options moneyness through the absolute difference between the underlying futures price and strike price given a put-call pair ($StrikeDistance_{imt}$). Thus, an increase in options strike distance reduces the moneyness of the call option (if the futures price is lower than the strike price) or the put option (if the futures price is higher than the strike price). Capelle-Blancard (2001) points out that options traders informed about futures price volatility (volatility traders) may crowd out those informed about the futures price, a concept referred to as the uncertainty hypothesis in Patel et al. (2020). We test this hypothesis considering futures volatility ($Volatility^{FUT}_{jmt}$) as a control variable.[25] Detailed descriptions of our control variables are shown in Table D1 of Appendix D. We also provide the summary statistics for the control variables in Table 3.

Table 4 presents the baseline OLS regression estimates. Results indicate that the options (percentage) price-improving quotes have a positive and statistically significant effect on options ILS in all specifications. Specification (1) only controls for options time-to-maturity and options volume. Results suggest that a 1% increase in options price-improving quotes leads to a 0.41% increase in options ILS. In terms of pooled sample standard deviation, a one-standard-deviation increase (6.67%) in it is expected to increase options ILS by 2.71% ($= 6.67 \times 0.406$), representing 5.27% ($= 6.67 \times 0.406/51.24$) of the options ILS sample mean. The coefficient declines from 0.406 to 0.373 when we also control for futures volatility in specification (2). This suggests that when the futures market experiences larger price fluctuations, the influence of options price-improving quotes on options price discovery declines. Consistent with Patel et al. (2020), our results do not support the uncertainty hypothesis as the coefficient of futures volatility is significantly positive in all specifications, which implies that options contribute more to price discovery during volatile periods in futures markets. This is consistent with options price discovery increasing when public reports are released (Table E3). Specification (3) extends the model in (2) by controlling for futures price-improving quotes. The variable has a negative and statistically significant effect on options ILS, with a one-standard-deviation increase (0.95%) in futures price-improving

news arrive. When the daily futures return at $t+1$ is unchanged (i.e., $r = 0$), we calculate leverage for each put-call pair as the simple average of put and call omega. Weak statistical significance of options leverage is also found if we consider call (put) option omega when the daily futures return at $t+1$ is positive (negative).

[25] We do not include the quoted spread in the control variables group because it is highly correlated with options price-improving quotes. Our control variables primarily focus on option characteristics that are unlikely to be influenced by options price discovery characteristics to avoid endogeneity. Futures volatility and futures price-improving quotes are more likely to be affected by market conditions in futures, instead of options price discovery. Hence, our regression is not likely to introduce additional endogeneity through control variables.

quotes resulting in a 3.62% ($= 0.95 \times 3.811$) decrease in options ILS, representing 7.07% ($= 0.95 \times 3.778/51.24$) of the options ILS sample mean. Notice that changes in futures price-improving quotes have a larger impact on options ILS (7.07%) than changes in options (5.27%). We control for options leverage in specification (5), which is significantly and negatively correlated to options ILS at 10% level. Hence, options leverage does not attract informed traders to the market. Following Patel et al. (2020), we also consider options strike distance and implied volatility as alternative leverage measures, and find that only options strike distance is positively significantly related to options price discovery, implying that options that are deeper in- or out-of-the-money contribute to price discovery more than at-the-money options.[26] Consistent with Figure 1, options time-to-maturity is positively related and highly statistically significant across all specifications. According to specification (1), an increase in options time-to-maturity by 30 days increases options ILS by 16.71% ($= 30 \times 0.557$). Options volume has a positive and statistically significant effect on options ILS in 3 of 6 specifications at 10% level or higher. However, the economic magnitudes of the coefficients are marginal as a one-standard-deviation increase in options volume (18.05 million dollars) is expected to increase options ILS by 0.48%, representing merely a 0.95% of its sample mean. Overall, our results indicate that the binding tick size helps explain price discovery between futures and options.

3.3.3 *Identification strategy*

The OLS regression results in section 3.3.2 should be carefully interpreted as the submission of price-improving quotes may be endogenous to price discovery. Increased price discovery in options may attract informed traders to reveal their information by posting more price-improving quotes, which may affect the binding nature of the tick size in options. To facilitate causal inference, we employ a 2SLS-IV regression.

Similar to Comerton-Forde and Putniņš (2015) and Foley and Putniņš (2016), our identification strategy is based on an exogenous market structure change affecting options trading; the closure of the options floor trading on March 16, 2020, due to precautionary measures related to the COVID-19 pandemic.[27] Thus, we use a dummy variable $FloorClose_t$ that equals one after the floor trading closes and zero otherwise as an instrumental variable.

[26] We verify this argument by running regressions of specifications (2) and (4) across three subsamples based on the quantiles of options strike distance, with results reported in Table E4 of Appendix E.4. Consistent with our main regression findings, we show that options price-improving quotes have a progressively stronger effect on the options ILS as the options moneyness decreases. Specifically, the effect ranges from negative or insignificant for the high moneyness (short strike distance) subsample shown in columns (1) and (2), to significantly positive for the low moneyness (long strike distance) subsamples shown columns (3) to (6).

[27] https://investor.cmegroup.com/news-releases/news-release-details/cme-group-close-chicago-trading-floor-precaution.

Literature suggests that floor traders execute large trades for their clients (e.g., Hasbrouck and Sofianos 1993) and provide additional liquidity to markets (e.g., Madhavan and Sofianos 1998; Sofianos and Werner 2000). Gousgounis and Onur (2024), along with insights from conversations with CME market participants, suggest that since the closure of the floor venue, floor traders now participate in the electronic venue where they compete with high-frequency traders (HFTs). Since floor traders generally trade at a slower pace than HFTs, their trading strategy in the electronic venue likely favors placing price-improving quotes that prioritize price over speed (Yao and Ye 2018). Hence, liquidity provision by floor traders in the electronic venue is likely to have changed the percentage of price-improving quotes submitted after the closure of the floor venue. This argument is consistent with Madhavan and Sofianos (1998) who find the NYSE (floor) specialists compete with other liquidity providers and participate more when quoted spreads are wide.[28]

We validate our identification strategy in Figure 2, where we show the daily option percentage price-improving quotes across the sample period for the pooled sample, day, and night sessions. The horizontal dash lines indicate the sample means before and after March 16, 2020. We find that after the floor venue was closed, options price-improving quotes increased to 11.93% from 7.81%, and the interquartile change also became wider in the pooled sample. This increase is more pronounced over the night trading session where options price-improving quotes increased by 6.91% from 10.52%. A smaller increase is observed in the day trading session with a magnitude of 1.33%. We conduct (one-sided) Welch t-tests to assess whether the sample means during the post-close period are statistically higher than those during the pre-close period. The t-statistics are reported in Figure 2 and show that the average price-improving quote percentage after the floor trading closure is significantly higher at 1% level.

Figure 2 also conveys another important message. The floor trading closure may have also changed the distribution of options price-improving quotes between day and night trading sessions, with a larger increase occurring in the night trading session. This suggests that previous floor traders not only participated during the day but also during the night trading session where they may post a greater percentage of price-improving quotes during the post-close period. Our unreported results show that after the floor venue closed, the average number of BBO updates declined by 17.06% (4.74%) and the number of price-improving quotes increased by 31.41% (29.42%) during the night (day) trading session. This resulted

[28]NYSE specialists can trade for their own accounts by offering a price improvement that is at least one-tick better than the current best quotes, which is similar to price-improving quotes (e.g., Harris and Hasbrouck 1996; Knez and Ready 1996; Ready 1999). Thus, liquidity takers can trade at slightly better price. Empirical evidence from Ready (1999) shows that 64.7% of market orders with two-tick ($1/4) quoted spread receive one-tick price improvements (price-improving quotes) from specialists during 1990 to 1991.

in a larger increase in the percentage at the night trading session. Our IV satisfies the exclusion restriction since the options markets rely on quotes instead of trades, as results indicated in Table 4. Thus, it is unlikely that the floor closure affected price discovery through other channels, such as changing the trading volume ratio between futures and options (e.g., Chakrabarty, Cox, and Upson 2021).[29]

3.3.4 *2SLS-IV regression*

Considering price-improving quoting activities may be affected by similar activities in preceding days, thus, in addition to the floor closure dummy variable $FloorClose_t$, we include the lagged value of the percentage of price-improving quotes ($\%PriceImprove^{OPT}_{ijm,t-1}$) as an additional IV.[30] Using lagged endogenous variables as IVs is common in the literature (e.g., Sarkar and Schwartz 2009; Foley and Putniņš 2016; Buti, Rindi, and Werner 2022). The first-stage regression is specified as follows:

$$\begin{aligned}\%PriceImprove^{OPT}_{ijmt} =& \beta_1 FloorClose_t + \beta_2 \%PriceImprove^{OPT}_{ijm,t-1} + \boldsymbol{Controls} + \\ & \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt},\end{aligned} \tag{15}$$

where $FloorClose_t$ equals one for both day and night trading sessions after March 16, 2020, and zero otherwise. We include the same control variables and fixed effects as those in the baseline OLS regression (Equation 13), resulting in the same six regression specifications as in Table 4.

Table 5 reports the results from the first-stage regression. As expected, we find the floor closure has a positive and statistically significant effect on options price-improving quotes, with coefficients ranging between 1.08 and 1.94. We find a significantly negative relationship between the options price-improving quotes and options time-to-maturity. No significant relationship between options leverage and options price-improving quotes is found, suggesting that options leverage does not significantly influence options price-improving quoting. The Montiel Olea and Pflueger (2013) effective F statistics in our first-stage regression all imply that the selected set of IVs are not weak. We also conduct an overidentification test and the Hansen J test p-values show that 5 of 6 models cannot reject the null hypothesis that at least one IV is exogenous at 5% level.

Our second-stage regression identifies how the percentage of options price-improving

[29] We take the daily volume ratio between options and futures as the endogenous variable and use a similar setting in the 2SLS-IV regression. Our unreported results show the volume ratio does not have a statistically significant effect on options ILS for all specifications.

[30] Our results are robust if we only use $FloorClose_t$ as an instrumental variable, except in the specification where futures price-improving quoting is included as a control variable, as discussed in section 4.2.

quotes affects the options price discovery:

$$ILS_{ijmt}^{OPT} = \beta \times \%\widehat{PriceImprove}_{ijmt}^{OPT} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt}, \tag{16}$$

where $\%\widehat{PriceImprove}_{ijmt}^{OPT}$ is the fitted value of options price-improving quotes from the first-stage regression (Equation 15). We use the same control variables and fixed effects as those in the baseline regression, resulting in the same six regression specifications as in Table 4.

Table 6 reports the results from the second-stage regression. Consistent with the baseline OLS regression, the coefficients of our variable of interest are all statistically significant at 1% level. The results indicate that options price-improving quotes have a positive and statistically significant effect on options price discovery. A 1% increase in options price-improving quotes leads to a 0.43% increase in options ILS. Alternatively, a one-standard-deviation increase (3.71%) in the options price-improving quotes is expected to increase options ILS by 1.58% (= 3.71 × 0.425), representing 3.10% (= 3.71 × 0.425/50.93) of its sample mean when controlling for options time-to-maturity and options volume (specification (1)). The magnitude is slightly higher than that in the baseline OLS regression (0.43% vs 0.41%, for a 1% increase in variable of interest). When we additionally control for futures volatility, the coefficient remains statistically positive but slightly smaller. This results in a reduced impact of options price-improving quotes on options ILS, which drops to 1.51% (= 3.74 × 0.404) (specification (2)). Specification (3) also controls for futures price-improving quotes whose increase by one standard deviation (0.94%) reduces options ILS by 3.69% (= 0.94 × 3.929), representing 7.25% of its sample mean (= 0.94 × 3.929/50.93), which is slightly higher than the baseline OLS regression (3.73% vs. 3.62%). In terms of other control variables considered in specifications (4) to (6), neither implied volatility nor options leverage significantly affect the options ILS. Like in our baseline OLS regression, options time-to-maturity is negatively correlated to the options price discovery. The results still do not support the uncertainty hypothesis as the coefficients of futures volatility are positive and statistically significant for all specifications. We find options volume has economically marginal effect on options ILS and is statistically significant in 3 of 6 specifications, which is consistent to our baseline OLS regression. Our 2SLS-IV regressions imply that the endogeneity issue is not severe, as we generally obtain results similar to the baseline OLS regression.

3.3.5 *Heterogenous analysis*

Since price-improving quotes can only be placed when the quoted spread is larger than one tick, in this section we investigate how options price discovery changes over different subsamples characterized by various levels of the $\%OneTick$ variable. For each put-call pair, we calculate the one-tick percentage of the call ($\%OneTick^{call}$) and the put ($\%OneTick^{put}$) option. We sort put-call pairs into three subsamples representing different market tick-constraining conditions. The first subsample includes observations where both $\%OneTick^{call}$ and $\%OneTick^{put}$ are zero, implying that neither put nor call options are constrained. The second subsample includes observations where either $\%OneTick^{call}$ or $\%OneTick^{put}$ is zero, but not both, indicating that half of the options selected are constrained. The last subsample includes observations where neither $\%OneTick^{call}$ nor $\%OneTick^{put}$ are zero, which indicates all options face tick size binding constraints.

We first replicate the summary statistics presented in Table 3 for each subsample and report the results in Table F1 of Appendix F, where panels A to C correspond to the three cases described above, presented in the same order. We find that the second subsample accounts for about 90% of the pooled sample while the remaining two account for 5% each. Average options ILSs are remarkably close across the three subsamples. However, median ILSs decline as the market becomes more constrained (from panels A to C). Price-improving quotes are likely to occur in put-call pairs when the tick size is less binding, with the average percentage declining from 14.58% to 5.49%. We also find the percentage of price-improving quotes in futures slightly declines from 2.04% to 1.29%. This may be related to the correlation between the two markets in several dimensions, particularly in price discovery. We find options leverage slightly increases as the markets become more constrained, from 1.59 to 3.78. This suggests that as the tick size becomes more constraining, option omega increases, leading to a greater percentage change in an option value when futures price changes. No substantial differences of implied volatility between different subsamples are found, implying that forward looking volatility may not be strongly related to the tick size binding nature. We find that options with earlier maturities are generally more likely to have a binding tick size than those with later maturities, which is consistent with the link between price discovery and maturity. Our results show that average options volume increases from 4.05 to 36.82 million dollars as markets become constrained, implying that price discovery may switch from price-improving quotes to trades when tick size becomes more binding. This is consistent with our intuition that price-improving quotes are less likely to be posted in a tick-constrained market.

We run the OLS and 2SLS-IV regressions for each subsample to assess the heterogeneous effects. We use two specifications with options leverage, futures volatility, options volume, and options time-to-maturity as control variables due to limited space. We report the results in Table F2 of Appendix F. In terms of the first subsample, options price-improving quotes have a positive and statistically significant effect on options ILSs under both OLS and 2SLS-

IV regressions, though the effect is only statistically significant at 10% level for one 2SLS-IV regression. A 1% increase in options price-improving quotes is expected to increase the options ILS by 0.30% and 0.35% in the OLS and 2SLS-IV regressions, respectively, according to specifications (1) and (2). In the second subsample, options price-improving quotes are positively and significantly related to options ILS. A 1% in options price-improving quotes is expected to increase options ILS by 0.40% and 0.44%, in the OLS and 2SLS-IV regressions, respectively, according to specifications (5) and (6). In terms of the third subsample, options price-improving quotes have a negative but not statistically significant effect on options ILS in the OLS regression. The coefficient becomes negative and statistically significant in the 2SLS-IV regression. This evidence indicates that the price-improving quotes are not informative for options that are completely constrained. Futures volatility and options time-to-maturity have the same signs and statistical significance as our main results, except for futures price volatility in the first subsample. Our results show that options volume has a positive and statistically significant effect on options ILS at 5% level for the OLS regressions in the third subsample, though the coefficient is not statistically significant for the 2SLS-IV regression. However, we find options volume has no explanatory power to options ILS in the second subsample and has a significantly negative effect on options ILS in the first subsample. As expected, we show that price discovery may switch to trades when markets are tick-constrained.

Overall, our heterogeneous analysis validates our main results and implies that price discovery is mostly driven by the put-call pairs whose at least one of put and call options is tick-unconstrained. Price-improving quotes do not contribute to price discovery when both put and call options are tick-size constrained.

4 Robustness

4.1 *The weighted midpoint price*

We estimate the error term $\varepsilon_t(K,T)$ in Equation 3 by using the midpoint prices of the futures, the put, and the call. However, Hagströmer (2021) points out that the midpoint price is not a continuous variable and assumes symmetry in the best quotes between the bid and ask sides. Hence, we apply the weighted midpoint price proposed by Hagströmer (2021) that considers the quote imbalance between best bid and ask, which is defined as

$$p^{wm} = \frac{p^{bid}q^{ask} + p^{ask}q^{bid}}{q^{bid} + q^{ask}}, \tag{17}$$

where p^{ask} (p^{bid}) and q^{bid} (q^{ask}) denotes the best ask (bid) price and the best bid (ask) quote, respectively. Table G1 of Appendix G reports the summary statistics of information leadership shares, where the results are qualitatively similar to those reported in Table 2. We find options lead futures at both day and night trading sessions in all markets, regardless of mean and median values. However, the leadership of option markets is more pronounced if we use the weighted midpoint price. For instance, in our pooled sample, options ILS is 59.23% on average, which is 8% higher than the results reported in Table 2 where the midpoint price is applied. This enhanced leadership is also found at each trading session in each market. Consistently, our paired t-tests suggest that the differences in ILSs are statistically significant at 1% level between futures and options for both corn and soybean markets. One reason for improved leadership in options could be that the weighted midpoint price considers the quote imbalance, unlike the arithmetic midpoint price, thereby introducing greater variability in estimating the proxy for fundamental value.

4.2 *Robustness to a simpler instrumental variable*

To address potential endogeneity concerns with using the lagged value of options price-improving quotes as an IV may be endogenous, we run a regression using a simpler instrument variable. Specifically, we use only the floor trading closure dummy as an instrument (omitting the lagged options price-improving quotes). The regression results are reported in Table G2 of Appendix G. Our results are robust to using the floor trading closure as the only instrument, except in the specification where futures price-improving quoting is included as a control variable, resulting in a negative R^2 (not reported). Similar to Foley and Putniņš (2016), we find the magnitude of coefficients is higher than that estimated when using the lagged options price-improving quotes as an additional IV.

4.3 *Falsification tests using pseudo price-improving quote percentages*

To rule out the effects of potential confounders that may affect the impact of options price-improving quotes on price discovery in our OLS regression, we conduct a falsification test. The test involves creating a pseudo variable for $\%PriceImprove$. Specifically, we construct $Pseudo\%PriceImprove$ by randomly assigning percentages of options price-improving quotes to put-call pairs. By repeating the process 1,000 times, we generate 1,000 subsamples. We expect that the pseudo variables will bear no relationship with options ILS. For each subsample, we re-estimate the baseline OLS regression and record $\hat{\beta}^{pseudo}$, the coefficient of $Pseudo\%PriceImprove$. We choose to re-estimate the model by OLS given the small differences between OLS and 2SLS-IV parameters reported above (Tables 4 and 6). Figure G1 of Appendix G displays the distribution of the impact of $Pseudo\%PriceImprove$ on options ILS using regression specifications (1)-(6) in Table 4. The blue line is the estimated kernel density, and the black vertical line is the actual OLS estimate in Table 4. We find that the distributions of the pseudo coefficients do not contain the original coefficient, as they are far to the right of the latter. Generally, these results imply that our main conclusions are not likely to be driven by chance.

4.4 *Robustness to an alternative proxy of binding tick size*

Though we use percentage price-improving quotes as the proxy in our main results, we test the robustness of our selection using an alternative proxy–the weighted average of put and call one-tick proportions within a put-call pair–denoted as $\%OneTick^{pair}$. We take the number of BBO updates of put and call within a put-call pair as the weights. Weights increase the severity of the tick-size constraint in the most active contracts. We have a similar setting for the first-stage regression and specify our second-stage regression as follows:

$$ILS^{OPT}_{ijmt} = \beta \times \%\widehat{OneTick}^{pair}_{ijmt} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt}, \tag{18}$$

where $\%\widehat{OneTick}^{pair}_{ijmt}$ is the fitted value of the put-call pair one-tick proportion from the first-stage regression. We also include the futures one-tick proportion ($\%OneTick^{FUT}_{jmt}$) in our control variables and the results are reported in Table G3 of Appendix G. We find the put-call pair one-tick proportion has a negative and statistically significant effect on options ILS, indicating that a more binding tick size is expected reduce the options ILS. Consistently, higher futures one-tick proportion is expected to increase options ILS since a higher binding tick size restricts the informativeness in futures and promotes higher price discovery share in options.

4.5 *Robustness to different fixed effects*

We test the robustness of our 2SLS-IV regression by using different fixed effects. We introduce the interacted market × session fixed effects, assuming that unobserved market effects vary by session and unobserved session effects vary by market. Thus, we estimate the following second-stage regression:

$$ILS^{OPT}_{ijmt} = \beta \times \%\widehat{PriceImprove}^{OPT}_{ijmt} + \boldsymbol{Controls} + \lambda_i + \eta_{jm} + \varepsilon_{ijmt}, \tag{19}$$

where η_{jm} is the interacted market $m \times$ session j fixed effect. We use the same control variables as in Table 4. We report the results in Table G4 of Appendix G. We obtain qualitatively similar results, where a one-standard-deviation increase (3.59%) in options price-improving quotes is expected to increase options ILS by 1.59% (= 3.59 × 0.543) according to specification (1), which is almost identical to the magnitude shown in Table 4.

4.6 *Robustness to an alternative independent variable*

We test the robustness of our 2SLS-IV regression by using the log ratio of price-improving quotes in options ($\%PriceImprove^{OPT}_{ijmt}$) over those in futures ($\%PriceImprove^{FUT}_{jmt}$) as the variable of interest denoted as $RatioPriceImp_{ijmt}$. We use a similar setting in the first-stage regression with $RatioPriceImp_{ijmt}$ as the endogenous variable and run the following second-stage regression:

$$ILS^{OPT}_{ijmt} = \beta \times \%Ratio\widehat{Price}Imp_{ijmt} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m \varepsilon_{ijmt}, \tag{20}$$

where $\%Ratio\widehat{Price}Imp_{ijmt}$ is the fitted value of the log ratio ($\log\left(\frac{\%PriceImprove^{OPT}_{ijmt}}{\%PriceImprove^{FUT}_{jmt}}\right)$) from the first-stage regression and the results are reported in Table G5 of Appendix G. We obtain qualitatively similar results, where a 1% increase in the ratio of price-improving quotes is expected to increase options ILS by 0.08% (= 8.043 × log(1.01)), with that increase being 0.16% (= 8.043×log(1.01)/50.93) of the options ILS sample mean, according to specification (1). Though options volume has a statistically significant effect on options ILS in all settings, their economic magnitudes are still marginal.

4.7 *Robustness to an alternative estimation method*

We also check the robustness of our main results using the two-step generalized method of moments (GMM) estimator. Qualitatively similar results are reported in Table G6 of Appendix G though the options price-improving quotes have a smaller impact on options price discovery.

5 Conclusions

The tick size, representing the minimum price increment at which trades can occur, is a relevant characteristic of financial markets and can influence price discovery. A large nominal tick size may result in a tick-constrained market in which the bid-ask spread is usually one tick. In a tick-constrained market, posting quotes that improve the best bid or best offer price (price-improving quotes) is more challenging compared to tick-unconstrained markets. Since informed traders may use price-improving quotes to reveal information in the market (e.g., Brogaard, Hendershott, and Riordan 2019), tick-unconstrained markets may facilitate more information incorporation through price-improving quotes than constrained venues.

This is the first study that investigates how the tick size affects price discovery between agricultural futures and options. Agricultural options, with lower trading volume and half the tick size of futures, encourage more price-improving quotes compared to futures. We focus on the CME corn and soybean markets from January 2019 to June 2020, using CME Market Depth data. We present summary statistics of market liquidity in options markets and compare them with liquidity metrics in futures markets. We find that futures markets are characterized by a one-tick quoted spread over 90% of the time, whereas this number is only about 10% in the option markets. Options exhibit a dollar quoted spread that is, on average, 1.5 to 3.1 times larger than futures. Unlike futures, options are less traded and driven more by quotes, resulting in a percentage of price-improving quotes that is five times larger than that in futures.

Our price discovery results are consistent with Bohmann, Michayluk, and Patel (2019) and show that, despite thin trading, options are as informative as futures. We quantify the relationship between price discovery and tick size constraints using the percentage of price-improving quotes for each put-call pair as a proxy. To address potential endogeneity, we use the closure of CME options floor trading on March 16, 2020 as an exogenous instrument, along with lagged price-improving quoting activity. The closure likely prompted floor traders to use price-improving quotes on the electronic platform to gain price priority (Yao and Ye 2018). We observe a 4.12% increase in price-improving quotes after the closure, validating our conjecture. Regression results suggest that a one-standard-deviation (3.71%) increase in price-improving quotes is expected to increase the options information leadership share by 1.58%, representing 3.10% of its sample mean. Our results remain robust across various robustness checks and are reinforced by our heterogeneous analysis, which shows that price-improving quoting plays no role in price discovery for tick-constrained put-call pairs.

CME has initiated a survey and solicited feedback from market participants on a potential reduction of the tick size in the corn futures calendar spread market by half. Currently, most CME commodity futures markets are tick-constrained. A reduction in tick size in the calendar spread market has implications for the outright market. CME implements an implied functionality to connect the liquidity between outright and spread markets. Each leg of the spread market is routed to the outright market, increasing the likelihood of execution. While the CME initiative to reduce the tick size applies only to calendar spreads, its implementation may necessitate identical pricing grids for both the spread and outright markets to facilitate the implied functionality. This could eventually lead to the same reduction in tick size in the outright market. Otherwise, quotes from calendar spread market cannot be routed to the outright market. Our results support the relevance of the initiative in terms of price discovery. Additionally, with a smaller tick size, limit orders may scatter across a finer pricing grid, potentially reducing the clustering of depths at the top of the book (Werner et al. 2023). This may also improve price discovery within the calendar spread market as trades gain greater potential to influence the midpoint price due to decreased depths at the BBO.

References

Adjemian, M. K. and S. H. Irwin (2018). USDA announcement effects in real-time. *American Journal of Agricultural Economics 100*, 1151–1171.

Anand, A. and S. Chakravarty (2007). Stealth trading in options markets. *Journal of Financial and Quantitative Analysis 42*, 167–187.

Baillie, R. T., G. G. Booth, Y. Tse, and T. Zabotina (2002). Price discovery and common factor models. *Journal of Financial Markets 5*, 309–321.

Baldauf, M. and J. Mollner (2021). Trading in Fragmented Markets. *Journal of Financial and Quantitative Analysis 56*, 93–121.

Blume, M. E. and R. F. Stambaugh (1983). Biases in computed returns. An application to the size effect. *Journal of Financial Economics 12*(3), 387–404.

Boehmer, E., K. Fong, and J. J. Wu (2021). Algorithmic Trading and Market Quality: International Evidence. *Journal of Financial and Quantitative Analysis 56*, 2659–2688.

Bohmann, M. J., D. Michayluk, and V. Patel (2019). Price discovery in commodity derivatives: Speculation or hedging? *Journal of Futures Markets 39*(9), 1107–1121.

Booth, G. G., J.-C. Lin, T. Martikainen, and Y. Tse (2002). Trading and pricing in upstairs and downstairs stock markets. *Review of Financial Studies 15*, 1111–1135.

Boyd, N. and P. Locke (2014). Price discovery in futures and options markets. *Journal of Futures Markets 34*, 853–867.

Brogaard, J., T. Hendershott, and R. Riordan (2019). Price discovery without trading: Evidence from limit orders. *Journal of Finance 74*, 1621–1658.

Buti, S., B. Rindi, and I. M. Werner (2022). Diving into dark pools. *Financial Management 51*, 961–994.

Capelle-Blancard, G. (2001). Volatility trading in options market: How does it affect where informed traders trade?

Chaboud, A., E. Hjalmarsson, and F. Zikes (2021). The evolution of price discovery in an electronic market. *Journal of Banking and Finance 130*, 106171.

Chakrabarty, B., J. Cox, and J. E. Upson (2021). Tick size pilot program and price discovery in U.S. stock markets. *Journal of Financial Markets*, 100658.

Chakravarty, S., H. Gulen, and S. Mayhew (2004). Informed trading in stock and option markets. *Journal of Finance 59*, 1235–1258.

Chao, Y., C. Yao, and M. Ye (2019). Why discrete price fragments U.S. Stock exchanges and disperses their fee structures. *Review of Financial Studies 32*, 1068–1101.

Chordia, T., T. C. Green, and B. Kottimukkalur (2018). Rent seeking by low-latency traders: Evidence from trading on macroeconomic announcements. *Review of Financial Studies 31*, 4650–4687.

Collin-Dufresne, P. and V. Fos (2015). Do prices reveal the presence of informed trading? *Journal of Finance 70*, 1555–1582.

Comerton-Forde, C. and T. J. Putniņš (2015). Dark trading and price discovery. *Journal of Financial Economics 118*, 70–92.

Demsetz, H. (1968). The cost of transacting. *Quarterly Journal of Economics 82*, 33–53.

Dyhrberg, A. H., S. Foley, and J. Svec (2023). When bigger is better: The impact of a tiny tick size on undercutting behavior. *Journal of Financial and Quantitative Analysis 58*, 2387–2416.

Easley, D., M. L. de Prado, and M. O'Hara (2016). Discerning information from trade data. *Journal of Financial Economics 120*, 269–285.

Fleming, M., B. Mizrach, and G. Nguyen (2018). The microstructure of a U.S. treasury ecn: The brokertec platform. *Journal of Financial Markets 40*, 2–22.

Fleming, M., G. Nguyen, and F. Ruela (2024). Tick size, competition for liquidity provision, and price discovery: Evidence from the U.S. Treasury market. *Management Science 70*, 332–354.

Foley, S., T. G. Meling, and B. A. Ødegaard (2023). Tick size wars: The market quality effects of pricing grid competition. *Review of Finance 27*, 659–692.

Foley, S. and T. J. Putniņš (2016). Should we be afraid of the dark? Dark trading and market quality. *Journal of Financial Economics 122*, 456–481.

Goettler, R. L., C. A. Parlour, and U. Rajan (2009). Informed traders and limit order markets. *Journal of Financial Economics 93*, 67–87.

Gonzalo, J. and C. Granger (1995). Estimation of common long-memory components in cointegrated systems. *Journal of Business and Economic Statistics 13*, 27–35.

Gousgounis, E. and E. Onur (2024). The end of an era: Who paid the price when the livestock futures pits closed? *American Journal of Agricultural Economics 106*, 1111–1140.

Grammig, J. and F. J. Peter (2013). Telltale tails: A new approach to estimating unique market information shares. *Journal of Financial and Quantitative Analysis 48*, 459–488.

Hagströmer, B. (2021). Bias in the effective bid-ask spread. *Journal of Financial Economics 142*, 314–337.

Hagströmer, B. and A. J. Menkveld (2019). Information revelation in decentralized markets. *Journal of Finance 74*, 2751–2787.

Han, Y. and D. Lesmond (2011). Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. *Review of Financial Studies 24*, 1590–1629.

Harris, L. and J. Hasbrouck (1996). Market vs. limit orders : The superdot evidence on order submission strategy. *Journal of Financial and Quantitative Analysis 31*, 213–231.

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *The Journal of Finance 50*, 1175–1199.

Hasbrouck, J. (2003). Intraday price formation in U.S. equity index markets. *Journal of Finance 58*(6), 2375–2400.

Hasbrouck, J. and G. Sofianos (1993). The trades of market makers: An empirical analysis of nyse specialists. *Journal of Finance 48*, 1565–1593.

Hsieh, W. L. G., C. S. Lee, and S. F. Yuan (2008). Price discovery in the options markets: An application of put-call parity. *Journal of Futures Markets 28*, 354–375.

Huang, J., T. Serra, and P. Garcia (2022). "Fast money" around Federal statistics releases. *American Journal of Agricultural Economics 105*, 1248–1266.

Hupperets, E. C. J. and A. Menkveld (2002). Intraday analysis of market integration: Dutch blue chips traded in amsterdam and new york. *Journal of Financial Markets 5*, 57–82.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica 59*, 1551–1580.

Kaniel, R. and H. Liu (2006). So what orders do informed traders use? *Journal of Business 79*, 1867–1913.

Knez, P. J. and M. J. Ready (1996). Estimating the profits from trading strategies. *Review of Financial Studies 9*, 1121–1163.

Kwan, A., R. Masulis, and T. H. McInish (2015). Trading rules, competition for order flow and market fragmentation. *Journal of Financial Economics 115*, 330–348.

Lee, C. M. (1993). Market integration and price execution for nyse-listed securities. *Journal of Finance 48*, 1009–1038.

Ma, R. R. and T. Serra (forthcoming). Is liquidity provision informative? Evidence from agricultural futures markets. *American Journal of Agricultural Economics*.

Madhavan, A. and G. Sofianos (1998). An empirical analysis of nyse specialist trading. *Journal of Financial Economics 48*, 189–210.

McInish, T. H. and R. A. Wood (1992). An analysis of intraday patterns in bid/ask spreads for NYSE stocks. *Journal of Finance 47*, 753–764.

Montiel Olea, J. L. and C. Pflueger (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics 31*, 358–369.

Muravyev, D., N. D. Pearson, and J. P. Broussard (2013). Is there price discovery in equity options? *Journal of Financial Economics 107*, 259–283.

Narayan, S. and R. Smyth (2015). The financial econometrics of price discovery and predictability. *International Review of Financial Analysis 42*, 380–393.

O'Hara, M. (2003). Presidential address: Liquidity and price discovery. *Journal of Finance 58*, 1335–1354.

Parlour, C. A. and U. Rajan (2003). Payment for order flow. *Journal of Financial Economics 68*, 379–411.

Patel, V., T. J. Putniņš, D. Michayluk, and S. Foley (2020). Price discovery in stock and options markets. *Journal of Financial Markets 47*, 10054.

Putniņš, T. J. (2013). What do price discovery metrics really measure? *Journal of Empirical Finance 23*, 68–83.

Ready, M. J. (1999). The specialist's discretion: Stopped orders and price improvement. *Review of Financial Studies 12*, 1075–1112.

Sarkar, A. and R. A. Schwartz (2009). Market sidedness: Insights into motives for trade initiation. *Journal of Finance 64*, 375–423.

Sofianos, G. and I. Werner (2000). The trades of NYSE floor brokers. *Journal of Financial Markets 3*, 139–176.

Werner, I. M., B. Rindi, S. Buti, and Y. Wen (2023). Tick size, trading strategies, and market quality. *Management Science 69*, 3818–3837.

Yan, B. and E. Zivot (2010). A structural analysis of price discovery measures. *Journal of Financial Markets 13*, 1–19.

Yao, C. and M. Ye (2018). Why trading speed matters: A tale of queue rationing under price controls. *Review of Financial Studies 31*, 2157–2183.

Table 1: Summary statistics: Market liquidity.

This table reports the summary statistics of market liquidity in both futures (Panel A) and options (Panel B) markets during the day trading session and night trading session in the CME corn and soybean markets, respectively. The two markets are organized by columns. Each liquidity measure is calculated per day and summarized across all futures (option)-day observations. For futures markets, the most-traded futures are considered. For options, we consider all option contracts whose underlying assets are the most-traded futures with various maturities. The following criteria are applied to select valid options: 1) we use options with positive daily total daily trading volume on the CME, and 2) presence of BBO quoting activities, with option prices at the top of the book being positive for a trading session. Detailed variable definitions are shown in Table D1 of Appendix D. We report the day and night trading sessions separately. We exclude the pre-open auction. Our sample spans from January 7, 2019, to June 26, 2020.

	Corn						Soybean					
	Day			Night			Day			Night		
	Mean	Std.	Med.	Mean	Std.	Med.	Mean	Std.	Med.	Mean	Std.	Med.
Panel A: Futures market.												
$Spread$ (cents)	0.25	0.01	0.25	0.26	0.01	0.26	0.26	0.01	0.26	0.27	0.02	0.27
$\%OneTick$ (%)	98.83	1.81	99.31	96.26	3.62	97.27	95.81	2.20	96.24	90.04	6.31	91.40
$BBOupdates$ ($\times 1000$)	175.36	65.76	157.60	37.73	18.17	33.32	271.00	612.25	266.11	54.97	19.33	51.35
$Ntrades$ ($\times 1000$)	9.86	4.45	8.71	2.47	1.42	2.14	13.07	3.92	12.42	3.86	1.59	3.55
$NPriceImprove$	1506	1221	1109	545	452	410	4499	1725	3997	1667	879	1438
$Volatility$	1.26	1.07	0.97	0.72	0.48	0.57	2.09	1.06	1.82	1.49	0.84	1.34
Futures-day obs.	372			368			372			368		
Panel B: Options market.												
$Spread$ (cents)	0.38	0.71	0.23	0.62	1.49	0.31	0.41	0.50	0.23	0.85	1.57	0.35
$\%OneTick$ (%)	29.13	32.32	13.42	15.45	26.84	0.52	27.84	31.45	11.24	10.92	22.10	0.26
$BBOupdates$ ($\times 1000$)	21.61	14.46	18.61	4.92	4.34	3.89	30.95	16.43	28.60	6.99	5.43	5.86
$Ntrades$	16	40	6	3	8	1	17	31	6	4	10	1
$NPriceImprove$	616	713	444	328	417	204	1314	1449	816	802	1280	431
$Volatility$	0.56	0.82	0.31	0.34	0.52	0.18	0.72	0.92	0.33	0.55	0.79	0.23
Option-day obs.	23,615			23,305			19,921			19,558		

Table 2: Price discovery: Information leadership shares and Hasbrouck's information shares.

This table reports the summary statistics of information leadership shares (ILSs) and information shares (ISs) across the different futures and option put-call pairs for both the day trading session (Panel A) and night trading session (Panel B) for the CME corn and soybean markets (organized by columns). We also provide summary statistics from pooling day and night trading sessions for both corn and soybean markets (Panel C). ILSs and ISs are calculated based on the bivariate vector error correction model (VECM) between the log futures midpoint price (p_t^{fut}) and the log option-implied futures midpoint price (p_t^{opt}) derived for each put-call pair

$$\Delta \boldsymbol{p}_t = \boldsymbol{\alpha}(\boldsymbol{\beta}' \boldsymbol{p}_{t-1} - \mu) + \sum_{j=1}^{J} \boldsymbol{\Gamma}_j \Delta \boldsymbol{p}_{t-j} + \boldsymbol{\varepsilon}_t,$$

where $\boldsymbol{p}_t = (p_t^{fut}, p_t^{opt})'$ and $\boldsymbol{\beta}'$ denotes a 1×2 cointegrating vector that allows a constant term μ in the long-run equilibrium relationship. ILSs and ISs are calculated per day and summarized across all put-call-pair-day observations for each market. We use a paired t-test to assess whether the means of ILSs are statistically different between futures and option markets, and the t-statistics are reported in row "t-stat." *** denotes statistical significance at 1% level. We consider all options whose underlying assets are the most-traded futures with various maturities. We select the put-call pairs that meet the following criteria: 1) Daily CME Globex trading volume and quoting activities are positive; 2) The options-implied futures midpoint prices are positive; 3) Information leadership share metrics for each futures and put-call pair can be calculated for both day and night trading sessions in a trading day and for at least 5 days. Our sample spans from January 7, 2019, to June 26, 2020.

	Corn (%)						Soybean (%)					
	ILS			*IS*			*ILS*			*IS*		
	Mean	Std	Med	Mean	Std	Med	Mean	Std	Med	Mean	Std	Med
Panel A: Day trading session.												
Futures	44.54	25.25	48.09	74.85	14.48	74.74	46.93	23.72	49.77	82.52	10.02	83.42
Options	55.46	25.25	51.91	25.15	14.48	25.26	53.07	23.72	50.23	17.48	10.02	16.58
t-stat.	−25.19***						−14.44***					
Obs.	13,556						12,421					
Panel B: Night trading session.												
Futures	49.13	27.68	52.35	83.47	14.21	85.96	54.85	28.75	57.36	91.12	8.01	92.80
Options	50.87	27.68	47.65	16.53	14.21	14.04	45.15	28.75	42.64	8.88	8.01	7.20
t-stat.	−3.66***						18.81***					
Obs.	13,556						12,421					

	Panel C: Pooled sample (%).					
	ILS			*IS*		
	Mean	Std	Med	Mean	Std	Med
Futures	48.77	26.69	51.81	82.82	13.41	85.25
Options	51.23	26.69	48.19	17.18	13.41	14.75
t-stat.	−10.48***					
Obs.	51,954					

Table 3: Summary statistics: Pooled sample.

This table reports the summary statistics for the pooled sample. Superscripts FUT and OPT denote futures and options, respectively. Table D1 of Appendix D provides definitions of the variables. We consider all options whose underlying assets are the most-traded futures (see Table B1 of Appendix B). We select the put-call pairs that meet the following criteria: 1) Daily CME Globex trading volume and quoting activities are positive; 2) The options-implied futures midpoint prices are positive; 3) Information leadership share metrics for each futures and put-call pair can be calculated for both day and night trading sessions in a trading day and for at least 5 days. Our sample spans from January 7, 2019, to June 26, 2020.

	Mean	Std	Min	P25	Med	P75	Max
ILS^{OPT} (%)	51.24	26.69	0.00	30.26	48.21	73.46	100.00
$\%PriceImprove^{OPT}$ (%)	8.59	6.67	0.13	4.13	6.62	10.67	65.91
$\%PriceImprove^{FUT}$ (%)	1.72	0.95	0.23	1.00	1.54	2.31	5.79
$Impvolatility$	0.22	0.07	0.01	0.16	0.20	0.26	0.69
$Leverage$	2.64	4.50	0.00	1.06	2.01	3.57	455.13
$StrikeDistance$ (cents)	54.78	48.90	0.00	18.50	41.00	77.50	441.00
$Volatility^{FUT}$	1.45	1.06	0.14	0.71	1.16	1.88	9.51
$TimeMaturity^{OPT}$ (days)	39.33	28.53	0.00	18.00	32.00	52.00	151.00
$Volume^{OPT}$ (mi.dollars)	8.17	18.05	0.00	0.10	1.10	7.43	288.42

Table 4: Price discovery and price-improving quotes: OLS regression.

This table reports the OLS regression results of options information leadership shares on the proportion of put-call pair price-improving quotes. The regression specification is

$$ILS^{OPT}_{ijmt} = \beta \times \%PriceImprove^{OPT}_{ijmt} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt},$$

where ILS^{OPT}_{ijmt} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j in market m on day t. $\%PriceImprove^{OPT}_{ijmt}$ is the proportion of put-call pair price-improving quotes, defined as the total number of price-improving quotes (sum of put and call) relative to the total number of BBO updates (sum of put and call). Our control variables include $\%PriceImprove^{FUT}_{jmt}$, $Leverage_{imt}$, $StrikeDistance_{imt}$, $Impvolatility_{imt}$, $Volatility^{FUT}_{jmt}$, $Volume^{OPT}_{imt}$ and $TimeMaturity^{OPT}_{imt}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_i, γ_j, and δ_m denote put-call pair, trading session, and market fixed effects, respectively. Standard errors are double clustered by put-call pair and day, and reported in parentheses. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS^{OPT}_{ijmt}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\%PriceImprove^{OPT}_{ijmt}$	0.406***	0.373***	0.464***	0.371***	0.369***	0.367***
	(0.056)	(0.056)	(0.055)	(0.056)	(0.056)	(0.056)
$\%PriceImprove^{FUT}_{jmt}$			−3.811***			
			(0.712)			
$Leverage_{imt}$					−0.096*	
					(0.058)	
$StrikeDistance_{imt}$						0.035**
						(0.017)
$Impvolatility_{imt}$				4.092		−0.285
				(11.671)		(11.998)
$Volatility^{FUT}_{jmt}$		1.488***	1.961***	1.466***	1.481***	1.466***
		(0.418)	(0.408)	(0.419)	(0.418)	(0.419)
$Volume^{OPT}_{imt}$	0.027**	0.017	0.023*	0.018	0.019	0.030**
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
$TimeMaturity^{OPT}_{imt}$	0.557***	0.554***	0.567***	0.555***	0.551***	0.556***
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	51,928	51,928	51,928	51,928	51,928	51,928
Adj. R^2	0.535	0.537	0.541	0.537	0.537	0.538

Table 5: Price discovery and price-improving quotes: First-stage regression.

This table reports the results of the first-stage instrumental variable (IV) regression of the proportion of put-call pair price-improving quotes on our IVs and control variables. The regression specification is

$$\%PriceImprove^{OPT}_{ijmt} = \beta_1 FloorClose_t + \beta_2 \%PriceImprove^{OPT}_{ijm,t-1} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt}.$$

$\%PriceImprove^{OPT}_{ijmt}$ is the proportion of put-call pair price-improving quotes, defined as the total number of price-improving quotes (sum of put and call) relative to the total number of BBO updates (sum of put and call). The instrumental variables are $FloorClose_t$ (a dummy variable that equals one for both day and night trading session through March 16, 2020 to June 26, 2020 when the CME option floor trading closes and zero otherwise), and $\%PriceImprove^{OPT}_{ijm,t-1}$ (the lagged value of the price-improving quote proportion). Our control variables include $\%PriceImprove^{FUT}_{jmt}$, $Leverage_{imt}$, $StrikeDistance_{imt}$, $Impvolatility_{imt}$, $Volatility^{FUT}_{jmt}$, $Volume^{OPT}_{imt}$, and $TimeMaturity^{OPT}_{imt}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_i, γ_j, and δ_m denote put-call pair, trading session, and market fixed effects, respectively. Standard errors are double clustered by put-call pair and day, and reported in parentheses. We conduct the Hansen J test for overidentification and report the p-value. We also report the Montiel Olea and Pflueger (2013) effective F statistic for weak instrumental variables. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: $\%PriceImprove^{OPT}_{ijmt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$FloorClose_t$	1.942**	1.767***	1.080*	1.423**	1.754***	1.453**
	(0.753)	(0.658)	(0.652)	(0.722)	(0.657)	(0.718)
$\%PriceImprove^{OPT}_{ijm,t-1}$	0.524***	0.522***	0.493***	0.520***	0.521***	0.519***
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
$\%PriceImprove^{FUT}_{jmt}$			1.434***			
			(0.237)			
$Leverage_{imt}$					−0.027	
					(0.018)	
$StrikeDistance_{imt}$						0.010***
						(0.003)
$Impvolatility_{imt}$				4.119		2.781
				(2.751)		(2.832)
$Volatility^{FUT}_{jmt}$		0.587***	0.400***	0.567***	0.584***	0.566***
		(0.095)	(0.096)	(0.095)	(0.095)	(0.094)
$Volume^{OPT}_{imt}$	−0.002	−0.006***	−0.008***	−0.006***	−0.006***	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$TimeMaturity^{OPT}_{imt}$	−0.018***	−0.019***	−0.024***	−0.019***	−0.020***	−0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
M-P F stat.	261.948	295.008	254.397	279.440	293.601	281.235
Hansen J p-val.	0.058	0.078	0.028	0.072	0.079	0.068
N	50,058	50,058	50,058	50,058	50,058	50,058
Adj. R^2	0.610	0.616	0.625	0.616	0.616	0.617

Table 6: Price discovery and price-improving quotes: Second-stage regression.

This table reports the results of the second-stage instrumental variable (IV) regression of options information leadership shares on the proportion of put-call pair price-improving quotes. The regression specification is

$$ILS^{OPT}_{ijmt} = \beta \times \widehat{\%PriceImprove}^{OPT}_{ijmt} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt},$$

where ILS^{OPT}_{ijmt} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j in market m on day t. $\widehat{\%PriceImprove}^{OPT}_{imt}$ is the fitted value of the proportion of put-call pair price-improving quotes from the first-stage regression

$$\%PriceImprove^{OPT}_{ijmt} = \beta_1 FloorClose_t + \beta_2 \%PriceImprove^{OPT}_{ijm,t-1} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt}.$$

The instrumental variables are $FloorClose_t$ (a dummy variable that equals one for all trading sessions through March 16, 2020 to June 26, 2020 when the CME option floor trading closes and zero otherwise), and $\%PriceImprove^{OPT}_{ijm,t-1}$ (the lagged value of the price-improving quote proportion). Our control variables include $\%PriceImprove^{FUT}_{jmt}$, $Leverage_{imt}$, $StrikeDistance_{imt}$, $Impvolatility_{imt}$, $Volatility^{FUT}_{jmt}$, $Volume^{OPT}_{imt}$, and $TimeMaturity^{OPT}_{imt}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_i, γ_j, and δ_m denote put-call pair, trading session, and market fixed effects, respectively. Standard errors are double clustered by put-call pair and day, and reported in parentheses. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: $\%ILS^{OPT}_{ijmt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\%PriceImprove}^{OPT}_{ijmt}$	0.425***	0.404***	0.560***	0.387***	0.397***	0.385***
	(0.118)	(0.118)	(0.123)	(0.118)	(0.119)	(0.118)
$\%PriceImprove^{FUT}_{jmt}$			−3.929***			
			(0.787)			
$Leverage_{imt}$					−0.094	
					(0.058)	
$StrikeDistance_{imt}$						0.035**
						(0.018)
$Impvolatility_{imt}$				6.196		1.654
				(11.903)		(12.204)
$Volatility^{FUT}_{jmt}$		1.548***	1.980***	1.525***	1.543***	1.523***
		(0.423)	(0.414)	(0.422)	(0.422)	(0.422)
$Volume^{OPT}_{imt}$	0.028**	0.018	0.024*	0.018	0.020	0.031**
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
$TimeMaturity^{OPT}_{imt}$	0.563***	0.559***	0.575***	0.561***	0.557***	0.561***
	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)	(0.020)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	50,058	50,058	50,058	50,058	50,058	50,058
Adj. R^2	0.281	0.285	0.291	0.285	0.286	0.286

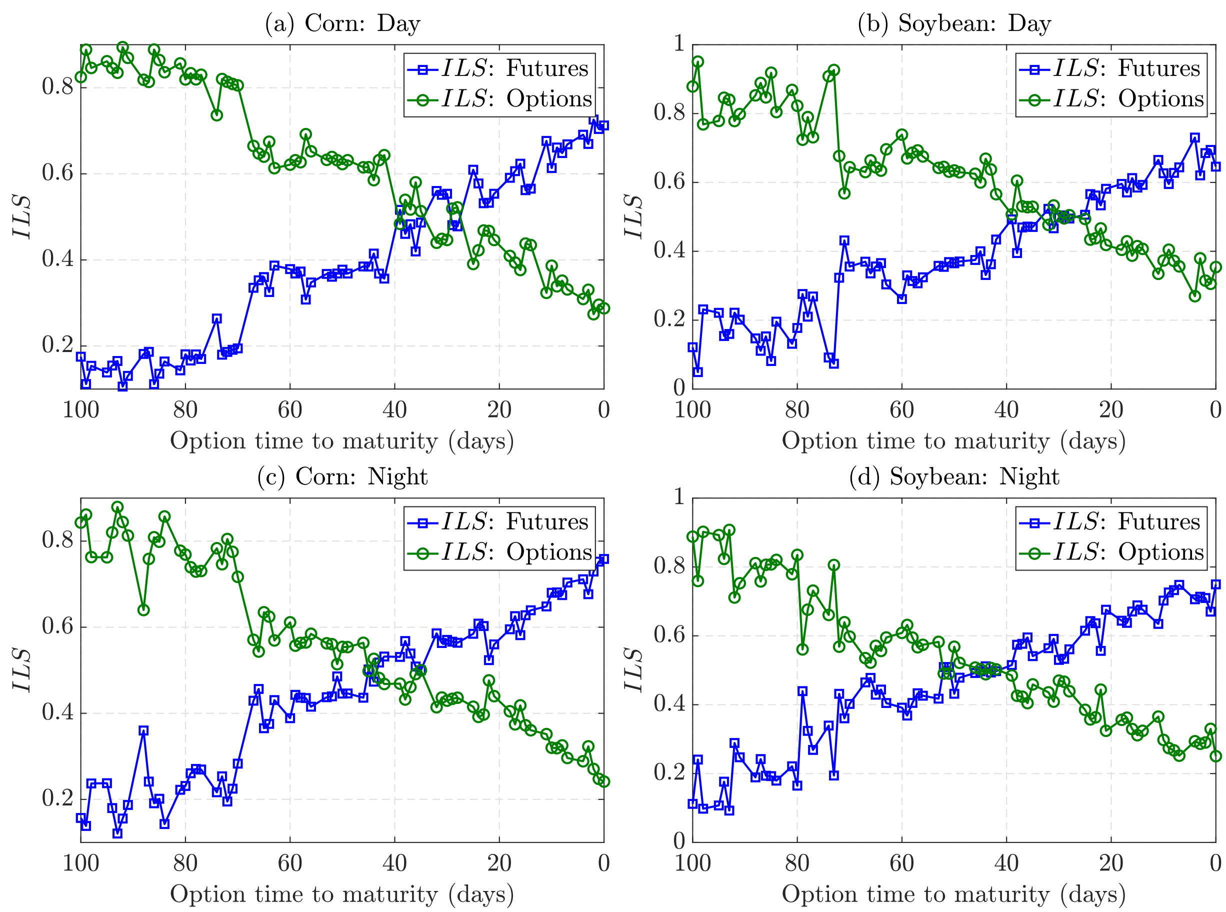

Figure 1: Price discovery and option time to maturity.

This figure displays the average information leadership shares (ILSs) of futures and options over the option time to maturity of for day (panels (a) and (b)) and night trading sessions (panels (c) and (d)) in the CME corn and soybean markets. The two markets are organized by columns. The ILSs of futures and options are averaged across all option pairs at each time to maturity. We select the put-call pairs that meet the following criteria: 1) Daily CME Globex trading volume and quoting activities are positive; 2) The options-implied futures midpoint prices are positive; 3) Information leadership share metrics for each futures and put-call pair can be calculated for both day and night trading sessions in a trading day and for at least 5 days. Our sample spans from January 7, 2019, to June 26, 2020.

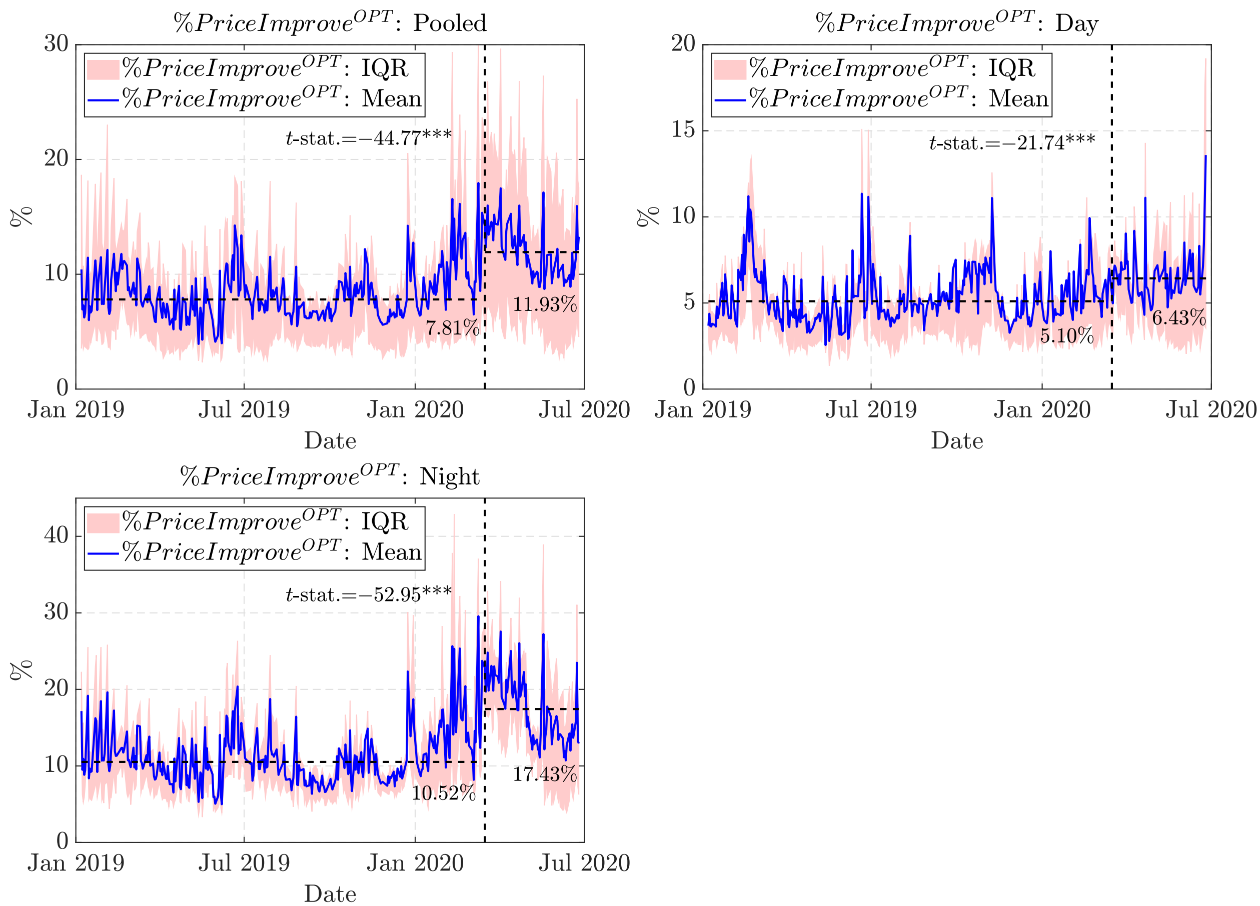

Figure 2: Proportion of put-call pair price-improving quotes.

This figure displays the daily mean and interquartile range (IQR) of the proportion of put-call pair price-improving quotes ($\%PriceImprove^{OPT}$) using the pooled sample, day sample, and night sample across the sample period. The proportion of put-call pair price-improving quotes is defined as the number of put-call pair price-improving quotes (sum of call and put) relative to the total number of put-call pair quote updates at the best-bid-offer (sum of put and call). The vertical dash line indicates the CME closure of option floor trading on March 16, 2020. The horizontal dash lines indicate the sample means before and after March 16, 2020. Numbers in the figure report the sample mean values. We conduct equal mean Welch t-tests to assess whether the sample means before and after March 16, 2020 are statistically different and report the t-statistics. *** denotes statistical significance at 1% level. We select the put-call pairs that meet the following criteria: 1) Daily CME Globex trading volume and quoting activities are positive; 2) The options-implied futures midpoint prices are positive; 3) Information leadership share metrics for each futures and put-call pair can be calculated for both day and night trading sessions in a trading day and for at least 5 days. Our sample spans from January 7, 2019, to June 26, 2020.

Appendix

A Tick size constraint

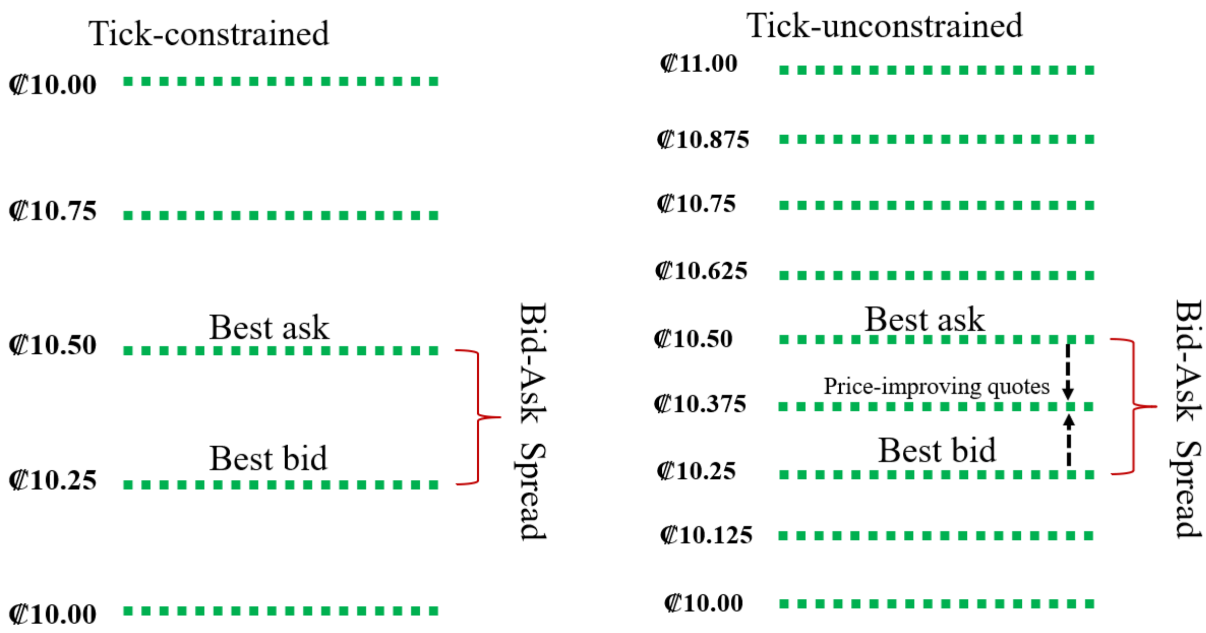

Figure A1: Hypothetical limit order books: Tick-constrained and tick-unconstrained markets.

This figure displays hypothetical limit order books for both tick-constrained and tick-unconstrained markets. In the tick-constrained market, the tick size is 0.25 cents. The best bid (ask) price is 10.25 (10.50) cents with the bid-ask spread of 0.25 cents (one tick). In the tick-unconstrained market, the tick size is half of that in the tick-constrained market, i.e., 0.125 cents. Though the bid-ask spreads are identical in the markets, the tick-unconstrained market allows price improving quotes at 10.375 cents to improve either the best bid or the best ask price.

B CME institutional details

B.1 *Options contract information*

Table B1: Options contracts and their underlying futures contracts.

This table reports options contracts and their underlying futures contracts in the CME corn and soybean markets. Contract codes are presented in parentheses. We focus on the most-traded futures. We roll over to the next most-traded futures when the latter has higher trading volume than the former for three consecutive trading days. By doing this, the September contract for corn futures and August and September contracts for soybean futures are not selected. Since we consider all options whose underlying futures are the most-traded contracts in the two markets, August and September options contracts for both the corn and soybean markets are not selected either.

	Underlying futures contract month	
Option contract month	Corn	Soybean
January (F)	March (H)	January (F)
February (G)	March (H)	March (H)
March (H)	March (H)	March (H)
April (J)	May (K)	May (K)
May (K)	May (K)	May (K)
June (M)	July (N)	July (N)
July (N)	July (N)	July (N)
October (V)	December (Z)	November (X)
November (X)	December (Z)	November (X)
December (Z)	December (Z)	January (F)

B.2 *CME Globex sessions and trading hours*

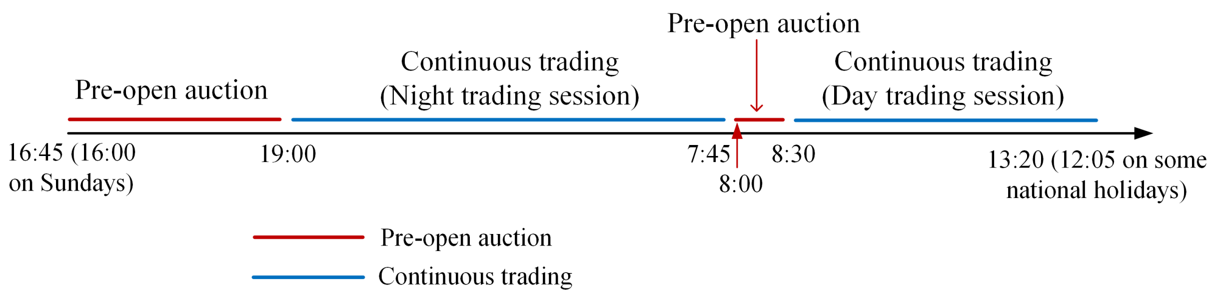

Figure B1: CME Globex sessions and trading hours: Futures and options.

This figure displays the CME Globex sessions and hours over a trading day in U.S. Central Time (CT). The pre-open auction starts at 16:00 (16:45) on Sundays (weekdays). The day trading session is from 8:30 to 13:20 CT and the night session from 19:00 to 7:45 CT. Generally, in our sample markets, CME replaces the continuous trading sessions by extended pre-open auctions on national holidays and may also shorten the continuous trading hours on some specific national holidays. Details on CME holidays calendar can be found at https://www.cmegroup.com/tools-information/holiday-calendar.html.

B.3 *An example of CME options Market Depth data*

Table B2: An example of options Market Depth data.

This table displays sample messages from the options Market Depth data on May 29, 2019. Each row is called a message. In the first row, the available quantity at the 1st depth (0.25 cents/bushel) of the ask side is revised to 6944 (4) contracts (orders). Subsequently, the available quantity at the 2nd depth (0.375 cents/bushel) of the ask side is revised to 544 (2) contracts (orders). The rest of messages can be interpreted analogously. This table shows limited information from the raw data. All messages are timestamped in nanoseconds and price is expressed in cents/bushel. "Code" shows the option symbol with "OZC" denoting corn option, "N" denoting the July contract, "9" denoting a 2019 contract, "C" denoting call option, and "0640" denoting strike price. "Type" indicates the market activity (e.g. limit order submissions, deletions, revisions, executions) motivating a change in the limit order book (LOB). "Quantity" shows the number of contracts and "order" indicates how many orders sit at a price level (depth) within the limit order book (LOB). "Depth" is the price level where a message happens within the LOB. "Seq. #" stands for sequence number.

Date	Time	Code	Type	Side	Price	Quantity	Order	Depth	Seq. #
2019-05-29	2019-05-29 10:22:20.030086265	OZCN9 C0640	Revision	Ask	0.25	6944	4	1	84972
2019-05-29	2019-05-29 10:22:20.031022743	OZCN9 C0640	Revision	Ask	0.375	544	2	2	84973
2019-05-29	2019-05-29 10:22:20.083928227	OZCN9 C0640	Revision	Ask	0.25	7624	4	1	84974
2019-05-29	2019-05-29 10:22:20.109651641	OZCN9 C0640	Deletion	Bid	0.02	294	1	1	84975
2019-05-29	2019-05-29 10:22:20.109651641	OZCN9 C0640	Revision	Ask	0.25	5339	3	1	84976
2019-05-29	2019-05-29 10:22:20.121319241	OZCN9 C0640	Revision	Ask	0.25	3751	3	1	84977
2019-05-29	2019-05-29 10:22:20.126404501	OZCN9 C0640	Revision	Ask	0.25	2661	3	1	84978
2019-05-29	2019-05-29 10:22:20.129870317	OZCN9 C0640	Revision	Ask	0.25	2935	3	1	84979
2019-05-29	2019-05-29 10:22:20.130934953	OZCN9 C0640	Revision	Ask	0.25	3751	3	1	84980
2019-05-29	2019-05-29 10:22:20.131783635	OZCN9 C0640	Revision	Ask	0.375	334	2	2	84981
2019-05-29	2019-05-29 10:22:20.132050715	OZCN9 C0640	Revision	Ask	0.25	5339	3	1	84982
2019-05-29	2019-05-29 10:22:20.132090129	OZCN9 C0640	Submission	Bid	0.02	294	1	1	84983

B.4 *An example of CME futures Market Depth data*

Table B3: An example of futures Market Depth data.

This table displays sample messages from the futures Market Depth data on May 29, 2019. Each row is called a message. In the first row, the available quantity at the 4th depth (419.75 cents/bushel) of the ask side is revised to 67 (13) contracts (orders) and only outright liquidity participates. Subsequently, the available quantity at the 1th depth (419.00 cents/bushel) of the ask side is revised to 33 (11) contracts (orders) and only outright liquidity participates. The rest of messages can be interpreted analogously. This table only shows limited information from the raw data. All messages are timestamped in nanoseconds and price is expressed in cents/bushel. "Code" shows the base symbol "ZC" denoting corn, "N" denoting the July futures contract and "9" denoting a 2019 contract. "Type" indicates activities at each price level, including submissions, deletions, and revisions. "Quantity" shows the number of contracts and "order" indicates how many orders sit at a price level (depth) within the limit order book (LOB). "Depth" means at which price level a message happens within the LOB. "Seq. #" stands for sequence number. "Out/Imp" shows whether the liquidity is provided through outright liquidity or implied liquidity. CME does not define the number of orders involved in implied liquidity, thus the "order" column for implied orders is left blank.

Date	Time	Code	Type	Side	Price	Quantity	Order	Depth	Out/Imp	Seq. #
2019-05-29	2019-05-29 10:20:22.198038183	ZCN9	Revision	Ask	419.75	67	13	4	Outright	2241768
2019-05-29	2019-05-29 10:20:22.198047973	ZCN9	Revision	Ask	419.00	33	11	1	Outright	2241769
2019-05-29	2019-05-29 10:20:22.198489315	ZCN9	Revision	Bid	418.75	13		1	Implied	2241770
2019-05-29	2019-05-29 10:20:22.198922925	ZCN9	Revision	Bid	418.00	107	16	4	Outright	2241771
2019-05-29	2019-05-29 10:20:22.199022911	ZCN9	Revision	Bid	418.50	30		2	Implied	2241772
2019-05-29	2019-05-29 10:20:22.201268903	ZCN9	Revision	Bid	418.50	50		2	Implied	2241773
2019-05-29	2019-05-29 10:20:22.201270879	ZCN9	Revision	Bid	418.50	70		2	Implied	2241774
2019-05-29	2019-05-29 10:20:22.201587335	ZCN9	Revision	Bid	418.50	73		2	Implied	2241775
2019-05-29	2019-05-29 10:20:22.201709331	ZCN9	Revision	Ask	419.00	24	10	1	Outright	2241776
2019-05-29	2019-05-29 10:20:22.201906241	ZCN9	Revision	Ask	419.00	22	9	1	Outright	2241777
2019-05-29	2019-05-29 10:20:22.202404053	ZCN9	Revision	Bid	418.50	93		2	Implied	2241778
2019-05-29	2019-05-29 10:20:22.202573769	ZCN9	Revision	Ask	419.00	20	8	1	Outright	2241779

B.5 *Reconstruction of consolidated limit order book*

Panel A: Outright and implied LOBs.

Outright limit order book			Implied limit order book	
Ask			Ask	
# Orders	Quantity	Price	Quantity	Price
16	57	446.50		
14	54	446.25		
47	348	446.00		
22	78	445.75		
15	63	445.50		
18	78	445.25		
72	421	445.00		
26	370	444.75		
23	627	444.50	100	444.50
7	55	444.25	40	444.25
22	175	444.00	60	444.00
22	551	443.75	120	443.75
25	127	443.50		
15	86	443.25		
27	116	443.00		
15	84	442.75		
17	99	442.50		
23	108	442.25		
21	79	442.00		
20	130	441.75		
# Orders	Quantity	Price	Quantity	Price
Bid			Bid	

Panel B: Consolidated LOB.

Consolidated limit order book		
Ask		
# Orders	Quantity	Price
16	57	446.50
14	54	446.25
47	348	446.00
22	78	445.75
15	63	445.50
18	78	445.25
72	421	445.00
26	370	444.75
23	**727 (=627+100)**	444.50
7	**95 (=55+40)**	444.25
22	**235 (=175+60)**	444.00
22	**671 (=551+120)**	443.75
25	127	443.50
15	86	443.25
27	116	443.00
15	84	442.75
17	99	442.50
23	108	442.25
21	79	442.00
20	130	441.75
# Orders	Quantity	Price
Bid		

Figure B2: Reconstruction of consolidated limit order book.

This figure displays how hypothetical outright and implied limit order books (LOBs, Panel A) consolidates after a consolidated limit order book (Panel B). CME disseminates the outright (implied) LOB for up to ten (two) depths. CME does not define the number of orders involved in implied liquidity, thus no "# Orders" column is shown in the implied LOB. In this case, the best bid and ask prices in outright and implied LOBs are the same, i.e., 444.25 cents/bushel and 444.00 cents/bushel, respectively. Thus, the best bid (ask) quantity in the consolidated LOB are the aggregated quantities of best bid (ask) quantity between outright and implied LOBs, i.e., 95 (235) contracts. The second best bid/ask quantity can be interpreted analogously.

C Descriptive statistics: Options

Table C1: Descriptive statistics: Options

This table reports descriptive statistics of options across all option-day observations in our sample in the CME corn (Panel A) and soybean (Panel B) markets. We consider all options whose underlying assets are the most-traded futures contracts. The price refers to the option daily settlement price, expressed in cents. Delta is the change in the option's price due to the change in the underlying futures price. Omega is defined as the absolute delta multiplied by the ratio of the futures price relative to the option price. We report the omega-adjusted trading volume (open interest), which is calculated as the option dollar trading volume (open interest) multiplied by the option omega and expressed in million dollars. Option (Futures) volume refers to the CME daily total trading volume in option (futures) market, expressed in million dollars. Open interest is the number of outstanding option positions that have not been closed. Implied volatility refers to the expected volatility of the underlying futures over the life of an option. Option delta, contract trading volume, and implied volatility are obtained from the CME End of Market-Standard data. We exclude option-day observations with zero settlement prices. Our sample spans from January 7, 2019 to June 26, 2020.

	Panel A: Corn.						
	Mean	Std.	Min.	P25	Med.	P75	Max.
Price (cents)	143.53	244.40	1.00	6.00	42.00	173.00	6182
Delta	0.37	0.35	0.00	0.05	0.25	0.69	1.00
Omega	2.33	2.44	0.00	1.09	1.90	3.04	190.13
Options volume	4.78	12.63	0.00	0.04	0.46	3.51	475.01
Futures volume	3611.19	1521.48	969.89	2555.41	3262.25	4332.72	10142.88
Options open int.	44.71	78.76	0.00	1.39	10.39	51.68	793.17
Futures open int.	12338.12	3205.24	1220.01	9655.02	13456.27	15028.38	17564.43
Implied volatility	0.25	0.08	0.02	0.19	0.24	0.30	0.75
Option-day obs.	26,505						

	Panel B: Soybean.						
	Mean	Std.	Min.	P25	Med.	P75	Max.
Price (cents)	197.34	390.07	1.00	5.00	36.00	222.00	6341.00
Delta	0.32	0.35	0.00	0.03	0.15	0.61	1.00
Omega	3.48	4.68	0.00	1.83	3.06	4.56	455.13
Options volume	5.42	12.93	0.00	0.04	0.47	4.36	285.21
Futures volume	4853.87	1356.26	2639.13	3854.09	4674.41	5572.85	9543.31
Options open int.	42.43	70.29	0.00	1.18	9.51	55.34	577.31
Futures open int.	13461.02	2978.72	1078.87	12253.73	14497.71	15313.72	18364.29
Implied volatility	0.19	0.05	0.00	0.15	0.18	0.22	0.43
Option-day obs.	22,319						

D Variable descriptions

Table D1: Variable descriptions.

Variable	Description
Market liquidity	
$Spread_{ijmt}$ (cents)	Time-weighted average quoted spread calculated for each option/futures i, trading session j, market m, and day t. It is defined as the difference between best ask (A_{ijmt}) and bid (B_{ijmt}) prices, both expressed in cents and sampled at the second-level.
$\%OneTick_{ijmt}$ (%)	The proportion of time, measured in seconds, over each option/futures i, trading session j, market m, and day t that the quoted spread equals one tick (0.25 cents for futures and 0.125 cents for options).
$BBOupdates_{ijmt}$ ($\times 1000$)	The total number of best-bid-offer (BBO) quote updates for each option/futures i, trading session j, market m, and day t, expressed in thousands.
$Ntrades_{ijmt}$	Total number of trades for each option/futures i, trading session j, market m, and day t.
$NPriceImprove_{ijmt}$	Total number of quotes that improve the BBO using event time data for each option/futures i, trading session j, market m, and day t.
Regression	
$\%PriceImprove^{OPT}_{ijmt}$ (%)	The proportion of put-call pair price-improving quotes, defined as the total number of price-improving quotes of put and call options relative to the total number of BBO updates of put and call options for each put-call pair i in trading session j, market m, and day t.
$\%PriceImprove^{FUT}_{jmt}$ (%)	The proportion of futures price-improving quotes, defined as the total number of price-improving quotes relative to the total number of BBO updates in each trading session j, market m, and day t.
$Volatility^{FUT}_{jmt}$	The standard deviation of second-level futures midpoint price for each trading session j, market m, and day t.
$Impvolatility_{imt}$	Implied volatility of an option for each put-call pair i, market m, and day t. See details at https://www.cmegroup.com/confluence/display/EPICSANDBOX/End+of+Market+Summary+-+Standard.
$Leverage_{imt}$	The leverage proxy for a put-call pair i, market m, and day t. Following Patel et al. (2020), $Leverage_{imt} = Leverage^{call}_{imt}\mathbf{1}\{r<0\} + Leverage^{put}_{imt}\mathbf{1}\{r>0\}$, where $Leverage^{call}_{imt}$ and $Leverage^{put}_{imt}$ are the call and the put option omega, respectively. $\mathbf{1}\{r>0\}$ ($\mathbf{1}\{r<0\}$) is an indicator function that equals 1 if the daily futures return at $t+1$ is positive (negative). When the daily futures return at $t+1$ is unchanged (i.e., $r=0$), we calculate leverage for each put-call pair as the simple average of put and call omega.
$StrikeDistance_{imt}$ (cents)	The absolute difference between the underlying futures price and the strike price for each put-call pair i, market m, and day t.
$Volume^{OPT}_{imt}$ (mi. dollars)	Electronic trading volume for each put-call pair i, market m, and day t, which is calculated as the sum of put and call option omega-adjusted dollar trading volume and expressed in million dollars.
$TimeMaturity^{OPT}_{imt}$ (days)	The number of days until a put-call pair i expires, calculated for each market m, and day t.

E Price discovery

E.1 *Options-implied futures midpoint price*

Table E1: Options-implied futures midpoint price: Volatility and quoted spread. This table reports summary statistics of the volatility of the options-implied futures midpoint price, the time-weighted quoted spread between options-implied futures best ask and best bid prices (expressed in cents), and the time-weighted price difference (expressed in cents) between options-implied futures midpoint price and actual futures midpoint price. We also report the quoted spread between options-implied futures best ask and best bid prices. Both measures are calculated for the day (Panel A) and night trading session (Panel B) in the CME corn and soybean markets. We also report the summary statistics of the pooled sample (Panel C). The options-implied futures bid/ask price is defined as

$$Implied\ Bid = e^{r(T-t)}\left[C_t^{Bid}(K,T) - P_t^{Ask}(K,T) + Ke^{-r(T-t)} - v_t(K,T)\right],$$
$$Implied\ Ask = e^{r(T-t)}\left[C_t^{Ask}(K,T) - P_t^{Bid}(K,T) + Ke^{-r(T-t)} - v_t(K,T)\right],$$

where C_t^{Bid} (C_t^{Ask}) denotes the best bid (ask) price of a call option and P_t^{Bid} (P_t^{Ask}) denotes the best bid (ask) price of a put option. T is the option maturity date and K is the option strike price. $v_t(K,T)$ denotes the option early exercise premium. The options-implied futures midpoint price is calculated as the arithmetic mean of $Implied\ Bid$ and $Implied\ Ask$. The volatility is defined as the standard deviation of second-level options-implied futures midpoint price. "Obs." reports the number of put-call-pair-day observations. Our sample spans from January 7, 2019, to June 26, 2020.

	Volatility			Quoted spread (cents)			Price difference (cents)		
	Mean	Std.	Med.	Mean	Std.	Med.	Mean	Std.	Med.
Panel A: Day trading session.									
Corn	3.85	7.73	1.86	3.92	11.32	1.37	−0.04	1.28	−0.01
Obs.	13,556			13,556			13,556		
Soybean	4.63	4.95	3.07	2.62	3.04	1.77	−0.13	1.34	−0.02
Obs.	12,421			12,421			12,421		
Panel B: Night trading session.									
Corn	2.28	3.41	1.23	7.83	35.95	2.30	0.07	1.26	0.12
Obs.	13,556			13,556			13,556		
Soybean	3.01	2.66	2.14	5.48	6.08	3.60	0.04	0.92	0.16
Obs.	12,421			12,421			12,421		
Panel C: Pooled sample.									
	3.43	5.19	2.03	5.00	19.63	2.17	−0.01	1.22	0.08
Obs.	51,954			51,954			51,954		

E.2 ***Noise ratios***

Table E2: Noise ratios: Futures and options.

This table reports summary statistics of noise ratios of futures and option put-call pairs during the day trading session (Panel A) and night trading session (Panel B) in the CME corn and soybean markets. We also report summary statistics of the pooled sample (Panel C). We define the option (futures) noise as the mean absolute difference between the options-implied futures midpoint price (futures midpoint price) and the estimated common efficient price. The option (Futures) noise ratio is the ratio of option (futures) noise relative to the sum of option and futures noise, expressed in percent (%). Following Gonzalo and Granger (1995), the common efficient price is the weighted average of the option and futures prices, with their respective component shares as the weights. "Obs." reports put-call-pair-day observations. Our sample spans from January 7, 2019, to June 26, 2020.

	Noise ratio: Options (%)			Noise ratio: Futures (%)		
	Mean	Std.	Med.	Mean	Std.	Med.
Panel A: Day trading session.						
Corn	75.67	17.15	76.88	24.33	17.15	23.12
Obs.	13,556			13,556		
Soybean	82.89	11.13	84.11	17.11	11.13	15.89
Obs.	12,421			12,421		
Panel B: Night trading session.						
Corn	82.29	16.11	85.90	17.71	16.11	14.10
Obs.	13,556			13,556		
Soybean	89.64	9.38	91.97	10.36	9.38	8.03
Obs.	12,421			12,421		
Panel C: Pooled sample.						
	82.47	14.81	85.78	17.53	14.81	14.22
Obs.	51,954					

E.3 *Price discovery: WASDE announcements*

Table E3: Price discovery: WASDE announcements

This table reports summary statistics of the information leadership shares (ILSs) of futures and option put-call pairs during both WASDE announcement and non-announcement days, across the whole sample in the CME corn and soybean markets. The two markets are organized by columns. We report summary statistics by market (Panel A) and for the pooled sample (Panel B). ILSs are calculated based on the bivariate vector error correction model (VECM) between log futures midpoint price (p_t^{fut}) and log options-implied futures midpoint price (p_t^{opt}) for each put-call pair

$$\Delta \boldsymbol{p}_t = \boldsymbol{\alpha}(\boldsymbol{\beta}'\boldsymbol{p}_{t-1} - \mu) + \sum_{j=1}^{J} \boldsymbol{\Gamma}_j \Delta \boldsymbol{p}_{t-j} + \boldsymbol{\varepsilon}_t,$$

where $\boldsymbol{p}_t = (p_t^{fut}, p_t^{opt})'$ and $\boldsymbol{\beta}'$ denotes a 1×2 cointegrating vector that allows a constant term μ in the long-run equilibrium relationship. ILSs are calculated per day and summarized across all put-call-pair-day observations for each market. We consider all options whose underlying assets are the first nearby futures with various maturities. We conduct equal means Welch t-test of ILSs between announcement and non-announcement days and report the t-statistics in column "t-stat." Paired t-tests are also used to assess whether the means of ILSs are statistically different between futures and options markets during announcement and non-announcement days and the t-statistics are reported in row "t-stat." * and *** denote statistical significance at 10% and 1% levels, respectively. We select the put-call pairs that meet the following criteria: 1) Daily CME Globex trading volume and quoting activities are positive; 2) The options-implied futures midpoint prices are positive; 3) Information leadership share metrics for each futures and put-call pair can be calculated for both day and night trading sessions in a trading day and for at least 5 days. Our sample spans from January 7, 2019, to June 26, 2020.

	Information leadership shares: Corn (%)							Information leadership shares: Soybean (%)						
	Announcements			Non-announcements				Announcements			Non-announcements			
	Mean	Std	Med	Mean	Std	Med	t-stat.	Mean	Std	Med	Mean	Std	Med	t-stat.
Panel A: Information leadership shares by market.														
Futures	36.67	31.07	31.34	44.92	24.87	48.77	−6.58***	44.55	29.96	48.35	47.04	23.37	49.80	−1.96*
Options	63.33	31.07	68.66	55.08	24.87	51.23	6.58***	55.45	29.96	51.65	52.96	23.37	50.20	1.96*
t-stat.	−10.79***			−23.21***				−4.35***			−13.78***			
Obs.	632			12,924				573			11,848			

	Panel B: Pooled sample (%).						
	Announcements			Non-announcements			
	Mean	Std	Med	Mean	Std	Med	t-stat.
Futures	40.42	30.79	38.10	45.94	24.19	49.34	−6.13***
Options	59.58	30.79	61.90	54.06	24.19	50.66	6.13***
t-stat.	−10.80***			−26.45***			
Obs.	1,205			24,772			

E.4 ***Price discovery and options strike distance***

Table E4: Price discovery and price-improving quotes: Subsample analyses by options strike distance.

This table reports the OLS regression results of options information leadership shares on the proportion of put-call pair price-improving quotes by three subsamples based on options strike distance ($StrikeDistance$). The first subsample includes observations where the options strike distance is lower than its first quantile (<P25). The second subsample includes observations where the options strike distance is between its first quantile and third quantile ([P25, P75]). The third subsample (Panel C) includes observations where options strike distance is greater than its third quantile (>P75). The regression specification is

$$ILS_{ijmt}^{OPT} = \beta \times \%PriceImprove_{ijmt}^{OPT} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt},$$

where ILS_{ijmt}^{OPT} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j in market m on day t. $\%PriceImprove_{ijmt}^{OPT}$ is the proportion of put-call pair price-improving quotes, defined as the total number of price-improving quotes (sum of put and call) relative to the total number of BBO updates (sum of put and call). Our control variables include $Impvolatility_{imt}$, $Volatility_{jmt}^{FUT}$, $Volume_{imt}^{OPT}$ and $TimeMaturity_{imt}^{OPT}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_i, γ_j, and δ_m denote put-call pair, trading session, and market fixed effects, respectively. Standard errors are double clustered by put-call pair and day, and reported in parentheses. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS_{ijmt}^{OPT}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\%PriceImprove_{ijmt}^{OPT}$	−0.117	−0.197**	0.367***	0.326***	0.527***	0.507***
	(0.097)	(0.100)	(0.067)	(0.067)	(0.064)	(0.064)
$Impvolatility_{imt}$		−3.566		4.445		2.339
		(14.462)		(14.164)		(15.984)
$Volatility_{jmt}^{FUT}$		2.151***		1.361***		2.159***
		(0.412)		(0.507)		(0.446)
$Volume_{imt}^{OPT}$	0.036***	0.022**	0.055*	0.037	−0.018	−0.075
	(0.010)	(0.010)	(0.033)	(0.031)	(0.133)	(0.138)
$TimeMaturity_{imt}^{OPT}$	0.690***	0.684***	0.579***	0.577***	0.480***	0.478***
	(0.027)	(0.026)	(0.024)	(0.024)	(0.026)	(0.026)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	<P25	<P25	[P25,P75]	[P25, P75]	>P75	>P75
N	12,850	12,850	26,114	26,114	12,964	12,964
Adj. R^2	0.659	0.663	0.512	0.514	0.511	0.517

F Heterogeneous analyses

Table F1: Summary statistics: Subsamples by one-tick proportions.

This table reports summary statistics for three subsamples based on one-tick proportions of call and put options for each put-call pair. The first subsample (Panel A) includes observations where both one-tick proportions of call and put options are zero ($\%OneTick^{call} = 0$ & $\%OneTick^{put} = 0$). The second subsample (Panel B) includes observations where either one-tick proportion of call or of put option is zero ($\%OneTick^{call} = 0$ $\%OneTick^{put} = 0$), but not both. The third subsample (Panel C) includes observations where both one-tick proportions of call and put options are not zero ($\%OneTick^{call} \neq 0$ & $\%OneTick^{put} \neq 0$). All variables are measured for each trading session and market. Superscripts FUT and OPT denote futures and put-call pairs, respectively. Table D1 of Appendix D provides definitions of the variables. We consider all options whose underlying assets are the most-traded futures with various maturities. We apply the following criteria to select valid put-call pairs: 1) Daily CME Globex trading volume and quoting activities are positive; 2) The options-implied futures midpoint prices are positive; 3) Information leadership share metrics for each futures and put-call pair can be calculated for both day and night trading sessions in a trading day and for at least 5 days. Our sample spans from January 7, 2019, to June 26, 2020.

	Mean	Std.	Min	P25	Med.	P75	Max
Panel A: $\%OneTick^{call} = 0$ *&* $\%OneTick^{put} = 0$.							
ILS^{OPT} (%)	51.50	28.98	0.00	26.90	50.28	77.35	100.00
$\%PriceImprove^{OPT}$ (%)	14.58	8.93	1.09	8.15	12.46	18.59	65.91
$\%PriceImprove^{FUT}$ (%)	2.04	1.03	0.23	1.16	2.00	2.83	5.64
$Impvolatility$	0.22	0.07	0.01	0.17	0.21	0.27	0.61
$Leverage$	1.59	1.28	0.00	0.71	1.27	2.17	9.36
$StrikeDistance$ (cents)	59.06	53.54	0.00	18.75	43.75	84.25	373.50
$Volatility^{FUT}$	1.26	0.94	0.14	0.65	1.05	1.59	9.51
$Volume^{OPT}$ (mi. dollars)	4.05	10.90	0.00	0.01	0.22	2.70	288.42
$TimeMaturity^{OPT}$ (days)	40	31	0	15	32	60	151
Observations	4,798						
Panel B: $\%OneTick^{call} = 0$ *or* $\%OneTick^{put} = 0$.							
ILS^{OPT} (%)	51.21	26.44	0.00	30.51	48.04	73.05	100.00
$\%PriceImprove^{OPT}$ (%)	7.96	6.05	0.13	3.95	6.24	9.73	59.11
$\%PriceImprove^{FUT}$ (%)	1.69	0.94	0.23	0.98	1.52	2.26	5.79
$Impvolatility$	0.22	0.07	0.01	0.16	0.20	0.26	0.69
$Leverage$	2.75	4.70	0.00	1.11	2.13	3.74	455.13
$StrikeDistance$ (cents)	54.34	48.37	0.00	18.50	40.75	76.75	411.00
$Volatility^{FUT}$	1.47	1.07	0.14	0.71	1.17	1.90	9.51
$Volume^{OPT}$ (mi. dollars)	8.61	18.59	0.00	0.13	1.24	8.05	288.42
$TimeMaturity^{OPT}$ (days)	39	28	0	18	32	52	151
$\%OneTick^{call}$ (%)	22.20	30.48	0.00	0.00	2.68	42.05	100.00
$\%OneTick^{put}$ (%)	12.65	45.22	0.00	0.00	0.00	8.66	100.00
Observations	47,014						
Panel C: $\%OneTick^{call} \neq 0$ *&* $\%OneTick^{put} \neq 0$.							
ILS^{OPT} (%)	51.50	24.19	0.00	32.68	47.49	70.22	100.00
$\%PriceImprove^{OPT}$ (%)	5.49	4.25	1.03	2.63	4.27	6.57	48.43
$\%PriceImprove^{FUT}$ (%)	1.29	0.78	0.23	0.70	1.13	1.65	5.79
$Impvolatility$	0.19	0.06	0.01	0.14	0.17	0.23	0.44
$Leverage$	3.78	13.24	0.00	1.83	2.67	4.06	455.13
$StrikeDistance$ (cents)	9.25	11.33	0.00	2.56	5.75	11.25	108.00
$Volatility^{FUT}$	1.49	1.12	0.14	0.71	1.16	1.93	9.51
$Volume^{OPT}$ (mi. dollars)	36.82	33.97	0.00	12.67	26.61	50.29	288.42
$TimeMaturity^{OPT}$ (days)	33	28	0	14	25	45	151
$\%OneTick^{call}$ (%)	9.61	18.13	0.00	0.13	1.14	9.03	100.00
$\%OneTick^{put}$ (%)	7.45	14.72	0.00	0.11	0.83	6.26	100.00
Observations	4,568						

Table F2: Price discovery and price-improving quotes: Heterogeneous effects.

This table reports heterogeneous effects of the proportion of put-call pair price-improving quotes on options information leadership shares. The first subsample (Panel A) includes observations where both one-tick proportions of call and put options are zero ($\%OneTick^{call} = 0$ & $\%OneTick^{put} = 0$). The second subsample (Panel B) includes observations where either one-tick proportion of call or of put option is zero ($\%OneTick^{call} = 0$ $\%OneTick^{put} = 0$), but not both. The third subsample (Panel C) includes observations where both one-tick proportions of call and put options are not zero ($\%OneTick^{call} \neq 0$ & $\%OneTick^{put} \neq 0$). We report two models: (1) OLS; (2) two-stage least squares (2SLS). ILS^{OPT}_{ijmt} denotes the information leadership share (on a scale of 0–100) of each put-call pair i at trading session j in market m on day t. $\%PriceImprove^{OPT}_{ijm,t}$ is the proportion of put-call pair price-improving quotes, defined as the total number of price-improving quotes of put and call options relative to the total number of BBO updates of put and call options. For the 2SLS model, we regress $\%PriceImprove^{OPT}_{ijmt}$ on $FloorClose_t$ and $\%PriceImprove^{OPT}_{ijm,t-1}$, the two instrumental variables, and control variables in the first stage. The instrumental variables are $FloorClose_t$ (a dummy variable that equals one through March 16, 2020 to June 26, 2020 when the CME option floor trading closes and zero otherwise), and $\%PriceImprove^{OPT}_{ijm,t-1}$ (the lagged value of the price-improving quote proportion). In the second stage, we regress ILS^{OPT}_{ijmt} on the fitted value of $\%PriceImprove^{OPT}_{ijmt}$ from the first stage and control variables. Our control variables include $Leverage_{imt}$, $Volatility^{FUT}_{jmt}$, $Volume^{OPT}_{imt}$, and $TimeMaturity^{OPT}_{imt}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_i, γ_j, and δ_m denote put-call pair, trading session, and market fixed effects, respectively. Standard errors are double clustered by put-call pair and day, and reported in parentheses. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS^{OPT}_{ijmt}											
	$\%OneTick^{call} = 0$ & $\%OneTick^{put} = 0$				$\%OneTick^{call} = 0$ or $\%OneTick^{put} = 0$				$\%OneTick^{call} \neq 0$ & $\%OneTick^{put} \neq 0$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\%PriceImprove^{OPT}_{ijmt}$	0.300***		0.297***		0.402***		0.401***		−0.161		−0.159	
	(0.052)		(0.052)		(0.066)		(0.066)		(0.166)		(0.166)	
$\widehat{\%PriceImprove}^{OPT}_{ijmt}$		0.347*		0.340		0.441***		0.437***		−0.759**		−0.741*
		(0.197)		(0.208)		(0.146)		(0.146)		(0.375)		(0.378)
$Leverage_{imt}$			−0.158	−0.175			−0.091	−0.088			−0.026	−0.024
			(0.332)	(0.525)			(0.056)	(0.055)			(0.021)	(0.019)
$Volatility^{FUT}_{jmt}$	1.011	0.505	1.006	0.508	1.552***	1.633***	1.543***	1.626***	1.828***	2.336***	1.813***	2.313***
	(0.824)	(1.078)	(0.824)	(1.076)	(0.410)	(0.415)	(0.410)	(0.414)	(0.436)	(0.431)	(0.435)	(0.431)
$Volume^{OPT}_{imt}$	−0.068*	−0.084*	−0.067*	−0.082*	0.019	0.019	0.020	0.020	0.022**	0.015	0.023**	0.016
	(0.038)	(0.048)	(0.038)	(0.047)	(0.013)	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)
$TimeMaturity^{OPT}_{imt}$	0.416***	0.415***	0.415***	0.414***	0.570***	0.576***	0.567***	0.573***	0.659***	0.671***	0.658***	0.670***
	(0.029)	(0.037)	(0.029)	(0.038)	(0.020)	(0.021)	(0.021)	(0.021)	(0.035)	(0.036)	(0.035)	(0.036)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
N	4,798	3,496	4,798	3,496	47,014	45,144	47,014	45,144	4,568	3,966	4,568	3,966
Adj. R^2	0.631	0.187	0.631	0.187	0.537	0.288	0.537	0.288	0.704	0.459	0.704	0.459

G Robustness

Table G1: Price discovery: Robustness to weighted midpoint price.

This table reports summary statistics of the information leadership shares (ILSs) of futures and option put-call pairs using the weighted midpoint price to estimate the error term $\epsilon_t(K,T)$ in equation (3), across the whole sample in the CME corn and soybean markets. The weighted midpoint price is defined as

$$p^{wm} = \frac{p^{bid}q^{ask} + p^{ask}q^{bid}}{q^{bid} + q^{ask}},$$

where p^{ask} (p^{bid}) and q^{bid} (q^{ask}) denotes the best ask (bid) price and the best bid (ask) quote, respectively. The two markets are organized by columns. We report summary statistics by market (Panel A) and for the pooled sample (Panel B). ILSs are calculated based on the bivariate vector error correction model (VECM) between log futures midpoint price (p_t^{fut}) and log options-implied futures midpoint price (p_t^{opt}) for each put-call pair. ILSs are calculated per day and summarized across all put-call-pair-day observations for each market. We use a paired t-test to assess whether the means of ILSs are statistically different between futures and option markets, and the t-statistics are reported in row "t-stat." *** denotes statistical significance at 1% level. We consider all options whose underlying assets are the first nearby futures with various maturities. We select the put-call pairs that meet the following criteria: 1) Daily CME Globex trading volume and quoting activities are positive; 2) The options-implied futures midpoint prices are positive; 3) Information leadership share metrics for each futures and put-call pair can be calculated for both day and night trading sessions in a trading day and for at least 5 days. Our sample spans from January 7, 2019, to June 26, 2020.

	Corn (%)						Soybean (%)					
	ILS			*IS*			*ILS*			*IS*		
	Mean	Std	Med	Mean	Std	Med	Mean	Std	Med	Mean	Std	Med
Panel A: Day trading session.												
Futures	33.54	35.03	16.19	58.16	28.78	60.83	38.76	35.82	26.30	57.91	30.67	58.33
Options	66.46	35.03	83.81	41.84	28.78	39.17	61.24	35.82	73.70	42.09	30.67	41.67
t-stat.	−54.43***						−34.94***					
Obs.	13,411						12,395					
Panel B: Night trading session.												
Futures	43.81	35.21	38.28	82.22	20.92	91.10	47.33	36.07	44.35	77.66	23.44	87.94
Options	56.19	35.21	61.72	17.78	20.92	8.90	52.67	36.07	55.65	22.34	23.44	12.06
t-stat.	−20.35***						−8.24***					
Obs.	13,411						12,395					

	Panel C: Pooled sample (%)					
	ILS			*IS*		
	Mean	Std	Med	Mean	Std	Med
Futures	40.77	35.90	31.28	69.03	28.46	80.16
Options	59.23	35.90	68.72	30.97	28.46	19.84
t-stat.	−58.39***					
Obs.	51,612					

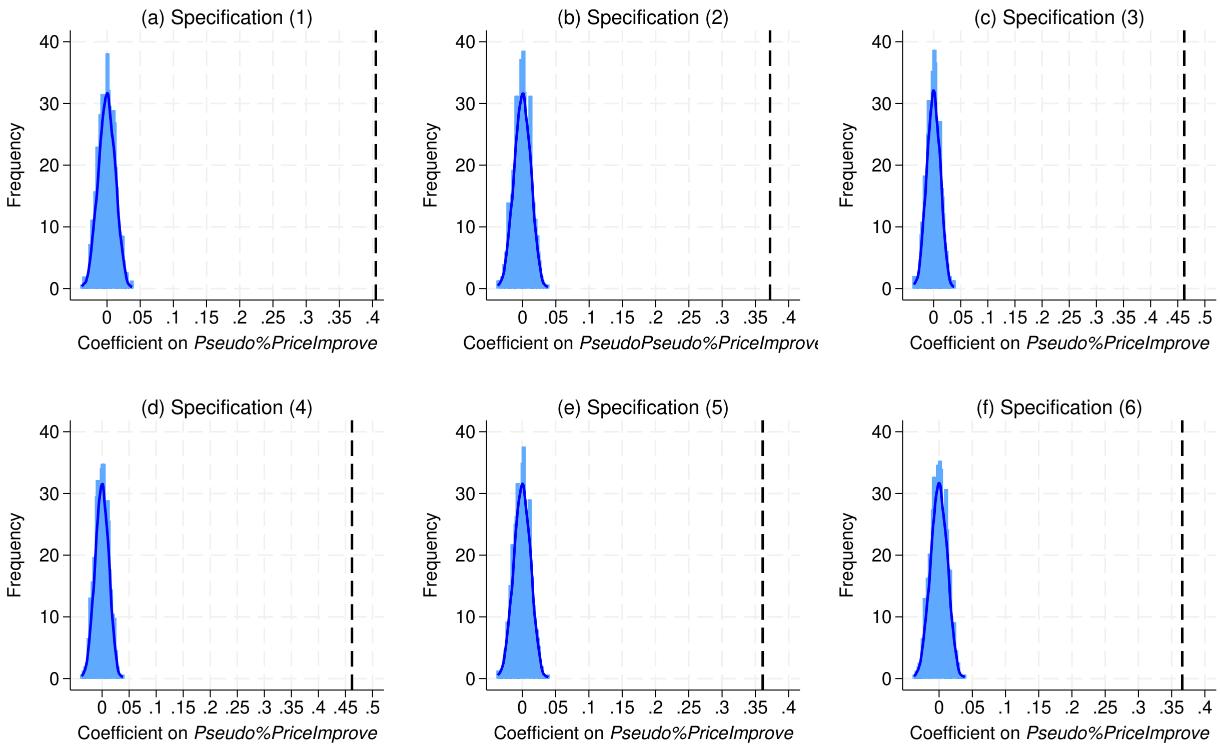

Figure G1: Robustness analysis: Falsification test using a pseudo proportion of put-call pair price-improving quotes.

This figure displays the results of a falsification test on our baseline OLS regressions shown in Table 4. We construct a variable $Pseudo\%PriceImprove$ by randomly permuting the proportion of put-call price-improving quotes 1,000 times. For each permutation, we estimate the OLS regression specifications (1)-(6). The figure shows the distributions of coefficients $\widehat{\beta}^{pseudo}$ for each model in panels (a)-(f). The same control variables and fixed effects are used as described in our baseline OLS regressions. Standard errors are double clustered by put-call pair and day. The vertical black line indicates the actual β coefficients obtained from the baseline OLS regressions and the blue lines are the estimated kernel densities.

Table G2: Price discovery shares and price-improving quotes: Robustness to a simpler instrumental variable.

This table reports the results of the second-stage instrumental variable (IV) regression of options information leadership shares on the proportion of put-call pair price-improving quotes. The regression specification is

$$ILS^{OPT}_{ijmt} = \beta \times \%\widehat{PriceImprove}^{OPT}_{ijmt} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt},$$

where ILS^{OPT}_{ijmt} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j in market m on day t. $\%\widehat{PriceImprove}^{OPT}_{imt}$ is the fitted value of the proportion of put-call pair price-improving quotes from the first-stage regression

$$\%PriceImprove^{OPT}_{ijmt} = \beta_1 FloorClose_t + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt}.$$

The instrumental variables are $FloorClose_t$ (a dummy variable that equals one for all trading sessions through March 16, 2020 to June 26, 2020 when the CME option floor trading closes and zero otherwise). Our control variables include $\%PriceImprove^{FUT}_{jmt}$, $Leverage_{imt}$, $StrikeDistance_{imt}$, $Impvolatility_{imt}$, $Volatility^{FUT}_{jmt}$, $Volume^{OPT}_{imt}$, and $TimeMaturity^{OPT}_{imt}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_i, γ_j, and δ_m denote put-call pair, trading session, and market fixed effects, respectively. Standard errors are double clustered by put-call pair and day, and reported in parentheses. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS^{OPT}_{ijmt}				
	(1)	(2)	(3)	(4)	(5)
$\%\widehat{PriceImprove}^{OPT}_{ijmt}$	1.804**	1.751**	2.382*	1.746**	2.397*
	(0.803)	(0.860)	(1.284)	(0.867)	(1.270)
$Leverage_{imt}$				−0.029	
				(0.048)	
$StrikeDistance_{imt}$					0.013
					(0.025)
$Impvolatility_{imt}$			−26.227		−28.068
			(23.420)		(22.217)
$Volatility^{FUT}_{jmt}$		0.557	0.284	0.557	0.274
		(0.722)	(0.912)	(0.722)	(0.906)
$Volume^{OPT}_{imt}$	0.031**	0.027*	0.030*	0.028*	0.035**
	(0.015)	(0.016)	(0.017)	(0.015)	(0.015)
$TimeMaturity^{OPT}_{imt}$	0.584***	0.581***	0.586***	0.581***	0.587***
	(0.028)	(0.029)	(0.032)	(0.030)	(0.032)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes
N	51928	51928	51928	51928	51928
Adj. R^2	0.185	0.193	0.088	0.193	0.085

Table G3: Price discovery shares and price-improving quotes: Robustness to an alternative proxy of binding tick size.

This table reports the results of the second-stage instrumental variable (IV) regression of options information leadership shares on the one-tick proportion of a put-call pair. The regression specification is

$$ILS^{OPT}_{ijmt} = \beta \times \widehat{\%OneTick}^{pair}_{ijmt} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt},$$

where ILS^{OPT}_{ijmt} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j in market m on day t. $\widehat{\%OneTick}^{pair}_{ijmt}$ is the fitted value of the one-tick proportion of a put-call pair from the first-stage regression

$$\%OneTick^{pair}_{ijmt} = \beta_1 FloorClose_t + \beta_2 \%OneTick^{pair}_{ijm,t-1} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt}.$$

The instrumental variables are $FloorClose_t$ (a dummy variable that equals one for all trading sessions through March 16, 2020 to June 26, 2020 when the CME option floor trading closes and zero otherwise), and $\%OneTick^{pair}_{ijm,t-1}$ (the lagged value of the one-tick proportion of a put-call pair). Our control variables include $\%OneTick^{FUT}_{jmt}$, $Leverage_{imt}$, $StrikeDistance_{imt}$, $Impvolatility_{imt}$, $Volatility^{FUT}_{jmt}$, $Volume^{OPT}_{imt}$, and $TimeMaturity^{OPT}_{imt}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_i, γ_j, and δ_m denote put-call pair, trading session, and market fixed effects, respectively. Standard errors are double clustered by put-call pair and day, and reported in parentheses. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS^{OPT}_{ijmt}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\%OneTick^{pair}_{ijmt}$	−0.089***	−0.081***	−0.085***	−0.077***	−0.079***	−0.127***
	(0.027)	(0.027)	(0.026)	(0.026)	(0.027)	(0.028)
$\%OneTick^{FUT}_{jmt}$			0.204*			
			(0.110)			
$Leverage_{imt}$					−0.093	
					(0.060)	
$StrikeDistance_{imt}$						0.073***
						(0.019)
$Impvolatility_{imt}$				10.983		0.532
				(11.645)		(11.780)
$Volatility^{FUT}_{jmt}$		1.718***	1.817***	1.661***	1.710***	1.607***
		(0.410)	(0.418)	(0.410)	(0.410)	(0.411)
$Volume^{OPT}_{imt}$	0.012	0.002	0.001	0.003	0.004	0.021
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
$TimeMaturity^{OPT}_{imt}$	0.539***	0.536***	0.539***	0.540***	0.534***	0.534***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	50,058	50,058	50,058	50,058	50,058	50,058
Adj. R^2	0.277	0.281	0.282	0.282	0.282	0.283

Table G4: Price discovery shares and price-improving quotes: Robustness to interacted market-session fixed effects.

This table reports the results of the second-stage instrumental variable (IV) regression of options information leadership shares on the proportion of put-call pair price-improving quotes. The regression specification is

$$ILS_{ijmt}^{OPT} = \beta \times \widehat{\%PriceImprove}_{ijmt}^{OPT} + \boldsymbol{Controls} + \lambda_i + \eta_{jm} + \varepsilon_{ijmt},$$

where ILS_{ijmt}^{OPT} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j in market m on day t. $\widehat{\%PriceImprove}_{ijmt}^{OPT}$ is the fitted value of the proportion of put-call pair price-improving quotes from the first-stage regression

$$\%PriceImprove_{ijmt}^{OPT} = \beta_1 FloorClose_t + \beta_2 \%PriceImprove_{ijm,t-1}^{OPT} + \boldsymbol{Controls} + \lambda_i + \eta_{jm} + \varepsilon_{ijmt}.$$

The instrumental variables are $FloorClose_t$ (a dummy variable that equals one for all trading sessions through March 16, 2020 to June 26, 2020 when the CME option floor trading closes and zero otherwise), and $\%PriceImprove_{ijm,t-1}^{OPT}$ (the lagged value of the price-improving quote proportion). Our control variables include $\%PriceImprove_{jmt}^{FUT}$, $Leverage_{imt}$, $StrikeDistance_{imt}$, $Impvolatility_{imt}$, $Volatility_{jmt}^{FUT}$, $Volume_{imt}^{OPT}$, and $TimeMaturity_{imt}^{OPT}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_i and η_{jm} denote put-call pair i and interacted market m × session j fixed effects, respectively. Standard errors are double clustered by put-call pair and day, and reported in parentheses. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS_{ijmt}^{OPT}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\%PriceImprove}_{ijmt}^{OPT}$	0.543***	0.519***	0.606***	0.504***	0.511***	0.501***
	(0.125)	(0.126)	(0.127)	(0.126)	(0.127)	(0.126)
$\%PriceImprove_{jmt}^{FUT}$			−3.398***			
			(0.842)			
$Leverage_{imt}$					−0.088	
					(0.054)	
$StrikeDistance_{imt}$						0.033*
						(0.018)
$Impvolatility_{imt}$				4.578		0.217
				(11.994)		(12.300)
$Volatility_{jmt}^{FUT}$		1.435***	1.855***	1.420***	1.431***	1.419***
		(0.417)	(0.415)	(0.417)	(0.417)	(0.417)
$Volume_{imt}^{OPT}$	0.029**	0.019	0.024*	0.019	0.021	0.031**
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
$TimeMaturity_{imt}^{OPT}$	0.566***	0.562***	0.574***	0.563***	0.560***	0.564***
	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)	(0.021)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Market × Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	50,058	50,058	50,058	50,058	50,058	50,058
Adj. R^2	0.283	0.287	0.290	0.287	0.287	0.288

Table G5: Price discovery shares and price-improving quotes: Robustness to the log ratio of $\%PriceImprove_{ijmt}^{OPT}$ to $\%PriceImprove_{ijmt}^{FUT}$.

This table reports the results of the second-stage instrumental variable (IV) regression of options information leadership shares on the log ratio of $\%PriceImprove_{ijmt}^{OPT}$ to $\%PriceImprove_{jmt}^{FUT}$ ($RatioPriceImp_{ijmt}$, $\log\left(\frac{\%PriceImprove_{ijmt}^{OPT}}{\%PriceImprove_{ijmt}^{FUT}}\right)$). The regression specification is

$$ILS_{ijmt}^{OPT} = \beta \times Ratio\widehat{PriceI}mp_{ijmt} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt},$$

where ILS_{ijmt}^{OPT} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j in market m on day t. $Ratio\widehat{PriceI}mp_{ijmt}$ is the fitted value of the log ratio of $\%PriceImprove_{ijmt}^{OPT}$ to $\%PriceImprove_{jmt}^{FUT}$ ($\log\left(\frac{\%PriceImprove_{ijmt}^{OPT}}{\%PriceImprove_{ijmt}^{FUT}}\right)$) from the first-stage regression

$$RatioPriceImp_{ijmt} = \beta_1 FloorClose_t + \beta_2 RatioPriceImp_{ijm,t-1} + \boldsymbol{Controls} + \lambda_i + \gamma_j + \delta_m + \varepsilon_{ijmt}.$$

The instrumental variables are $FloorClose_t$ (a dummy variable that equals one for all trading sessions through March 16, 2020 to June 26, 2020 when the CME option floor trading closes and zero otherwise), and $RatioPriceImp_{ijm,t-1}$ (the lagged value of the log ratio of $\%PriceImprove_{ijmt}^{OPT}$ to $\%PriceImprove_{jmt}^{FUT}$). Our control variables include $Leverage_{imt}$, $StrikeDistance_{imt}$, $Impvolatility_{imt}$, $Volatility_{jmt}^{FUT}$, $Volume_{imt}^{OPT}$, and $TimeMaturity_{imt}^{OPT}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_i, γ_j, and δ_m denote put-call pair, trading session, and market fixed effects, respectively. Standard errors are double clustered by put-call pair and day, and reported in parentheses. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS_{ijmt}^{OPT}				
	(1)	(2)	(3)	(4)	(5)
$Ratio\widehat{PriceI}mp_{ijmt}$	8.043***	8.444***	8.600***	8.384***	8.548***
	(1.277)	(1.235)	(1.221)	(1.238)	(1.232)
$Leverage_{imt}$				−0.080	
				(0.048)	
$StrikeDistance_{imt}$					0.009
					(0.016)
$Impvolatility_{imt}$			18.276		17.076
			(11.780)		(12.194)
$Volatility_{jmt}^{FUT}$		1.973***	1.874***	1.964***	1.873***
		(0.439)	(0.432)	(0.438)	(0.432)
$Volume_{imt}^{OPT}$	0.041***	0.029**	0.031**	0.030**	0.034***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
$TimeMaturity_{imt}^{OPT}$	0.584***	0.581***	0.587***	0.578***	0.587***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes
N	50,058	50,058	50,058	50,058	50,058
Adj. R^2	0.287	0.293	0.293	0.293	0.293

Table G6: Price discovery and price-improving quotes: Robustness to two-step GMM estimation.

This table reports the results of the regression of options information leadership shares on the proportion of put-call pair price-improving quotes using the two-step efficient generalized method of moments (GMM) estimator. The instrumental variables are $FloorClose_{jt}$ (a dummy variable that equals one for day trading session through March 16, 2020 to June 26, 2020 when the CME option floor trading closes and zero otherwise), and $\%PriceImprove^{OPT}_{ijm,t-1}$ (the lagged value of the price-improving quote proportion). Our control variables include $\%PriceImprove^{FUT}_{jmt}$, $Leverage_{imt}$, $StrikeDistance_{imt}$, $Impvolatility_{imt}$, $Volatility^{FUT}_{jmt}$, and $TimeMaturity^{OPT}_{imt}$. Detailed variable definitions are shown in Table D1 of Appendix D. Standard errors are double clustered by put-call pair and day, and reported in parentheses. Our sample spans from January 7, 2019, to June 26, 2020. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS^{OPT}_{imt}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\%\widehat{PriceImprove}^{OPT}_{ijmt}$	0.367***	0.352***	0.494***	0.347***	0.345***	0.343***
	(0.114)	(0.115)	(0.119)	(0.116)	(0.115)	(0.116)
$\%PriceImprove^{FUT}_{jmt}$			−3.951***			
			(0.786)			
$Leverage_{imt}$					−0.094	
					(0.058)	
$StrikeDistance_{imt}$						0.036**
						(0.018)
$Impvolatility_{imt}$				2.742		−2.117
				(11.746)		(12.027)
$Volatility^{FUT}_{jmt}$		1.502***	1.946***	1.487***	1.497***	1.486***
		(0.422)	(0.413)	(0.421)	(0.421)	(0.422)
$Volume^{OPT}_{imt}$	0.027*	0.017	0.024*	0.018	0.019	0.030**
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
$TimeMaturity^{OPT}_{imt}$	0.562***	0.559***	0.574***	0.558***	0.556***	0.560***
	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)	(0.020)
Put-call pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	50,058	50,058	50,058	50,058	50,058	50,058
Adj. R^2	0.281	0.285	0.291	0.285	0.286	0.286