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Tick size and price discovery: Futures-options evidence*

Richie R. Ma† and Teresa Serra‡

Abstract

The tick size, representing the minimum price increment in a financial market, can influence pricing efficiency. We examine its role in price discovery between futures and options in the Chicago Mercantile Exchange corn and soybean markets. Futures markets have a tick size twice that of options, often resulting in one-tick quoted spreads. This limits traders' ability to improve the best bid or offer price, reducing their capacity to incorporate information into the price. With less tick size constraint and despite thin and costly trading, we find that options are more informative than futures on average. Price-improving quotes from options traders enhance information impounded into prices, suggesting that an unconstrained tick size may enhance price discovery. Our study suggests that a "tight spread and deep depth" may not represent universally optimal market microstructure settings.

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1 Introduction

Most financial markets feature public limit order books, enhancing transparency in the price discovery process. This process involves incorporating 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. When the tick size exceeds the bid-ask spread required by market conditions (McInish and Wood 1992), the spread becomes constrained to one tick, making the tick size binding (Dyhrberg, Foley, and Svec 2023).[1] This paper focuses on the relevance of tick size constraints in price discovery when an asset or its derivatives are traded with different nominal tick sizes across venues. We show that price improvements allowed by unconstrained tick sizes enhance market informativeness relative to markets with constrained tick sizes.

The literature suggests that informed traders post price-improving quotes mostly to reveal information in the market (e.g., Brogaard, Hendershott, and Riordan 2019; Chaboud, Hjalmarsson, and Zikes 2021). These quotes improve the best bid or offer (BBO) price, leading to updates of the midpoint price that is commonly regarded as a proxy for the market fundamental price (e.g., Blume and Stambaugh 1983; Lee 1993; Han and Lesmond 2011). However, when tick size constraints force the spread to equal one tick, traders cannot further narrow this spread by posting better prices within the grid. This effectively limits informed traders' ability to post price-improving quotes, resulting in less frequent updates of the midpoint price. When an asset or its derivatives trade with different nominal tick sizes across different venues, informed traders may select where to reveal information (Narayan and Smyth 2015) based on the tick size characteristics of each market. Markets with unconstrained tick sizes allow for a finer pricing grid, enabling traders to post price-improving quotes more easily and update the midpoint price more frequently, compared to markets with constrained tick sizes.

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

CME agricultural options and futures markets offer a unique setting to investigate the role of the tick size in price discovery. They share the same underlying asset and are traded in the same exchange, which simplifies our analysis compared to U.S. stocks traded across numerous venues. The relatively complex market microstructure of U.S. stocks—especially characterized by market fragmentation (e.g., O'Hara and Ye 2011)—complicates the identification of the role of the tick size constraints on price discovery. The clocks on U.S. exchanges are not always perfectly synchronized, and the timestamps in the public consolidated data feed may lack the accuracy needed to properly sort quote and trade events that happen in

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

various exchanges, due to geographical differences among trading venues (Ding, Hanna, and Hendershott 2014). Since price discovery analyses closely focus on the speed of information corporation, this might result in a measurement error in our analysis. In contrast, all trade and quote data in CME agricultural futures and options markets are recorded using the same protocol, ensuring that their clocks are synchronized for sorting trade and quote events. This streamlined structure facilitates a clearer analysis of this relationship.

To compare futures and options prices, we use the put-call parity to derive options-implied futures midpoint prices. The put-call parity needs fewer assumptions compared to the Black-Scholes model, which is more appropriate for our analysis. We estimate Putniņš (2013)'s information leadership shares (ILSs) based on a bivariate vector error correction model (VECM) that models the dynamics of the futures midpoint prices and the options-implied futures midpoint prices. The ILS provides price discovery shares that are robust to differences in the degree of microstructure noise across markets. For the first time, we assess how the constraint 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.

We use price-improving quoting as our measure of the constraint of tick size since such quotes are only available if the quoted spread is not constrained to one tick. Our measure 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, Nguyen, and Ruela 2024), the number of empty ticks within the BBO (Dyhrberg, Foley, and Svec 2023), and the ratio of quoted spread to tick size (Foley, Meling, and Ødegaard 2023) as a measure of the tick size constraint. We focus on how the tick size affects the movements of the midpoint price through price-improving quotes, providing 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 trading activity, such as the CME agricultural options markets, as it captures how market participants convey information through price-improving limit orders.

Descriptive statistics suggest that quoted spreads are wider and trading activity is significantly lower in options compared to their underlying futures. However, options exhibit relatively more frequent quote updates than trades, indicating that options are essentially driven by quotes. Consistent with Bohmann, Michayluk, and Patel (2019), we find that average options ILSs are larger than those of futures, suggesting that options are more informative. Although options are thinly traded, their less constrained tick size enables timely incorporation of information through price-improving quoting. This ultimately leads to options dominating price discovery over futures. We find the informativeness of options is particularly pronounced during the release of public reports.

We explain options ILS by regressing it against our proxy for the constraint of the tick size, while controlling for options and futures market characteristics. However, the constraint of the tick size may be endogenous, as improved price discovery in options could attract informed traders to reveal their information by posting more price-improving quotes. This may in turn affect the constraint 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 as an instrumental variable 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 closed, these traders transitioned to the electronic venue, where they competed with high-frequency traders (HFTs). Given their slower pace compared to HFTs, floor traders in the electronic venue are likely to 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 may alter the proportion of price-improving quotes submitted after the floor venue closure.[2] Interestingly, though the trading floor only operated during the day trading session, we find that its closure might also increase price-improving quotes during the night trading session. Our instrumental variable 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), and especially with Brogaard, Matthew, and Dominik (2025) and Hu and Murphy (2021) who use the floor trading closure during COVID-19 as an event to causally interpret the impacts of floor trading on market quality and market close auction, respectively. Our 2SLS-IV regression results suggest that a one-standard-deviation (6.71%) increase in price-improving quotes is expected to increase the options ILS by 8.21%, representing 14.83% of its sample mean, thus showing evidence of the relevance of the tick size for price discovery.

We conduct heterogeneity analyses based on the moneyness of put-call pairs to shed light on how moneyness drives price discovery. We define the moneyness of a put-call pair as the absolute distance between strike prices and the underlying futures price. Our 2SLS-IV regression results show that put-call pairs closer to at-the-money status contribute more to price discovery. We then study the relationship between options price-improving quotes and changes in options' price discovery across three subsamples based on moneyness. We find that price-improving quotes enhance price discovery in put-call pairs that are near to the at-the-money status. Several robustness checks are conducted, and our main results are validated.

Previous research providing empirical evidence on the price discovery provided by options is inconclusive. In stocks-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 by using information leadership indicators 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 et al. (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.

[2] Since options markets rely heavily on quotes rather than trades, the closure of the floor trading is unlikely to impact price discovery through the trade volume ratio between options and futures. This is relevant for the exclusion restriction by ensuring that the closure of the floor trading affects options price discovery through price-improving quotes. Nevertheless, we emphasize that our causal interpretations rely on this intuitively appealing but untestable assumption.

Our contribution to the literature lies in evaluating the role of the tick size in price discovery by a quasi-natural experiment. Our results suggest that price improvements facilitated by a finer pricing grid enhance the informativeness of markets with unconstrained tick sizes. Our work may further help to interpret changes in the broader financial markets such as the improved 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 connect this decline 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). These studies find (aggressive) limit orders are jointly at least as informative as trades, suggesting that informed traders may reveal information through such orders. We extend this by showing limit orders can also affect price discovery across markets, particularly through the relative availability of price-improving quotes under different tick constraints. Furthermore, we take a step further by exploring the factors that affect the informativeness of price-improving quotes. Our study is closely related to recent research on odd-lot quotes that tighten the spread between National Best Bid and Offer in the U.S. stock markets Bartlett, McCrary, and O'Hara (2023), which also finds that price-improving quotes contribute to price discovery. We extend Bohmann, Michayluk, and Patel (2019) and provide microstructure evidence on options informativeness by showing that a more granular pricing grid in options helps explain price discovery between futures and options.

Our findings also contribute to the ongoing policy debate about setting the appropriate tick sizes. The literature suggests that a "one size fits all" approach is not suitable; smaller tick sizes may benefit 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). Additionally, our study also sheds light on that a "tight spread and deep depth" may not universally represent the optimal market microstructure setting. Previous studies (e.g., Yao and Ye 2018) reveal that markets with constrained tick sizes may favor fast traders while disadvantaging slower ones. Our study further suggests that such constraints can also impact price discovery across different markets.

Most CME commodity futures markets are tick-constrained, with heavy clustered depths at the top of the limit order book. The CME has recently requested 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, its implementation could 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 ability to combine orders from outright and spread markets to create liquidity 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 for (outright) futures markets, as it could incentivize the submission of price-improving quotes, thus bolstering price discovery – a fundamental function of the futures markets.

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

2 Data and institutional details

We use the CME Market Depth data for both futures and options in corn and soybean markets observed from January 7, 2019, to June 26, 2020. Following Bohmann, Michayluk, and Patel (2019), we concentrate on standard American-style options whose underlying contracts are the most-traded futures contracts. We select the most-traded futures contracts by rolling over to the next highest trading volume contract when it exceeds the current contract's volume for three consecutive trading days.[4] We pair options with futures contracts as indicated in Table B1 of Appendix B.1. We also use daily options information from the CME End-of-Market-Summary-Standard data, which includes metrics such as daily trading volume, expiration dates, delta, and implied volatility. 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 from 8:30 to 13:20 (19:00 to 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 the limit order book resulting from both trades and quotes with nanosecond timestamps. For quotes, the incremental updates are recorded based on the price levels in the limit order book up to ten levels. 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 options and futures Market Depth data, respectively. Unlike the futures markets, CME options markets do not support implied functionality (Arzandeh and Frank 2019). Hence, quotes in the options calendar spread markets are not allowed to be routed to the outright markets to provide liquidity and thus, all options quotes are trader-initiated. To reflect futures market 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). Following Easley, de Prado, and O'Hara (2016), we pre-process both the futures and options data to remove potentially erroneous observations. We delete observations with zero quoted prices and crossed/locked bid-ask spreads during continuous trading sessions in both the futures and options markets.

Table C1 of Appendix C reports descriptive statistics for options markets which we compare with futures descriptive statistics. 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, a proxy for leverage in options. The options omega allows us to compare the options volume with that of futures, as it ensures the options volume is equivalent to the futures in terms of dollar exposure. Results show that the soybean market has greater leverage than the corn market, with

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

the soybean options 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 options price, which in turn should reduce the options implied volatility. Consistently, soybean options, with higher leverage than corn options, display lower implied volatility.

3 Empirical design and results

3.1 *Market liquidity in options and futures markets*

For each day, we select valid individual options that meet two criteria: 1) positive total daily trading volume on the CME, and 2) positive BBO quoting activities and positive quoted prices per 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.[5]

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 commodities. We report the $\%OneTick$ metric measured as the percentage of time when the quoted spread equals one tick, as a proxy for the constraint of tick size (e.g., Yao and Ye 2018; Fleming, Mizrach, and Nguyen 2018). Consistent with smaller quoted spreads, futures markets have more constrained tick sizes than options, with the average $\%OneTick$ being from 3.4 to 8.2 times larger. Because a constrained tick size restricts price-improving quoting, 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). Notably, though the total number of price-improving quotes is usually more than twice as high in futures as in options, the options experience a percentage of price-improving quotes to the best quote updates for both day and night trading sessions about 3 to 6 times larger than futures. For example, during the day trading session for corn, price-improving quotes represent 0.86% in futures (= 1506/175360) and 2.85% in options (= 616/21610). Futures markets also exhibit higher volatility than options. Night trading sessions are generally less liquid across markets, with wider spreads and fewer trades and 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.

Options market liquidity may depend on options moneyness. Hence, we provide sum-

[5] 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 options markets.

mary statistics for individual options by moneyness in Table C2 of Appendix C. We classify options moneyness based on delta: $|\Delta| < 0.4$ for out-of-the-money (OTM), $0.4 \leq |\Delta| < 0.6$ for at-the-money (ATM), and $0.6 \leq |\Delta|$ for in-the-money (ITM). We find the ITM and OTM options have substantially more options-day observations than ATM options.[6] Based on best quote updates, ATM options are the most liquid, consistent with the number of trades. The ITM options are the least tick-constrained and have the highest number of price-improving quotes. This aligns with their largest midpoint price volatility and the widest quoted spreads.

Our market liquidity results may 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 for our price discovery analyses. Following Muravyev, Pearson, and Broussard (2013) and Bohmann, Michayluk, and Patel (2019), we use the adjusted European put-call pair parity to derive these options-implied futures prices:[7]

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

where F_t is the futures price at time t, $C_t\left(K,T\right)$ and $P_t\left(K,T\right)$ 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 $v_t\left(K,T\right)$. Hence,

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

The daily early exercise premium $v_t\left(K,T\right)$ is approximated by the error from the put-call parity relationship at every bid or ask quote update for either the call, the put, or the futures. We use midpoint prices for calls, puts and futures to estimate the error term:[8]

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

[6] Our unreported results suggest that the liquidity summary statistics are not affected by the thresholds used to define moneyness.

[7] The put-call parity needs fewer assumptions and is more flexible than the Black-Scholes model. 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.

[8] Our estimation of the error term is robust to using the weighted midpoint prices (Hagströmer 2021), as discussed in section 3.2.4.

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 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. Our price discovery analyses use the midpoint prices instead of trade prices because trades are rare in options markets and the midpoint prices can reflect both the quote and trade changes. 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, open interest, and quoting activities are positive; 2) The options-implied futures bid, ask, and midpoint prices are strictly positive; 3) Information leadership share metrics (discussed in section 3.2.2) can be calculated for each put-call pair and its underlying futures for both day and night trading sessions for at least 5 days; 4) The options time-to-maturity is between 1 and 123 days;[9] 5) The option is within 50% of being at-the-money, i.e., $|\log(F/K)| \leq 0.5$, where F and K denote daily futures settlement price and strike price, respectively.[10]

Criteria 1) and 2) exclude inactive options markets with no quoting activity or abnormal quoted prices. Criterion 3) ensures we include both day and night trading sessions for each trading day, mitigating the effect of singleton observations in our regression analyses. Criterion 4) accounts for differences in time-to-maturity between corn and soybean options, allowing us to include both markets in our sample for each trading day. Criterion 5) limits the value of the early exercise premia for both puts and calls. Ultimately, we obtain 50,576 put-call-pair-day observations.[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

[9] Due to the difference in options listing schedules between the corn and soybean markets (see Table B1 of Appendix B.1), we select options with a time-to-maturity of up to 123 days to ensure coverage of both markets for every trading day.

[10] This criterion excludes the options with strike prices very far from the futures price. Previous literature (e.g., Muravyev, Pearson, and Broussard 2013) that focuses on stocks-options cases uses a lower threshold than ours. We find this 50% threshold does not severely affect our analyses and qualitatively similar results are obtained if we do not use this criterion.

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

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 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 (permanent price component) 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):

$$\begin{aligned}\Delta p_t^{fut} =& \alpha_1 \left(p_{t-1}^{fut} - p_{t-1}^{opt}\right) + \sum_{i=1}^{p} \gamma_i \Delta p_{t-i}^{fut} + \sum_{j=1}^{p} \delta_j \Delta p_{t-j}^{opt} + \varepsilon_{1,t}, \\ \Delta p_t^{opt} =& \alpha_2 \left(p_{t-1}^{fut} - p_{t-1}^{opt}\right) + \sum_{k=1}^{p} \phi_k \Delta p_{t-k}^{fut} + \sum_{m=1}^{p} \psi_m \Delta p_{t-m}^{opt} + \varepsilon_{2,t}.\end{aligned} \tag{8}$$

Here, the (normalized) cointegrating vector is set to $[1, -1]'$, which ensures that every price series shares the same common efficient price.[13] α_1 and α_2 are the adjustment coefficients. The number of lags (p) is selected based on the Schwarz Information Criterion (SIC) with a maximum lag of 60 and the VECM is estimated using the Ordinary Least Squares (OLS).[14]

Following Baillie et al. (2002), we first calculate Gonzalo and Granger (1995)'s component

[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). Our results are qualitatively similar with 500-millisecond, 5-second, and 10-second sampling, as discussed in section 3.2.4.

[13] Hasbrouck (1995)'s information shares require extracting the permanent price component matrix through a transformation of the VECM into a vector moving average (VMA) process (see Beveridge and Nelson (1981)). Only if the cointegrating (beta) vector is set to $[1, -1]'$, all rows in the permanent price component matrix are identical, which represents the "common" efficient price. Otherwise, the Hasbrouck (1995)'s information shares are not defined. Intraday analyses generally assume this fixed cointegrating vector. Moreover, Hasbrouck (2007, sec. 10.3.3) states that "In microstructure analysis, however, cointegration or its absence tends to be an obvious feature ... The bids, asks, trade prices, and so on, even from multiple trading venues, for a single security cannot reasonably diverge without bound." Nevertheless, we conduct the Johansen (1991) test to assess whether cointegration exists between two price series. We remove those that are not cointegrated at the 99% critical value to ensure a strong support of cointegration in our analyses. We also estimate the unrestricted cointegrating beta and the average beta is -1.

[14] 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, 99.32% of the put-call-pair-day observations have less than 60 lags.

share (CS) and Hasbrouck (1995)'s information share (IS). In a bivariate setting, CS can be 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 residual covariance matrix of the 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.[15] 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)).[16]

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). When one market is slower (staler) and less noisy than the other, the estimated CS and IS are likely to be higher for this market due to its less noise, implying a biased leadership in price discovery. 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 mitigates the dependence on noise, providing an unbiased measure to capture

[15] 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).

[16] 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 31.11%, compared to at most 50% in Hupperets and Menkveld (2002) and about 80% in Booth et al. (2002).

the permanent price component:[17]

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

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 and soybean markets suggest that options are 4.86% and 8.16% more informative than futures (Panel A of Table 2). Median ILSs suggest a more balanced distribution of price discovery, with options being as informative as futures. This pattern is consistent in the night trading session, where mean ILSs also indicate that corn options contribute more to price discovery (56.04%) than corn futures (43.96%). For soybean, mean ILSs suggest that options lead price discovery by 18.16% overnight. Compared to the day trading session with around 16-17 trades, the night 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 the 1% level in ILSs between futures and options for both corn and soybean.

ISs differ significantly from ILSs and indicate that futures markets are significantly more informative than options markets.[18] Since the ILS is calculated based on the ratio of IS and CS instead of their magnitudes, it may fail to fully credit a fast and less noisy market—where both IS and CS are both high and closely aligned. In such cases, the ILS may be biased toward 50%. In our context, one potential concern is that the implied futures midpoint prices (derived from put-call pairs) could introduce staleness, potentially inflating the ILS if options markets are noisier. To assess the staleness, we compare the ratio of non-zero midpoint price returns between put-call pairs and futures using our 1-second sampled data. The results, shown in Figure E1 of Appendix E.3, indicate that both the mean and median of these ratios exceed 1, with distributions that are right-skewed. This implies that

[17] 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 complicate the second-stage analysis that explains the price discovery shares as a function of the options price-improving quotes. Specifically, the second-stage would require a nonlinear regression model (e.g., logit and probit), which is computationally cumbersome, especially when introducing multiple fixed effects.

[18] Options' price discovery dominance despite lower volume may seem counterintuitive. A robustness check shown in Table G3 confirms our main regression findings under IS measures.

midpoint prices update faster in the options than in the futures market. We now turn our attention to the degree of noise in these markets. We define noise as the mean absolute difference between each price series and the estimated common efficient price. The noise ratio for options and futures is calculated as the noise from options (or futures) relative to the total noise from both, expressed as a percentage. Following Gonzalo and Granger (1995), we estimate the common efficient price as the weighted average of options-implied futures and actual futures prices, using their respective CSs as weights.[19] We show noise ratios of both futures and options in Table E2 of Appendix E.3. Options exhibit higher noise than futures, with average options noise ratios being at least 3 times higher than those of futures in both day and night trading sessions, a finding supported by both our market-level and our pooled samples. These findings suggest that the enhanced price discovery in options is not driven by potential staleness. In summary, we conclude that IS underscores that disregarding the substantial noise differences between options and futures may generate biased results. Our price discovery findings indicate that while options are faster at incorporating new information into prices, they are also 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 and they are not informative to future stock returns. Despite allowing for substantial noise differences between stocks and options, Patel et al. (2020) find options ILS to be between 30% and 50%.[20]

We also examine how price discovery changes when monthly World Agricultural Supply and Demand Estimates (WASDE) reports are released by the USDA at 11:00 Central Time during the day trading session,[21] and the results are reported in Table E3 of Appendix E.4. Since the WASDE reports are released during the day trading session, our results do not consider the night trading session. On announcement days, we observe a notable increase in the informativeness of options. On average, ILSs suggest that options contribute 37.36% and 22.64% more to price discovery compared to futures in the corn and soybean markets, with mean differences in ILSs between options and futures being statistically significant at 1%. On non-announcement days, options leadership in price discovery declines, with op-

[19] We implement the method of Gonzalo and Granger (1995) as it is straightforward and well-suited for our analysis. Our results indicate that CSs are higher in futures markets than in options markets. Since CS measures may overstate the noise level in options when used as weights in calculating the noise ratio, we treat our resulting noise estimates as upper bounds. Thus, we employ the more conservative and unbiased ILS metric to validate the robustness of our findings.

[20] Although previous studies do not use ILSs that adjust for noise differences between stocks and options, most U.S. stock options are also tick-constrained, which may help explain why our findings differ from theirs. Patel et al. (2020, Table 1) focus on 35 large U.S. stocks (with average stock options price \$1.68) 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] WASDE announcement days are available at https://usda.library.cornell.edu/concern/publications/3t945q76s?locale=en

tions ILS being 3.32% and 7.44% larger than futures ILS in the corn and soybean market. Qualitatively similar results are also obtained from the pooled sample. The results imply that the options markets play a more important role in price discovery during occurrences that increase futures markets volatility. Our findings add a new dimension to the literature on price discovery during WASDE announcements by showing that options incorporate new information faster than futures. Previous studies mainly focus on futures price behavior (e.g., Ye and Karali 2016; Adjemian and Irwin 2018; Shang, Mallory, and Garcia 2018; Cao and Robe 2022) and trading strategies (e.g., Huang, Serra, and Garcia 2022; Ma and Serra 2025) in futures markets during WASDE announcements. Our results suggest that monitoring options markets alongside futures may be crucial for traders during public information releases.

3.2.4 *Robustness*

We estimate the early exercise premium as the error term $\varepsilon_t(K, T)$ in Equation 3 using the midpoint prices of the futures, put, and call options. Hagströmer (2021) notes that the midpoint price is not a continuous variable and assumes symmetry in the best quotes between the bid and ask sides. Hence, we use the weighted midpoint price p^{wm} proposed by Hagströmer (2021), which considers the quote imbalances between best bid and ask prices:

$$p^{wm} = \frac{p^{bid} q^{ask} + p^{ask} q^{bid}}{q^{ask} + q^{bid}}, \tag{13}$$

where p^{ask} (p^{bid}) and q^{bid} (q^{ask}) denotes the best ask (bid) price and the best bid (ask) quote, respectively. It is used for both futures and options call and put prices. Equation 13 is based on Glosten (1994)'s proposition that the depth posted at a given price level increases in distance to the fundamental value. If bid depth is lower than the ask depth, then the fundamental value is closer to the bid than the ask.

Table E4 in Appendix E.5 reports the summary statistics of the information leadership shares, where the results are qualitatively similar to Table 2. Options lead futures during both day and night trading sessions in all markets, regardless of mean and median values. However, the leadership of options markets is more pronounced if we use the weighted midpoint price. For instance, in our pooled sample, options ILS is 64.49% on average, which is 9.10% 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 the 1% level between futures and options for both corn and soybean markets. Consistent with Glosten (1994), our results suggest that the less liquid side of the book provides more informative signals than the more liquid side.

We also assess whether our information shares are sensitive to different sampling frequencies. Table E5 in Appendix E.6 reports the summary statistics of information leadership shares under three different sampling frequencies, 500 milliseconds (ms), 5 seconds (s), and 10 seconds. Consistent with our main results where data are sampled at 1s, the options markets still lead price discovery. We find that the futures ILSs decline from 48.22% (47.99%) to 40.08% (35.16%) when sampling frequency declines from 500ms to 10s in the corn (soybean) market during the day trading session. This corresponds to a gradual increase in options ILSs from 51.78% (52.01%) to 52.01% (64.84%) in the corn (soybean) market. Similar results are obtained for the night trading session, though the magnitude of futures ILSs is lower than that during the day trading session. The pattern is still persistent in our pooled sample. All paired t-tests show that the differences in ILSs between futures and options are statistically significant at the 1% level.

A potential concern is that options with specific moneyness may drive our price discovery results, despite our near-ATM data selection criteria. For instance, the higher price discovery shares observed in the options market could be primarily attributed to at-the-money (ATM) pairs. To address this concern, we assess the contribution of different moneyness categories to the overall results and the results are shown in Figure E2 of Appendix E.7. We categorize the strike distance into three subsamples. The first includes observations closer to ATM whose strike distance is below its 25th percentile, while the second includes those farther from ATM whose strike distance is between its 25th percentile and 75th percentile. The third includes those whose strike distance is above its 75th percentile. Options ILSs exhibit a similar distribution across all three subsamples. The average options ILS for observations above the 75th percentile is slightly (2.79%) higher than that within the interquartile range ([p25, p75]) in our pooled sample, suggesting that our results are not likely to be driven by the put-call pairs with specific moneyness.[22]

3.3 *Price discovery and price-improving quotes*

3.3.1 *Measure for tick size constraints*

In this section, we approximate the constraint of tick size to investigate its role in price discovery between options and futures. In our descriptive analysis we used $\%OneTick$ variable, measuring the time frequency of one-tick quoted spreads. We improve this measure to better assess the impact of tick size on price discovery. A constrained 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.

We define our measure as the ratio of the number of options price-improving quotes to the total number of options BBO updates ($\%PriceImprove^{OPT}$), reflecting liquidity providers' ability to enhance best bid/ask prices. A higher ratio suggests a less constrained tick size, which can influence price discovery between futures and options markets. Unlike the traditional $\%OneTick$, our measure allows a more nuanced understanding of how the constraint of 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 $\%PriceImprove^{OPT}$ as the sum of put and call price-improving quotes relative to the sum of put and call BBO

[22] Our unreported t-test results based on the pooled sample indicate that average option ILS in the strike distance group below the 25th percentile is not statistically different from those above the 75th percentile. However, a small but statistically significant difference of 2.79% is observed between the interquartile range group ([p25, p75]) and the group above the 75th percentile. This indicates that near-ATM options are as informative as those either deep ITM or OTM. Importantly, the magnitude of this difference is economically negligible, reinforcing that our results are not driven by specific levels of option moneyness. These findings are consistent with the heterogeneity analyses presented in Appendix F.

updates. We calculate this percentage using event-time data that capture all possible quote updates. We apply the same strategy to calculate the percentage of price-improving quotes in futures.

3.3.2 *Baseline OLS regression*

Before we illustrate our identification strategy, we regress options ILS against the percentage of options price-improving quotes using OLS, while controlling for option market characteristics:

$$ILS_{ijt}^{OPT} = \beta \times \%PriceImprove_{ijt}^{OPT} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt}, \tag{14}$$

where ILS_{ijt}^{OPT} denotes the information leadership share (on a scale of 0-100) of put-call pair i at trading session j on day t. $\%PriceImprove_{ijt}^{OPT}$ denotes the percentage of options price-improving quotes. For ease of exposition, we pool corn and soybean markets in one regression. Considering the same options might trade differently at day and night trading sessions, we include an options-session interacted fixed effects λ_{ij}, which captures the effect of time invariant options-session attributes on the outcome variable. Standard errors are clustered by put-call pair.

We rely on previous research when choosing our control variables ($\boldsymbol{Controls}$) representing options and futures market characteristics. We estimate different regressions with different controls, to test the robustness of our results. We control for the potential informativeness of the daily log trading volume ratio between options and futures ($VolumeRatio_{it}$), measured as the sum of call and put omega-adjusted volume relative to the futures volume.[23] We also consider options time to maturity ($TimeMaturity_{it}^{OPT}$), to control for changes in options ILS_{ijt}^{OPT} as the contract approaches maturity. We follow Patel et al. (2020) and control for put-call pairs leverage through the following weighted measure:

$$Leverage_{it} = Leverage_{it}^{call}\mathbf{1}\{r < 0\} + Leverage_{it}^{put}\mathbf{1}\{r > 0\}, \tag{15}$$

where $Leverage_{it}^{call}$ and $Leverage_{it}^{put}$ are the call and the put options 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 negative (positive). These indicators are defined based on the assumption that traders with good (bad) news are likely to sell put (call) options rather than to buy call (put) options.[24] We also use the average omega for a call and put options pair as a simple alternative leverage measure. Following Patel et al. (2020), we also consider the moneyness for a put-call pair by calculating the absolute difference between the underlying futures price and strike price

[23] We do not distinguish options volume by session as the CME trading volume is reported at the end of day.

[24] 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 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 the 1% level. Market surprises are measured as the difference between the actual value of the release and its median estimate from Bloomberg analysts (e.g., Chordia, Green, and Kottimukkalur 2018; Adjemian and Irwin 2018; Huang, Serra, and Garcia 2022). 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.

($StrikeDistance_{it}$).[25] An increase in the strike distance implies that a put-call pair is away from at-the-money. We use this variable to account for different informativeness of at-the-money (ATM) pairs relative to either out-the-money (OTM) or in-the-money (ITM) pairs. Capelle-Blancard (2001) notes that options traders who are informed about futures price volatility (commonly referred to as volatility traders) may crowd out those informed about the futures price. This phenomenon is known as the uncertainty hypothesis in Patel et al. (2020). We intend to test this hypothesis by considering and thus control for futures volatility ($Volatility_{jt}^{FUT}$). Detailed descriptions of our control variables are shown in Table D1 of Appendix D.[26]

We present summary statistics for both dependent and independent variables in the pooled sample in Table 3. On average, options exhibit 8.65% of price-improving quotes while futures exhibit a 1.72%, which aligns with the results reported in Table 1 indicating that options markets are not tick-constrained. We find that the mean absolute strike distance is almost 55 cents, with a median of about 41 cents. Consistent with the fact that options are thinly traded, the log volume ratio between options and futures is negative in our sample.

Table 4 presents the OLS regression estimates for the pooled sample. Results indicate that options 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. Results suggest that a 1% increase in options price-improving quotes leads to a 0.52% increase in options ILS. Alternatively, a one-standard-deviation increase (6.71% — see Table 3, hereafter) in options price-improving quotes is expected to increase options ILS by 3.46% ($= 6.71 \times 0.515$), representing 6.24% ($= 6.71 \times 0.515/55.38$) of the options ILS sample mean. The coefficient slightly increases from 0.515 to 0.548 and remains statistically significant at the 1% level when we control for the trading volume ratio in specification (2). In specification (3), after adding futures volatility, the positive relationship between options price-improving quotes and options ILS remains statistically significant. Consistent with Patel et al. (2020), the OLS results do not support the uncertainty hypothesis, as the coefficient for futures volatility is significantly positive in all specifications, suggesting that options contribute more to price discovery during volatile periods in futures markets. A one-standard-deviation (1.05) increase in futures volatility leads to a 3.52% ($= 1.05 \times 3.351$) increase in options ILS, representing 5.87% of the sample mean. The result is consistent with options price discovery increasing during the release of public reports (Table E3). Specification (4) extends the model in (3) by controlling for options' leverage. Our result is consistent with Patel et al. (2020) and theoretical predictions of Easley, O'Hara, and Srinivas (1998), suggesting that informed traders are likely to trade highly-leveraged options to reveal their information. The leverage effect on options price discovery persists in specification (5), where we use

[25] We are not able to measure the moneyness of a put-call pair by the option delta as the sum of put delta and call delta for the same strike price is always one.

[26] We do not include the percentage of price-improving quotes in the futures market since they are correlated to the futures volatility calculated from the futures midpoint price. Instead, we control for futures price volatility. While price-worsening quotes also contribute to price discovery (e.g., Brogaard, Hendershott, and Riordan 2019), we exclude them from our regression as they are highly correlated with options' price-improving quotes and not constrained by the tick size. Our control variables primarily focus on options characteristics that are unlikely to be influenced by options price discovery. Futures price volatility is more likely affected by futures' market conditions rather than by options' price discovery. Hence, we are not likely to introduce additional endogeneity through our control variables.

the simple average of options omega. Options strike distance is negatively and significantly related to options price discovery. A 10-cent increase in the options strike price distance is expected to decrease the options ILS by 0.4%, implying that options farther from the ATM (deeper ITM or OTM) contribute to price discovery less than ATM options. This suggests that informed traders may prefer liquid options — those that are ATM — to reveal information through price-improving quotes. Options time-to-maturity is positive 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 7.29% ($= 30 \times 0.243$). Trading volume ratio has a positive and statistically significant effect on options ILS. However, the economic magnitudes of the coefficients are marginal as a 1% increase in the trading volume ratio is expected to increase options ILS by 0.005% (0.5 basis points).

3.3.3 *Identification strategy*

The submission of price-improving quotes may be endogenous to price discovery due to reverse causality. Increased price discovery in options may attract informed traders to reveal their information in the options market by posting more price-improving quotes, which may eventually affect the constraint of the tick size in options. Hence, the OLS coefficient of options price-improving quotes does not reveal a causal relationship between tick size constraints and price discovery. To facilitate identification of causal inference, similar to Comerton-Forde and Putniņš (2015) and Foley and Putniņš (2016), we consider an exogenous market structure change affecting options trading; the closure of the options floor trading on March 16, 2020, due to the COVID-19 pandemic. The 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). A recent study by Brogaard, Matthew, and Dominik (2025) relies on a difference-in-differences analysis around the closure of floor trading and finds that the NYSE human floor traders contributed to improved quality during the COVID-19 pandemic. Hu and Murphy (2021) also consider the NYSE floor trading closure as an event to causally interpret the effect of floor broker orders on close auction efficiency and suggest the floor broker orders produce closing price inefficiencies. Gousgounis and Onur (2024), along with insights from conversations with CME market participants, suggest that since the closure of the floor venue, floor traders participate in the electronic venue where they compete with high-frequency traders (HFTs). Because they trade at a slower pace than HFTs, their trading strategy in the electronic venue may favor placing price-improving quotes that prioritize price over speed (Yao and Ye 2018). Hence, liquidity provision by floor traders in the electronic venue may have changed the percentage of price-improving quotes submitted after the floor's closure.

We validate our identification strategy in Table 5, which presents the percentage of daily options price-improving quotes across the sample period for the pooled sample, day, and night sessions. The pre-period is the sample period before March 16, 2020, while the post-period is the one after that date. We find that after the floor venue closed, price-improving quotes increased to 11.96% from 7.85%, and the interquartile range shifted to the right and widened in the pooled sample. This increase is more pronounced over the night trading session where the price-improving quotes increased by 6.88% from 10.60%. A smaller increase is observed in the day trading session with a magnitude of 1.34%. Welch t-tests show that sample means during the post-close period are statistically different from those during the pre-close period at the 1% level.

Table 5 also conveys another important message. Though the floor trading was only available during the day trading session, its closure may have changed the distribution of price-improving quotes between day and night trading sessions in the electronic platform, with a larger increase in the night trading session. This suggests that former floor traders participated both in the day and, more intensively, in the night trading sessions. One possible reason is that the COVID-19 pandemic intensified market uncertainties, and foreign traders, such as those from China, may trade during the night coinciding with the Chinese market open. 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 in a larger increase in the percentage at the night trading session.[27]

We use a dummy variable $FloorClose_t$ as an instrumental variable, which equals one for both the electronic day and night trading sessions after the floor trading closes, and zero otherwise. This dummy captures the effect of the floor closure on both the electronic day and night trading sessions. Since the CME closed the trading floor due to COVID-19, rather than for reasons related to market liquidity or low floor trading activity, which are endogenous to market conditions, our dummy is exogenous and can therefore be used as an IV.[28] Lastly, the exclusion restriction requires the floor trading closure to affect the options price discovery only through the options price-improving quotes. One may argue that changes in price-improving quotes may be driven not only by exogenous market structure change, but also by the economic conjecture related to the pandemic. Our results should be thus carefully interpreted. Our results, as shown in Table 1, indicate that the options markets rely more on quotes than on trades. Thus, it is unlikely that the floor closure affected price discovery through other channels, such as through the volume ratio between futures and options.[29] However, this is not testable empirically. Hence, we emphasize that our conclusions on causality are based on a logically compelling yet untestable argument.

Therefore, our 2SLS-IV regression results should be interpreted cautiously. To validate our results, we use the lagged value of price-improving quotes as an alternative IV and the results are qualitatively similar. Additionally, we conduct a placebo test using a pseudo floor closure dummy as the IV and rerun our 2SLS-IV regressions for 1,000 replications and our results are still robust. More details can be found in section 3.3.5.

[27] We also investigate the changes in the percentage of futures price-improving quotes after the closure of the options floor trading. Our unreported results suggest that it slightly increases by 0.13% on average in our pooled sample.

[28] The CME data do not record quote information of floor trading and we use floor trading volume to approximately measure its activeness. Our unreported result shows that floor volume accounts for 20% on average for put-call pairs with non-zero options floor trading volume prior to the closure, i.e., from January 7, 2019, to March 13, 2020.

[29] We conduct a t-test for log trading volume ratio between options and futures and our unreported results suggest that there is no statistically significant change before and after the floor trading closure at the 10% level.

3.3.4 *2SLS-IV regression*

We begin by estimating the following first-stage regression:

$$\%PriceImprove_{ijt}^{OPT} = \beta \times FloorClose_t + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt}, \tag{16}$$

where $FloorClose_t$ is the dummy variable that equals one for both day and night trading sessions after Match 16, 2020, and zero otherwise. We include the same control variables and fixed effects as those in the baseline OLS regression (Equation 14), resulting in the same six regression specifications as in Table 4.

Table 6 reports the results from the first-stage regression. As expected, the floor closure has a positive and statistically significant effect on the options price-improving quotes, with coefficients ranging between 3.11 and 4.30. We observe a negative and generally significant relationship between options price-improving quotes and options time-to-maturity. Additionally, the negative and significant relationship between options leverage and the options price-improving quotes suggests that options contribute less to price-improving quoting when they have higher leverage. The volume ratio has a significant and negative effect on the options price-improving quotes though the magnitude of coefficients is small. This implies that larger options volume is expected to decrease price-improving quotes. We find more price-improving quotes are submitted when futures markets are more volatile, except in specification (6). A one-standard-deviation increase (1.05) in futures volatility is expected to lead to a 0.62% ($= 1.05 \times 0.592$) increase in options price-improving quotes. Options price-improving quotes are not significantly correlated with options moneyness. The magnitude of the effective F-statistics from Montiel Olea and Pflueger (2013) indicate that our selected IV is not weak under heteroscedasticity. All specifications are exactly identified as we only include a single IV for one endogenous variable.

Our second-stage regression identifies how options price-improving quotes affect the options price discovery:

$$ILS_{ijt}^{OPT} = \beta \times \%\widehat{PriceImprove}_{ijt}^{OPT} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt}, \tag{17}$$

where $\%\widehat{PriceImprove}_{ijt}^{OPT}$ is the fitted value of options price-improving quotes from the first-stage regression (Equation 16). We use the same control variables and fixed effects as those in the first-stage regression, resulting in the same six regression specifications as in Table 6.

Table 7 presents the second-stage regression estimates. Consistent with the OLS regression, our variable of interest has a positive and statistically significant effect on options ILS across all specifications. A 1% increase in options price-improving quotes leads to a 1.22% increase in options ILS in specification (1) above the 0.52% derived from the OLS. Alternatively, a one-standard-deviation increase (6.71%) in options price-improving quotes is expected to increase options ILS by 8.21% ($= 6.71 \times 1.224$), representing 14.83% ($= 6.71 \times 1.224/55.38$) of the options ILS sample mean. When we control for volume ratio (specification (2)) the impact of the options price-improving quotes on options ILS drops to 7.62% ($= 6.71 \times 1.135$) for a one-standard-deviation increase in the variable of interest. Under specification (3) which controls for the futures volatility, the coefficient drops to 5.85%

($= 6.71 \times 0.875$) for a one-standard-deviation increase. The coefficients of futures volatility are positive and statistically significant for all specifications. Hence, they do not support the uncertainty hypothesis. In terms of other control variables considered in specifications (4) to (6), both the options leverage and the options omega significantly affect the options ILS. Like in our baseline OLS regression, options time-to-maturity is positively correlated to the options price discovery. Overall, our 2SLS-IV results indicate that the tick size constraint helps explain price discovery between futures and options. We complement our analysis by providing a heterogeneity analysis based on strike distance and the results are shown in Appendix F.

3.3.5 *Robustness*

We conduct several robustness checks to validate our main regression results, including a falsification test, an alternative instrumental variable, an alternative measure of options price-improving quotes, a placebo test and a test using the option information shares as the dependent variable.

In terms of the baseline OLS regression, to rule out potential confounders that may affect the impact of options price-improving quotes on price discovery, we conduct a falsification test by evaluating how randomly created variables affect our outcome variable. We create a pseudo variable for $\%PriceImprove$. Specifically, we construct $Pseudo\%PriceImprove$ by randomly assigning percentages of options price-improving quotes to put-call pairs and repeat the process 1,000 times, resulting in 1,000 subsamples. The pseudo variables should bear no relationship with options ILS. For each subsample, we re-estimate the baseline OLS regression and β^{pseudo}, the coefficient of $Pseudo\%PriceImprove$. Figure G1 of Appendix G.1 displays the distribution of β^{pseudo} derived using regression specifications (1)-(6) in Table 4. The blue curve is the estimated kernel density, and the black vertical dash line is the actual OLS estimate in Table 4. The distributions of the pseudo coefficients do not contain the actual coefficients, as they are far to the left of the latter. These results imply that our main conclusions are not likely to be driven by chance.

In another robustness check, we use the lagged value of options price-improving quotes ($\%PriceImprove^{OPT}_{ij,t-1}$) from the previous session as an alternative IV (e.g., Buti, Rindi, and Werner 2022). Using this type of IV relies on the "no dynamics in unobservables" assumption, which is untestable and challenging to justify. Nevertheless, we report the results in Table G1 of Appendix G.2, which are qualitatively similar to our main results. An increase in options price-improving quotes still leads to enhanced options price discovery, though the magnitude of the coefficients is generally lower than those in the main results. A 1% increase in the options price-improving quotes is expected to increase the options ILS between 0.82% and 1.09%, which contrasts with the range in Table 7, from 0.88% to 1.50%. In addition, the coefficients of the control variables are similar to those in the main results.

We approximate the constraint of the tick size using the percentage of price-improving quotes. Here, we test the robustness of our selection using an alternative measure. For each put-call pair, we calculate the number of options price-improving quotes and express it in log ($\log\left(PriceImprove^{OPT}_{ijt}\right)$). We use the same floor trading closure IV and add the log of options BBO updates (previously used to define $\%PriceImprove^{OPT}_{ijt}$) as a control in our robustness regression. We expect that the number of options price-improving quotes has a positive effect on the options ILS while the number of BBO updates has a negative effect. We report results in Table G2 of Appendix G.3. Both variables are statistically significant, indicating that a 1% increase in the number of options price-improving quotes is expected to contribute 0.14% to the options price discovery while a 1% increase in the number of BBO updates is expected to reduce the options ILS by 0.09%. Thus, our conclusion that a greater number of options price-improving quotes leads to a higher contribution in price discovery remains valid.

We provide additional evidence of robustness through a placebo (false treatment) test. We generate a pseudo closure IV variable ($FloorPlacebo_t$) by randomly permuting the actual floor closure dummy IV variable ($FloorClose_t$) and we rerun the 2SLS-IV regressions for all specifications 1,000 times. We expect the pseudo closure dummy IV to have no explanatory power in the first-stage regression and the subsequent second-stage regression through the fitted $(\widetilde{PriceImprove}_{ijt}^{OPT})$. We show the distributions of p-values for the coefficients of $\widetilde{PriceImprove}_{ijt}^{OPT}$ in Figure G2 of Appendix G.4. The green curve is the estimated kernel density, and the black vertical dashed line marks the 10% significance level (i.e., p-value$= 0.1$). The distributions of the p-values are strongly left-skewed, with almost all p-values exceeding the 10% significance level, except for a very small fraction in the left tail. Specifically, we find that at least 99.95% of the p-values exceed 0.1 across all specifications, indicating that at least 99.95% of placebo tests do not suggest statistical significance at the 10% level. These placebo results demonstrate that our findings are not attributable to chance.

Lastly, our findings remain robust if we use the option information shares as the dependent variable in the OLS regression, as shown in Table G3 of Appendix G. We find the options price-improving quotes still has a positive and significant results on the options IS across all specifications though their magnitudes are not as large as what we find in the main OLS regressions.

4 Conclusions

The tick size, representing the minimum price increment at which trades can occur, is a relevant characteristic of financial markets that can influence price discovery. A large nominal tick size may create a tick-constrained market, where the bid-ask spread is usually one tick. In such markets, posting quotes that improve the best bid or best offer price (price-improving quotes) is more challenging compared to tick-unconstrained markets. Because 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 these quotes than tick-constrained venues.

This study is the first to investigate how the tick size affects price discovery through price-improving quotes. We leverage the unique setting offered by agricultural derivatives for our research purposes. 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 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 options 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 2.5 to 4.6 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 more informative than 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. 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 4.11% increase in price-improving quotes after the closure, validating our conjecture. 2SLS-IV regression results suggest that a one-standard-deviation (6.71%) increase in price-improving quotes is expected to increase the options information leadership share by 8.21%, representing 14.83% of its sample mean. Our results remain robust across various robustness checks.

Our findings suggest that a "tight spread and deep depth" may not represent universally optimal market microstrucutre setting, as a constrained tick size diminishes the price priority and may also impact price discovery. CME has initiated a survey to gather feedback from market participants regarding a potential 50% reduction of the tick size in the corn futures calendar spread market. Currently, most CME commodity futures markets are tick-constrained. A reduction in tick size in the calendar spread market could have implications for the outright market, as CME implements an implied functionality to connect the liquidity between the two. Each leg of the spread market is routed to the outright market, increasing the likelihood of execution. While the tick size reduction initiative applies only to calendar spreads, it may require aligning pricing grids for both spread and outright markets to facilitate this functionality. This could eventually lead to the same tick size reduction in 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 trade price discovery within the calendar spread market as trades gain greater potential to influence the midpoint price due to decreased depths at the BBO.

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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 (options)-day observations. For futures markets, the most-traded futures are considered. For options, we consider all options contracts whose underlying assets are the most-traded futures. The following criteria are applied to select valid options: 1) we use options with positive total daily trading volume on the CME, and 2) with positive BBO quoting activities and positive quoted prices per trading session. 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
Options-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) calculated for each put-call-pair and underlying futures contract, 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 options-implied futures midpoint price (p_t^{opt}) derived for each put-call pair

$$\Delta p_t^{fut} = \alpha_1 \left(p_{t-1}^{fut} - p_{t-1}^{opt}\right) + \sum_{i=1}^{p} \gamma_i \Delta p_{t-i}^{fut} + \sum_{j=1}^{p} \delta_j \Delta p_{t-j}^{opt} + \varepsilon_{1,t},$$
$$\Delta p_t^{opt} = \alpha_2 \left(p_{t-1}^{fut} - p_{t-1}^{opt}\right) + \sum_{k=1}^{p} \phi_k \Delta p_{t-k}^{fut} + \sum_{m=1}^{p} \psi_m \Delta p_{t-m}^{opt} + \varepsilon_{2,t}.$$

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 options markets, and the t-statistics are reported in row "t-stat." *** denotes statistical significance at the 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, open interest, and quoting activities are positive; 2) The options-implied futures bid, ask, and midpoint prices are strictly 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; 4) The option's time to maturity is between 1 and 123 days. 5) The option is within 50% of being at-the-money, i.e., $|\log(F/K)| \leq 0.5$, where F and K denote daily futures settlement price and strike price, respectively.

	Corn (%)						Soybean (%)					
	ILS			*IS*			*ILS*			*IS*		
	Mean	Std	Med	Mean	Std	Med	Mean	Std	Med	Mean	Std	Med
Panel A: Day trading session.												
Futures	47.58	26.99	51.70	75.19	19.05	80.94	45.93	28.43	46.53	79.50	15.27	83.71
Options	52.42	26.99	48.30	24.81	19.05	19.06	54.07	28.43	53.47	20.50	15.27	16.29
t-stat.	−10.15***						−16.00***					
Obs.	12,823						12,465					
Panel B: Night trading session.												
Futures	43.97	25.07	48.04	77.17	18.22	81.18	40.91	26.19	40.98	79.07	12.64	80.50
Options	56.03	25.07	51.96	22.83	18.22	18.82	59.09	26.19	59.02	20.93	12.64	19.50
t-stat.	−27.22***						−38.73***					
Obs.	12,823						12,465					

	Panel C: Pooled sample (%).					
	ILS			*IS*		
	Mean	Std	Med	Mean	Std	Med
Futures	44.62	26.80	47.08	77.71	16.61	81.60
Options	55.38	26.80	52.92	22.29	16.61	18.40
t-stat.	−45.18***					
Obs.	50,576					

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, open interest, and quoting activities are positive; 2) The options-implied futures bid, ask, and midpoint prices are strictly 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; 4) The option's time to maturity is between 1 and 123 days. 5) The option is within 50% of being at-the-money, i.e., $|\log(F/K)| \leq 0.5$, where F and K denote daily futures settlement price and strike price, respectively.

	Mean	Std	Min	P25	Med	P75	Max
ILS^{OPT} (%)	55.38	26.80	< 0.01	34.28	52.92	78.36	100.00
$\%PriceImprove^{OPT}$ (%)	8.65	6.71	0.13	4.17	6.66	10.79	65.91
$Leverage$	2.64	2.07	0.00	1.10	2.07	3.61	18.43
$Omega$	2.60	1.44	0.12	1.66	2.29	3.21	16.31
$StrikeDistance$ (cents)	54.35	48.44	0.00	18.50	40.75	76.75	431.50
$Volatility^{FUT}$	1.45	1.05	0.14	0.71	1.16	1.89	9.51
$TimeMaturity^{OPT}$ (days)	37.44	25.02	1.00	18.00	32.00	51.00	123.00
$VolumeRatio$	-8.60	3.10	-23.20	-10.50	-8.12	-6.16	-2.74

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

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

$$ILS^{OPT}_{ijt} = \beta \times \%PriceImprove^{OPT}_{ijt} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt},$$

where ILS^{OPT}_{ijt} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j on day t. $\%PriceImprove^{OPT}_{ijt}$ 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 $Leverage_{it}$, $Omega_{it}$, $StrikeDistance_{it}$, $Volatility^{FUT}_{jt}$, $VolumeRatio_{it}$, and $TimeMaturity^{OPT}_{it}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_{ij} denotes put-call-pair (options) × session fixed effects. Standard errors are clustered by put-call pair, and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS^{OPT}_{ijt}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\%PriceImprove^{OPT}_{ijt}$	0.515***	0.548***	0.469***	0.502***	0.561***	0.467***
	(0.040)	(0.041)	(0.040)	(0.041)	(0.042)	(0.040)
$Leverage_{it}$				0.724***		
				(0.090)		
$Omega_{it}$					2.234***	
					(0.228)	
$StrikeDistance_{it}$						−0.044**
						(0.018)
$Volatility^{FUT}_{jt}$			3.351***	3.386***	3.485***	3.381***
			(0.140)	(0.140)	(0.140)	(0.141)
$VolumeRatio_{it}$		0.491***	0.365***	0.326***	0.202*	0.197*
		(0.110)	(0.110)	(0.109)	(0.110)	(0.103)
$TimeMaturity^{OPT}_{it}$	0.243***	0.233***	0.231***	0.253***	0.299***	0.233***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.022)	(0.020)
Options × Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	50,576	50,576	50,576	50,576	50,576	50,576
Adj. R^2	0.125	0.126	0.137	0.139	0.143	0.138

Table 5: Put-call pairs' price-improving quotes and CME trading floor closes.

This table reports the summary statistics of options' price-improving quotes before and after the CME trading floor closes on March 16, 2020 for both the day trading session (Panel A) and night trading session (Panel B). We also provide summary statistics from pooling day and night trading sessions (Panel C). The Put-call pair's price-improving quote is 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). A t-test is used to assess whether the means of put-call pairs' price-improving quotes are statistically different between pre- and post-periods, and the t-statistics are reported in column "t-stat." *** denotes statistical significance at the 1% level. We select the put-call pairs that meet the following criteria: 1) Daily CME Globex trading volume, open interest, 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; 4) The option's time to maturity is between 1 and 123 days. 5) The option is within 50% of being at-the-money, i.e., $|\log(F/K)| \leq 0.5$, where F and K denote daily futures settlement price and strike price, respectively.

	Options price-improving quotes (%)								
	N	Mean	Std.	Min	P25	Med	P75	Max	t-stat.
Panel A: Day trading session.									
Pre	20,363	5.11	3.72	0.13	3.00	4.20	5.84	50.59	
Post	4,925	6.45	3.86	1.30	3.55	6.05	7.83	40.44	21.95***
Panel B: Night trading session.									
Pre	20,363	10.60	6.33	0.50	6.50	8.82	12.79	65.91	
Post	4,925	17.48	8.58	1.16	11.79	16.57	22.07	61.64	52.93***
Panel C: Pooled sample.									
Pre	40,726	7.85	5.88	0.13	4.05	6.22	9.67	65.91	
Post	9,850	11.96	8.64	1.16	5.52	9.17	16.95	61.64	44.77***

Table 6: 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 IV and control variables. The regression specification is

$$\%PriceImprove_{ijt}^{OPT} = \beta_1 FloorClose_t + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt}.$$

$\%PriceImprove_{ijt}^{OPT}$ 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). The instrumental variable is $FloorClose_t$ (a dummy variable that equals one for both day and night trading sessions since March 16, 2020 when the CME options trading floor closes and zero otherwise). Our control variables include $Leverage_{it}$, $Omega_{it}$, $StrikeDistance_{it}$, $Volatility_{jt}^{FUT}$, $VolumeRatio_{it}$, and $TimeMaturity_{it}^{OPT}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_{ij} denotes put-call-pair (options) $\times$ session fixed effects. Standard errors are clustered by put-call pair, and reported in parentheses. We also report the Montiel Olea and Pflueger (2013) effective F statistic for the weak instrumental variable. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $\%PriceImprove_{ijt}^{OPT}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$FloorClose_t$	3.848***	4.026***	3.824***	3.635***	3.110***	4.302***
	(0.286)	(0.255)	(0.244)	(0.241)	(0.240)	(0.282)
$Leverage_{it}$				−0.277***		
				(0.018)		
$Omega_{it}$					−0.946***	
					(0.060)	
$StrikeDistance_{it}$						−0.006
						(0.004)
$Volatility_{jt}^{FUT}$			0.592***	0.573***	0.518***	−0.614***
			(0.025)	(0.025)	(0.024)	(0.038)
$VolumeRatio_{it}$		−0.364***	−0.381***	−0.360***	−0.295***	−0.369***
		(0.021)	(0.020)	(0.020)	(0.019)	(0.023)
$TimeMaturity_{it}^{OPT}$	−0.014***	−0.006*	−0.007*	−0.015***	−0.036***	−0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Options × Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Effective F-stat.	180.49	248.67	246.11	227.83	167.20	232.57
N	50,576	50,576	50,576	50,576	50,576	50,576
Adj. R^2	0.561	0.573	0.578	0.584	0.594	0.261

Table 7: 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 (ILSs) on the proportion of put-call pair price-improving quotes. The regression specification is

$$ILS_{ijt}^{OPT} = \beta \times \%\widehat{PriceImprove}_{ijt}^{OPT} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt},$$

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

$$\%PriceImprove_{ijt}^{OPT} = \beta_1 FloorClose_t + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt}.$$

The instrumental variable is $FloorClose_t$ (a dummy variable that equals one for both day and night trading sessions since March 16, 2020 when the CME options trading floor closes and zero otherwise). Our control variables include $Leverage_{it}$, $Omega_{it}$, $StrikeDistance_{it}$, $Volatility_{jt}^{FUT}$, $VolumeRatio_{it}$, and $TimeMaturity_{it}^{OPT}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_{ij} denotes put-call-pair (options) × session fixed effects. Standard errors are clustered by put-call pair, and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS_{ijt}^{OPT}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\%\widehat{PriceImprove}_{ijt}^{OPT}$	1.224***	1.135***	0.872**	1.029***	1.500***	0.994***
	(0.366)	(0.342)	(0.362)	(0.386)	(0.453)	(0.353)
$Leverage_{it}$				0.878***		
				(0.144)		
$Omega_{it}$					3.178***	
					(0.518)	
$StrikeDistance_{it}$						−0.042**
						(0.017)
$Volatility_{jt}^{FUT}$			3.098***	3.068***	2.976***	3.049***
			(0.278)	(0.283)	(0.292)	(0.273)
$VolumeRatio_{it}$		0.699***	0.515***	0.511***	0.467***	0.401**
		(0.164)	(0.175)	(0.175)	(0.170)	(0.176)
$TimeMaturity_{it}^{OPT}$	0.257***	0.240***	0.236***	0.264***	0.338***	0.239***
	(0.022)	(0.020)	(0.020)	(0.022)	(0.030)	(0.020)
Options × Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	50,576	50,576	50,576	50,576	50,576	50,576
Adj. R^2	0.023	0.030	0.048	0.047	0.033	0.045

Appendix

A Tick size constraint

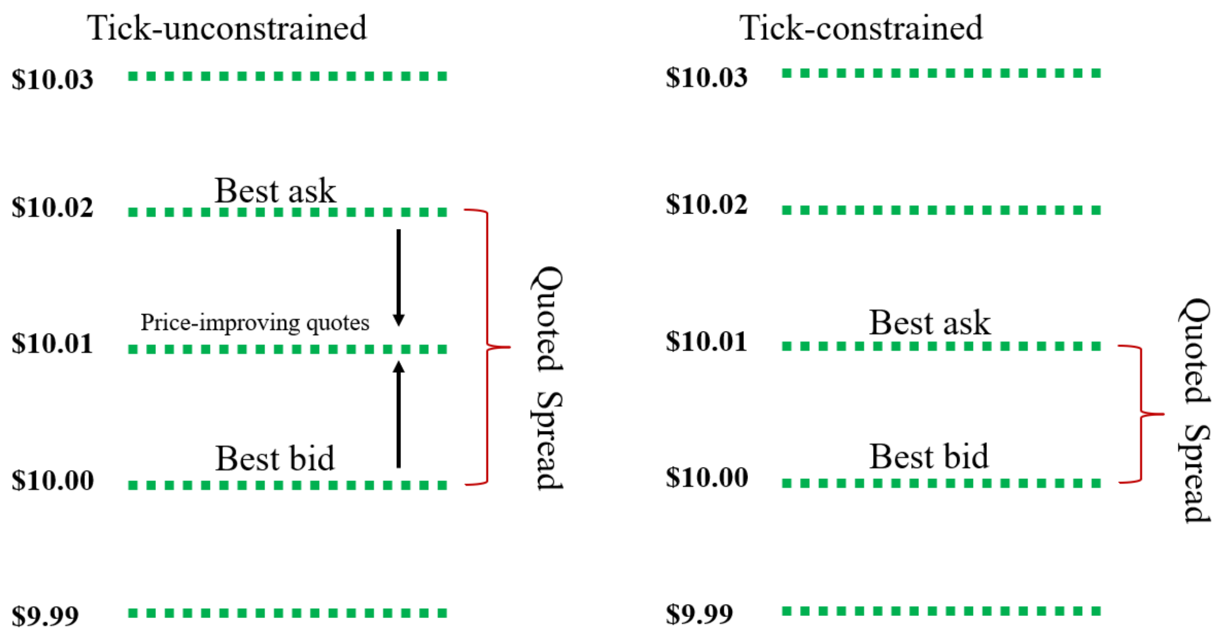

Figure A1: Hypothetical limit order books: Tick-constrained and tick-unconstrained markets.

This figure displays hypothetical limit order books for both tick-constrained and tick-unconstrained markets. In both markets, the tick size is 1 cent. On the right, the best bid (ask) price is $10.00 ($10.01) with a bid-ask spread of 1 cent (one tick) which denotes a tick-constrained market where traders cannot reduce the best ask or increase the best bid without crossing the spread. In the tick-unconstrained market, the best bid (ask) price is $10.00 ($10.02) with a bid-ask spread of 2 cents (two ticks). In this market, a midpoint improvement is still possible.

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. The CME stipulates that options that are traded in contract months in which the underlying futures are not traded, the underlying futures contract is the next one that is nearest to the option expiration.

	Underlying futures contract month	
Options 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*

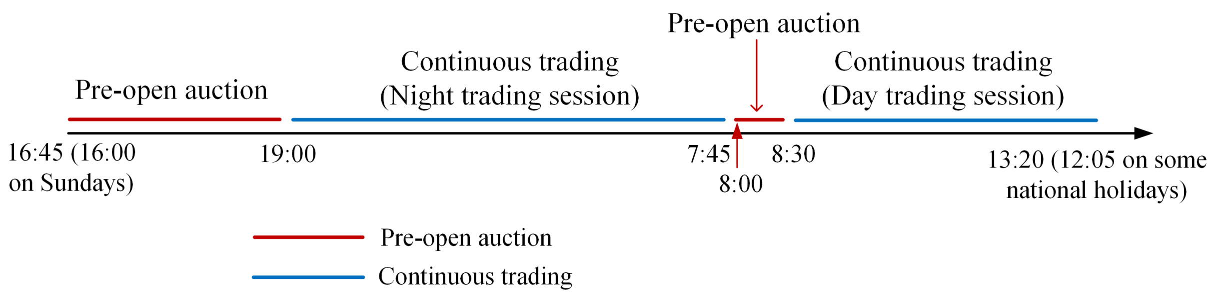

Figure B1: CME Globex sessions and trading hours: Futures and options.

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 corn options Market Depth data*

Table B2: An example of corn 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 ("Time" column) 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 corn futures Market Depth data*

Table B3: An example of corn 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 ("Time" column) 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) are consolidated (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 limit order book (LOB) is the aggregated quantity of the best bid (ask) between the outright and implied LOBs, specifically 95 contracts for the best bid and 235 contracts for the best ask.

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 options daily settlement price, expressed in cents per bushel. Delta is the change in the options' 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 options price. We report the omega-adjusted trading volume (open interest), which is calculated as the options dollar trading volume (open interest) multiplied by the option omega and expressed in million dollars. Options (Futures) volume refers to the CME daily total trading volume in the options (futures) market, expressed in million dollars. Open interest is the number of outstanding options 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 options-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
Options-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
Options-day obs.	22,319						

Table C2: Market liquidity by options moneyness.

This table reports the summary statistics of market liquidity in individual options markets by moneyness during the day trading session (Panel A) and night trading session (Panel B) in the CME corn and soybean markets, respectively. The two markets are organized by columns. Each market liquidity measure is calculated per day and summarized across all options-day observations for every market. We consider all options whose underlying assets are the first-nearby futures with various maturities. The moneyness is defined as the absolute value of the option daily delta: $|\Delta| < 0.4$ for out-of-the-money (OTM), $0.4 \leq |\Delta| < 0.6$ for at-the-money (ATM), and $0.6 \leq |\Delta|$ for in-the-money (ITM). The following criteria are applied to select valid options: 1) we use options with positive total daily trading volume on the CME, and 2) with positive BBO quoting activities and positive quoted prices per trading session. We exclude the pre-open auction. Our sample spans from January 7, 2019, to June 26, 2020.

	Corn						Soybean					
	OTM		ATM		ITM		OTM		ATM		ITM	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Panel A: Day trading session.												
Spread (cents)	0.20	0.12	0.34	0.25	0.76	1.21	0.21	0.22	0.42	0.12	0.97	0.70
%Onetick (%)	47.84	29.60	5.79	9.04	0.07	1.55	41.57	30.26	1.03	2.18	0.02	0.24
BBOupdates ($\times$ 1000)	22.09	14.22	34.77	14.38	15.35	10.71	32.40	16.42	42.96	16.29	21.76	10.99
NTrades	17	38	33	73	9	19	18	32	34	41	7	16
NPriceImprove	278	421	1083	703	1119	784	579	812	2702	1065	2822	1407
Volatility	0.21	0.35	0.73	0.69	1.19	1.10	0.25	0.36	1.14	0.62	1.89	1.02
Options-day obs.	14,021		2,746		6,848		13,287		1,970		4,664	
Panel B: Night trading session.												
Spread (cents)	0.26	0.17	0.57	0.49	1.39	2.57	0.35	0.66	0.76	0.43	2.29	2.53
%Onetick (%)	25.76	30.82	1.39	4.34	0.07	0.96	16.34	25.40	0.28	1.34	0.02	0.29
BBOupdates ($\times$ 1000)	5.04	4.28	6.60	4.93	4.00	3.99	6.67	4.91	9.17	5.78	7.00	6.39
NTrades	3.22	8.18	6	13	2	6	3.90	10.94	7.52	12.78	1.82	6.11
NPriceImprove	150	223	512	405	615	520	348	536	1526	1326	1784	1912
Volatility	0.12	0.16	0.42	0.32	0.76	0.75	0.19	0.33	0.81	0.51	1.44	1.05
Options-day obs.	13,815		2,707		6,783		13,026		1,941		4,591	

D Variable descriptions

Table D1: Variable descriptions.

Variable	Description
Market liquidity	
Spread (cents)	Time-weighted average quoted spread calculated for each options/futures. It is defined as the difference between best ask and bid prices, both expressed in cents and sampled at the second-level.
$\%OneTick$ (%)	The proportion of time, measured in seconds, during which the quoted spread equals one tick (0.25 cents for futures and 0.125 cents for options).
$BBOupdates$ (×1000)	The total number of best-bid-offer (BBO) quote updates for each options and futures contract, expressed in thousands.
$Ntrades$	Total number of trades for each options and futures contract.
$NPriceImprove$	Total number of quotes that improve the BBO using event time data for each options and futures contract.
Regression	
$\%PriceImprove^{OPT}_{ijt}$ (%)	The proportion of put-call pair price-improving quotes, defined as the total number of price-improving quotes for put and call options relative to the total number of BBO updates for those options. This is calculated for each put-call pair i in trading session j on day t.
$Volatility^{FUT}_{jt}$	The standard deviation of second-level futures midpoint price for each trading session j and day t.
$Leverage_{it}$	The leverage measure for a put-call pair i and day t. Following Patel et al. (2020), $Leverage_{it} = Leverage^{call}_{it}\mathbf{1}\{r<0\} + Leverage^{put}_{it}\mathbf{1}\{r>0\}$, where $Leverage^{call}_{it}$ and $Leverage^{put}_{it}$ 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.
$Omega_{it}$	The simple average of put and call omega within a put-call pair i at trading session j.
$StrikeDistance_{it}$ (cents)	The absolute difference between the underlying futures price and the strike price for each put-call pair i and day t.
$VolumeRatio_{it}$	Log ratio of the total volume of put-call pair i relative to the total futures trading volume on day t. The total volume of a put-call pair is calculated as the sum of the omega-adjusted dollar trading volume for put and call options (including trading floor and Globex), expressed in million dollars.
$TimeMaturity^{OPT}_{it}$ (days)	The number of days until a put-call pair i expires.

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 time-weighted 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

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

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 options maturity date and K is the options strike price. $\upsilon_t(K,T)$ denotes the options 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.

	Volatility			Spread (cents)			Price difference (cents)		
	Mean	Std.	Med.	Mean	Std.	Med.	Mean	Std.	Med.
Panel A: Day trading session.									
Corn	2.95	3.64	1.82	2.82	7.42	1.33	−0.05	0.70	−0.01
Obs.	12,823			12,823			12,823		
Soybean	4.65	4.95	3.08	2.63	3.06	1.77	−0.13	1.28	−0.02
Obs.	12,465			12,465			12,465		
Panel B: Night trading session.									
Corn	1.87	2.49	1.21	4.42	14.76	2.03	0.61	4.64	0.07
Obs.	12,823			12,823			12,823		
Soybean	2.93	3.04	2.08	4.45	4.38	3.09	0.99	8.14	0.07
Obs.	12,465			12,465			12,465		
Panel C: Pooled sample.									
	3.09	3.77	2.01	3.58	8.77	2.04	0.35	4.74	−0.01
Obs.	50,576			50,576			50,576		

E.2 *Noise ratios*

Table E2: Noise ratios: Futures and options.

This table reports summary statistics of noise ratios for futures and 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 for the pooled sample (Panel C). We define the options (futures) noise as the mean absolute difference between the options-implied futures midpoint price (futures midpoint price) and the estimated common efficient price. The options (futures) noise ratio is the ratio of options (futures) noise relative to the sum of options and futures noise, expressed in percent (%). Following Gonzalo and Granger (1995), the common efficient price is the weighted average of the options and futures prices, with their respective component shares as the weights. "Obs." reports put-call-pair-day observations.

	Noise ratio: Options (%)			Noise ratio: Futures (%)		
	Mean	Std.	Med.	Mean	Std.	Med.
Panel A: Day trading session.						
Corn	76.32	20.67	82.22	23.68	20.67	17.78
Obs.	12,823			12,823		
Soybean	81.81	12.20	82.05	18.19	12.20	17.95
Obs.	12,465			12,465		
Panel B: Night trading session.						
Corn	79.27	20.00	84.83	20.73	20.00	15.17
Obs.	12,826			12,826		
Soybean	83.07	11.43	83.06	16.93	11.43	16.94
Obs.	12,465			12,465		
Panel C: Pooled sample.						
	80.09	16.89	83.04	19.91	16.89	16.96
Obs.	50,576			50,576		

E.3 *Staleness checking of options ILS*

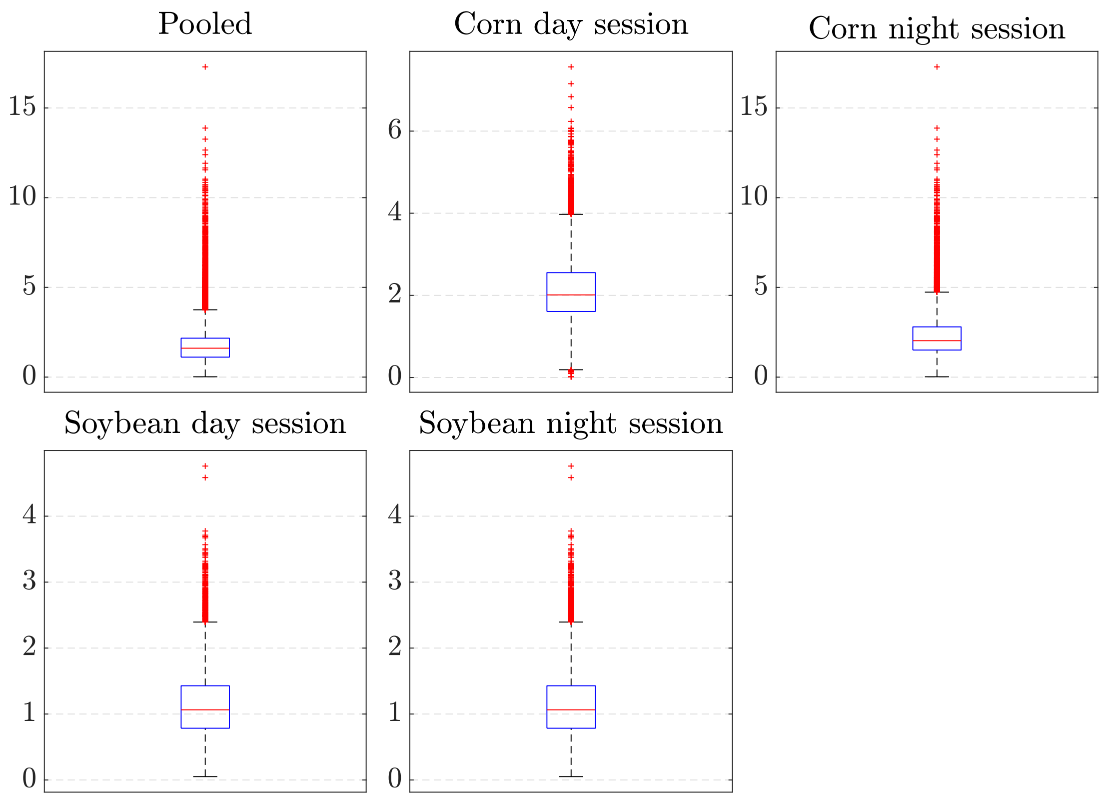

Figure E1: Non-zero midpoint returns between put-call pairs and futures.
This figure displays the boxplots of non-zero returns of midpoint prices between put-call pairs and futures from our 1-second sampling frequency data for our price discovery analyses. The ratio is calculated as the number of non-zero midpoint returns of a put-call pair over that of the corresponding futures contract. The midpoint returns are calculated as the log differences between two consecutive midpoint prices.

E.4 *Price discovery: WASDE announcements*

Table E3: Price discovery: WASDE announcements

This table reports summary statistics of the information leadership shares (ILSs) of futures and 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

$$\Delta p_t^{fut} = \alpha_1 \left(p_{t-1}^{fut} - p_{t-1}^{opt}\right) + \sum_{i=1}^{p} \gamma_i \Delta p_{t-i}^{fut} + \sum_{j=1}^{p} \delta_j \Delta p_{t-j}^{opt} + \varepsilon_{1,t},$$

$$\Delta p_t^{opt} = \alpha_2 \left(p_{t-1}^{fut} - p_{t-1}^{opt}\right) + \sum_{k=1}^{p} \phi_k \Delta p_{t-k}^{fut} + \sum_{m=1}^{p} \psi_m \Delta p_{t-m}^{opt} + \varepsilon_{2,t}.$$

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. 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." *** denotes statistical significance at the 1% level. We select the put-call pairs that meet the following criteria: 1) Daily CME Globex trading volume, open interest, and quoting activities are positive; 2) The options-implied futures bid, ask, and midpoint prices are strictly 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; 4) The option's time to maturity is between 1 and 123 days. 5) The option is within 50% of being at-the-money, i.e., $|\log(F/K)| \leq 0.5$, where F and K denote daily futures settlement price and strike price, respectively.

	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	31.32	28.59	24.53	48.35	26.67	52.63		38.68	30.22	35.29	46.28	28.29	46.83	
Options	68.68	28.59	75.47	51.65	26.67	47.37	14.07***	61.32	30.22	64.71	53.72	28.29	53.17	5.90***
t-stat.	−15.74***			−6.83***				−8.98***			−14.35***			
Obs.	581			12,242				576			11,890			

	Panel B: Pooled sample (%).						
	Announcements			Non-announcements			
	Mean	Std	Med	Mean	Std	Med	t-stat.
Futures	34.98	29.63	29.83	47.33	27.50	49.71	
Options	65.01	29.62	70.16	52.67	27.50	50.29	13.89***
t-stat.	−17.23***			−15.08***			
Obs.	1,156			24,132			

E.5 *Robustness results of weighted midpoint price*

Table E4: Price discovery: Robustness to weighted midpoint price.

This table reports summary statistics of the information leadership shares (ILSs) of futures and 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 trading session (Panels A and B) and for the pooled sample (Panel C). ILSs are calculated based on the bivariate vector error correction model (VECM, equation 8 in main text) between log futures weighted midpoint price ($p_t^{fut,wm}$) and log options-implied futures weighted midpoint price ($p_t^{opt,wm}$) 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 options markets, and the t-statistics are reported in row "t-stat." *** denotes statistical significance at the 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, open interest, and quoting activities are positive; 2) The options-implied futures bid, ask, and midpoint prices are strictly 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; 4) The option's time to maturity is between 1 and 123 days. 5) The option is within 50% of being at-the-money, i.e., $|\log(F/K)| \leq 0.5$, where F and K denote daily futures settlement price and strike price, respectively.

	Corn (%)						Soybean (%)					
	ILS			*IS*			*ILS*			*IS*		
	Mean	Std	Med	Mean	Std	Med	Mean	Std	Med	Mean	Std	Med
Panel A: Day trading session.												
Futures	32.19	27.43	24.69	73.12	18.68	77.80	38.53	30.73	33.39	74.52	18.93	79.57
Options	67.81	27.43	75.31	26.88	18.68	22.20	61.47	30.73	66.61	25.48	18.93	20.43
t-stat.	−73.53***						−41.66***					
Obs.	12,823						12,465					
Panel B: Night trading session.												
Futures	33.64	24.82	30.26	79.22	13.45	79.34	37.83	27.40	35.45	77.27	13.62	78.42
Options	66.36	24.82	69.74	20.78	13.45	20.66	62.17	27.40	64.55	22.73	13.62	21.58
t-stat.	−74.67***						−49.60***					
Obs.	12,823						12,465					

	Panel C: Pooled sample (%)					
	ILS			*IS*		
	Mean	Std	Med	Mean	Std	Med
Futures	35.51	27.78	30.66	76.18	16.43	78.81
Options	64.49	27.78	69.34	23.82	16.43	21.19
t-stat.	−117.28***					
Obs.	50,576					

E.6 ***Robustness results of different sampling frequencies***

Table E5: Price discovery: Robustness to different sampling frequencies.
This table reports summary statistics of the information leadership shares (ILSs) of futures and put-call pairs when sampling frequencies are 500 milliseconds (ms), 5 seconds (s), and 10 seconds (s) across the whole sample in the CME corn and soybean markets. The two markets are organized by columns. We report summary statistics by trading session (Panels A and B) and for the pooled sample (Panel C). 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 options markets, and the t-statistics are reported in row "t-stat." *** denotes statistical significance at the 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, open interest, and quoting activities are positive; 2) The options-implied futures bid, ask, and midpoint prices are strictly 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; 4) The option's time to maturity is between 1 and 123 days. 5) The option is within 50% of being at-the-money, i.e., $|\log(F/K)| \leq 0.5$, where F and K denote daily futures settlement price and strike price, respectively.

	Corn			Soybean		
	Avg. ILS (%)			Avg. ILS (%)		
	500ms	5s	10s	500ms	5s	10s
Panel A: Day trading session.						
Futures	48.23	43.05	40.09	48.00	38.61	35.16
Options	51.77	56.95	59.91	52.00	61.39	64.84
t-stat.	−7.33***	−30.73***	−44.42***	−7.68***	−46.87***	−64.72***
Obs.	12,823	12,823	12,821	12,465	12,465	12,465
Panel B: Night trading session.						
Futures	46.08	43.77	38.69	47.97	40.85	33.80
Options	53.92	56.23	61.30	52.03	59.15	66.20
t-stat.	−16.16***	−28.61***	−51.19***	−7.96***	−39.65***	−75.88***
Obs.	12,826	12,826	12,821	12,465	12,465	12,465
Panel C: Pooled sample.						
Futures	47.56	41.60	36.97			
Options	52.44	58.40	63.03			
t-stat.	−19.50***	−73.04***	−116.89***			
Obs.	50,576	50,576	50,569			

E.7 *Options ILS and strike distance*

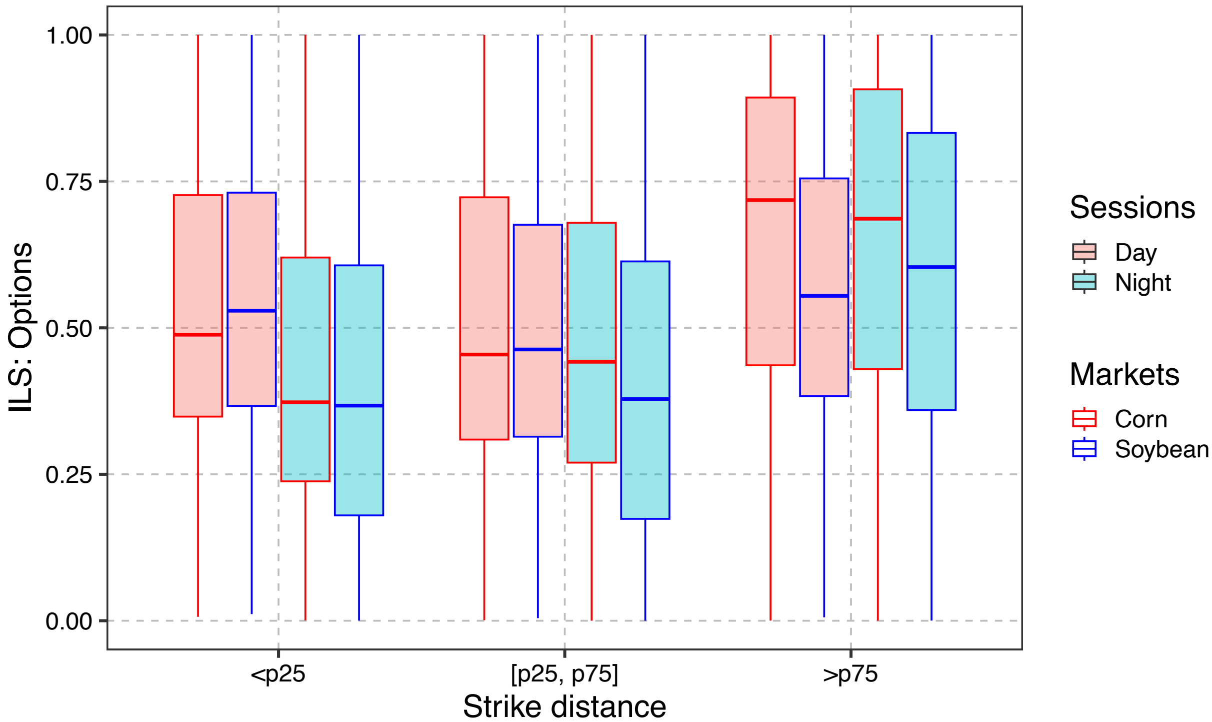

Figure E2: Options information leadership shares by strike distance.

This figure displays the options information leadership shares by put-pair strike distance for both day and night trading sessions in the CME corn and soybean markets. We categorize the strike distance based on its quantile. The first subsample includes observations where the options strike distance is below the 25th percentile ($< P25$). The second subsample includes observations where the options strike distance is between the 25th percentile and the 75th percentile ([P25, P75]). The third subsample includes observations where the options strike distance is above the 75th percentile ($> P75$). The strike distance is defined as the absolute difference between the underlying futures price and the strike price for each put-call pair at each trading day.

F Heterogeneity analysis

Different put-call pairs may have heterogeneous effects on options price discovery based on their moneyness. Our main results show a negative relationship between the put-call-pair strike distance and the options ILS (Table 7). We investigate how the effects of price-improving quotes on options price discovery vary over different subsamples with different strike distance ($StrikeDistance$), defined as the absolute difference between underlying futures price and the strike price. We divide put-call pairs into three subsamples. The first includes observations closer to ATM whose strike distance is below the 25th percentile, while the second includes those farther from ATM whose strike distance is between the 25th percentile and the 75th percentile. The third includes those whose strike distance is above the 75th percentile.

We provide summary statistics similar to those in Table 3 for each subsample in Table G1 of Appendix G. Average options ILSs are similar across the two subsamples and comparable to the pooled sample (Table 3). Price-improving quotes are more likely to occur in put-call pairs further from the ATM, with the average percentage increasing from 7.52% to 10.54%. Options farther from ATM have a slightly smaller leverage (3.15 as opposed to 2.12). The volume ratio is lower for the put-call pairs that are away from the ATM, which means that these put-call pairs are less traded. This aligns with the market liquidity results for individual options reported in Table C2 of Appendix C. Put-call pairs further from the ATM tend to have a slightly longer time to maturity on average.

We run the OLS regressions for each subsample to assess the heterogeneous effects. We use two specifications, controlling for options leverage, futures volatility, volume ratio, and options time-to-maturity. We report the results in Table G2 of Appendix G. For the first subsample, a 1% increase in options price-improving quotes is expected to increase the options ILS by 0.57% according to specification (1). After including other control variables, the coefficients decrease to 0.37%. For the second subsample, the relationship between options price-improving quotes and options ILS remains positive and significant, but the coefficient is slightly higher than that in the first subsample. A 1% increase in options price-improving quotes is expected to increase options ILS by 0.68% according to specification (3). For options that are the farthest from the ATM (third subsample), we find the effect of options price-improving quotes on options ILS is the lowest, and 1% increase in options price-improving quotes is expected to increase options ILS by 0.47%. Thus, our results indicate that the effects of options price-improving quotes generally decrease for the put-call pairs far away from the ATM. In terms of control variables, futures volatility and options time-to-maturity have the same signs and statistical significance as our main results. The options leverage does not have strong explanatory power on the options ILS for the first and third subsamples. The volume ratio either has negative or insignificant effects on the options ILS when options move away from the ATM, suggesting that options volume does not play a key role in options price discovery for these pairs. Overall, our results imply that the effects of options price-improving quotes on the options price discovery slightly decrease when the options move away from the ATM.

Table F1: Summary statistics: Subsamples by put-call pair strike distance.

This table reports summary statistics for three subsamples based on strike distance for each put-call pair. The first subsample (Panel A) includes observations whose strike distance is below the 25th percentile. The second subsample (Panel B) includes observations whose strike distance is between the 25th percentile and the 75th percentile. The third subsample (Panel C) includes observations whose strike distance is above the 75th percentile. Table D1 of Appendix D provides definitions of the variables. We apply the following criteria to select valid put-call pairs: 1) Daily CME Globex trading volume, open interest, 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; 4) The option's time to maturity is between 1 and 123 days. 5) The option is within 50% of being at-the-money, i.e., $|\log(F/K)| \leq 0.5$, where F and K denote daily futures settlement price and strike price, respectively.

	Mean	Std	Min	P25	Med	P75	Max
Panel A: Strike distance < P25.							
ILS^{OPT}	56.00	24.60	0.33	36.98	52.50	75.95	100.00
$\%PriceImprove^{OPT}$	7.25	5.61	1.00	3.35	5.59	8.97	65.91
$Leverage$	3.15	2.14	0.06	1.76	2.50	3.78	18.43
$Volatility^{FUT}$	1.24	0.96	0.14	0.61	0.97	1.58	9.51
$VolumeRatio$	−5.76	1.48	−17.85	−6.46	−5.47	−4.73	−2.74
$TimeMaturity$	33.09	23.68	1	15	29	49	123
N	12,534						
Panel B: Strike distance [P25, P75].							
ILS^{OPT}	54.37	26.81	0.21	33.29	51.98	76.90	100.00
$\%PriceImprove^{OPT}$	8.42	6.24	0.50	4.11	6.65	10.46	62.23
$Leverage$	2.65	2.08	0.00	1.14	1.94	3.61	14.51
$Volatility^{FUT}$	1.41	1.03	0.14	0.69	1.13	1.82	9.51
$VolumeRatio$	−8.66	2.63	−23.20	−10.06	−8.19	−6.76	−3.08
$TimeMaturity$	35.38	23.56	1	17	31	50	123
N	25,438						
Panel C: Strike distance > P75.							
ILS^{OPT}	56.82	28.75	0.00	32.89	56.23	83.33	100.00
$\%PriceImprove^{OPT}$	10.54	8.06	0.13	5.15	8.00	13.05	63.47
$Leverage$	2.12	1.83	0.00	0.64	1.17	3.43	8.64
$Volatility^{FUT}$	1.76	1.12	0.17	0.97	1.50	2.30	9.31
$VolumeRatio$	−11.30	2.65	−21.57	−13.06	−10.98	−9.40	−4.68
$TimeMaturity$	45.93	27.10	3	25	39	58	123
N	12,604						

Table F2: Price discovery and price-improving quotes: Heterogeneity analyses by put-call pairs strike distance.

This table reports the OLS regression results of options information leadership shares (ILSs) 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 below the 25th percentile (< P25). The second subsample includes observations where the options strike distance is between the 25th percentile and the 75th percentile ([P25, P75]). The third subsample includes observations where the options strike distance is above the 75th percentile (> P75). The regression specification is

$$ILS_{ijt}^{OPT} = \beta \times \%PriceImprove_{ijt}^{OPT} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt},$$

where ILS_{ijt}^{OPT} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j on day t. $\%PriceImprove_{ijt}^{OPT}$ 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 $Leverage_{it}$, $Volatility_{jt}^{FUT}$, $VolumeRatio_{it}$, and $TimeMaturity_{it}^{OPT}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_{ij} denotes put-call-pair (options) × session fixed effects. Standard errors are clustered by put-call pair, and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS_{ijt}^{OPT}					
	(1)	(2)	(3)	(4)	(5)	(6)
	> P25	> P25	[P25, P75]	[P25, P75]	> P75	> P75
$\%PriceImprove_{ijt}^{OPT}$	0.566***	0.367***	0.682***	0.573***	0.470***	0.451***
	(0.091)	(0.087)	(0.056)	(0.055)	(0.061)	(0.061)
$Leverage_{it}$	0.333	0.377*	0.647***	0.677***	−0.219	−0.185
	(0.225)	(0.223)	(0.114)	(0.113)	(0.169)	(0.173)
$Volatility_{jt}^{FUT}$		3.656***		3.728***		2.783***
		(0.314)		(0.207)		(0.253)
$VolumeRatio_{it}$	1.369***	1.065***	−0.160	−0.314**	0.159	0.080
	(0.284)	(0.290)	(0.126)	(0.123)	(0.152)	(0.152)
$TimeMaturity_{it}^{OPT}$	0.134***	0.130***	0.211***	0.208***	0.538***	0.538***
	(0.033)	(0.032)	(0.026)	(0.026)	(0.031)	(0.031)
Options × Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12504	12504	25378	25378	12538	12538
Adj. R^2	0.119	0.131	0.104	0.117	0.284	0.292

G Robustness of regression

G.1 *Falsification test*

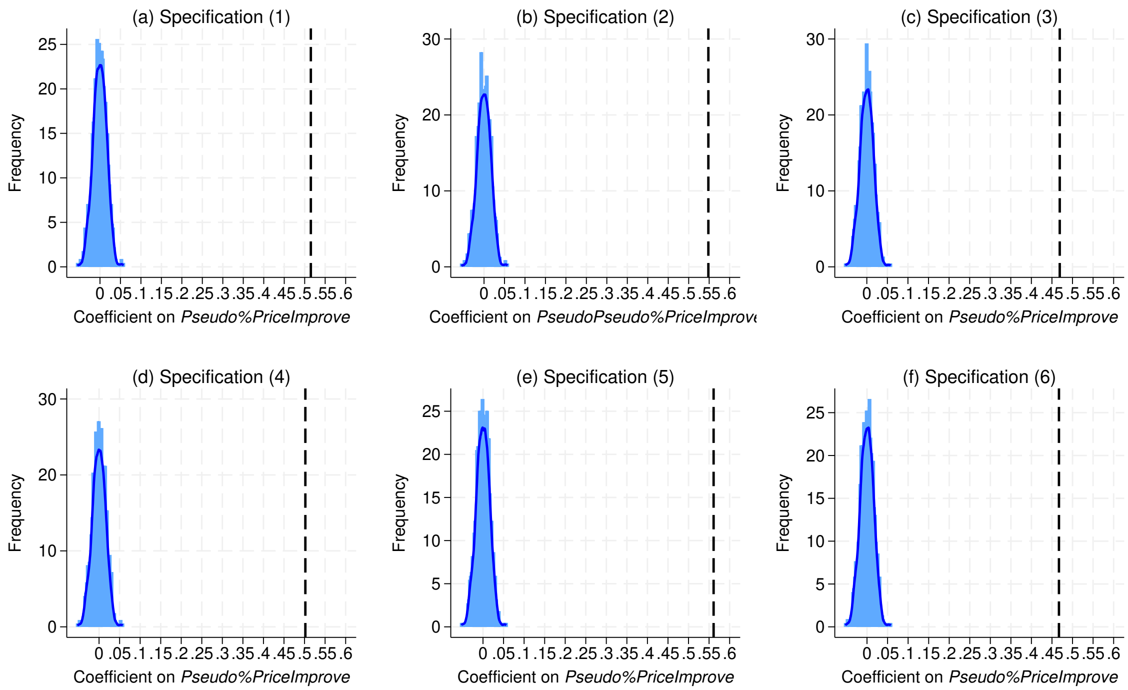

Figure G1: Falsification test using a pseudo proportion of options price-improving quotes

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 clustered by put-call pair. The vertical black line indicates the actual β coefficients obtained from the baseline OLS regressions and the blue lines are the estimated kernel densities.

G.2 *Robustness to an alternative instrumental variable*

Table G1: Price discovery shares and price-improving quotes: Robustness to an alternative instrumental variable.
This table reports the results of the second-stage instrumental variable (IV) regression of options information leadership shares (ILSs) on the proportion of put-call pair price-improving quotes. The regression specification is

$$ILS_{ijt}^{OPT} = \beta \times \widehat{\%PriceImprove}_{ijt}^{OPT} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt},$$

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

$$\%PriceImprove_{ijt}^{OPT} = \beta_1 \%PriceImprove_{ij,t-1}^{OPT} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt}.$$

The instrumental variable is $\%PriceImprove_{ij,t-1}^{OPT}$ (the lagged value of the price-improving quote proportion). Our control variables include $Leverage_{it}$, $Omega_{it}$, $StrikeDistance_{it}$, $Volatility_{jt}^{FUT}$, $VolumeRatio_{it}$, and $TimeMaturity_{it}^{OPT}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_{ij} denotes put-call-pair (options) × session fixed effects. Standard errors are clustered by put-call pair, and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS_{ijt}^{OPT}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\%PriceImprove}_{ijt}^{OPT}$	0.820***	0.897***	0.864***	0.953***	1.086***	0.858***
	(0.096)	(0.099)	(0.100)	(0.102)	(0.106)	(0.099)
$Leverage_{it}$				0.857***		
				(0.097)		
$Omega_{it}$					2.754***	
					(0.256)	
$StrikeDistance_{it}$						−0.041**
						(0.017)
$Volatility_{jt}^{FUT}$			3.135***	3.146***	3.230***	3.168***
			(0.150)	(0.149)	(0.148)	(0.151)
$VolumeRatio_{it}$		0.623***	0.518***	0.486***	0.349***	0.361***
		(0.115)	(0.115)	(0.113)	(0.112)	(0.107)
$TimeMaturity_{it}^{OPT}$	0.254***	0.242***	0.239***	0.267***	0.327***	0.242***
	(0.021)	(0.020)	(0.020)	(0.021)	(0.023)	(0.020)
Options × Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	48,710	48,710	48,710	48,710	48,710	48,710
Adj. R^2	0.035	0.036	0.048	0.049	0.050	0.048

G.3 *Robustness to an alternative measure of options price-improving quotes*

Table G2: Price discovery shares and price-improving quotes: Robustness to an alternative measure.

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

$$ILS^{OPT}_{ijt} = \beta_1 \times \log\left(\widehat{PriceImprove^{OPT}}\right)_{ijt} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt},$$

where ILS^{OPT}_{ijt} denotes the information leadership share (on a scale of 0–100) of put-call pair i at trading session j on day t. $\log\left(\widehat{PriceImprove^{OPT}}\right)_{ijt}$ is the fitted value of the log number of price-improving quotes for each put-call pair from the first-stage regression

$$\log\left(PriceImprove^{OPT}\right)_{ijt} = \beta_1 FloorClose_t + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt}.$$

The instrumental variable is $FloorClose_t$ (a dummy variable that equals one for both day and night trading sessions since March 16, 2020 when the CME options trading floor closed and zero otherwise). Our control variables include $Leverage_{it}$, $Omega_{it}$, $StrikeDistance_{it}$, $Volatility^{FUT}_{jt}$, $VolumeRatio_{it}$, and $TimeMaturity^{OPT}_{it}$. We also include $\log\left(Quotes\right)_{ijt}$, the log total number of BBO quotes of put-call pair i (sum of call and put) as a control variable. Detailed variable definitions are shown in Table D1 of Appendix D. λ_{ij} denotes put-call-pair (options) $\times$ session fixed effects. Standard errors are clustered by put-call pair, and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ILS^{OPT}_{ijt}				
	(1)	(2)	(3)	(4)	(5)
$\log\left(\widehat{PriceImprove^{OPT}}\right)_{ijt}$	14.246***	11.618**	13.802**	20.995***	12.286**
	(4.675)	(5.278)	(5.770)	(7.446)	(4.877)
$Leverage_{it}$			0.939***		
			(0.175)		
$Omega_{it}$				3.599***	
				(0.724)	
$StrikeDistance_{it}$					−0.020
					(0.021)
$Volatility^{FUT}_{jt}$		2.218***	2.038***	1.405*	2.177***
		(0.650)	(0.693)	(0.839)	(0.625)
$\log\left(Quotes\right)_{ijt}$	−8.907**	−8.220**	−9.858**	−15.044***	−8.867**
	(3.824)	(3.902)	(4.266)	(5.477)	(3.513)
$VolumeRatio_{it}$	0.362**	0.364**	0.337**	0.200	0.313*
	(0.146)	(0.142)	(0.141)	(0.131)	(0.163)
$TimeMaturity^{OPT}_{it}$	0.226***	0.228***	0.257***	0.338***	0.230***
	(0.020)	(0.020)	(0.022)	(0.033)	(0.020)
Options $\times$ Session FE	Yes	Yes	Yes	Yes	Yes
N	50,576	50,576	50,576	50,576	50,576
Adj. R^2	0.039	0.050	0.048	0.026	0.048

G.4 *Placebo test: OLS regressions*

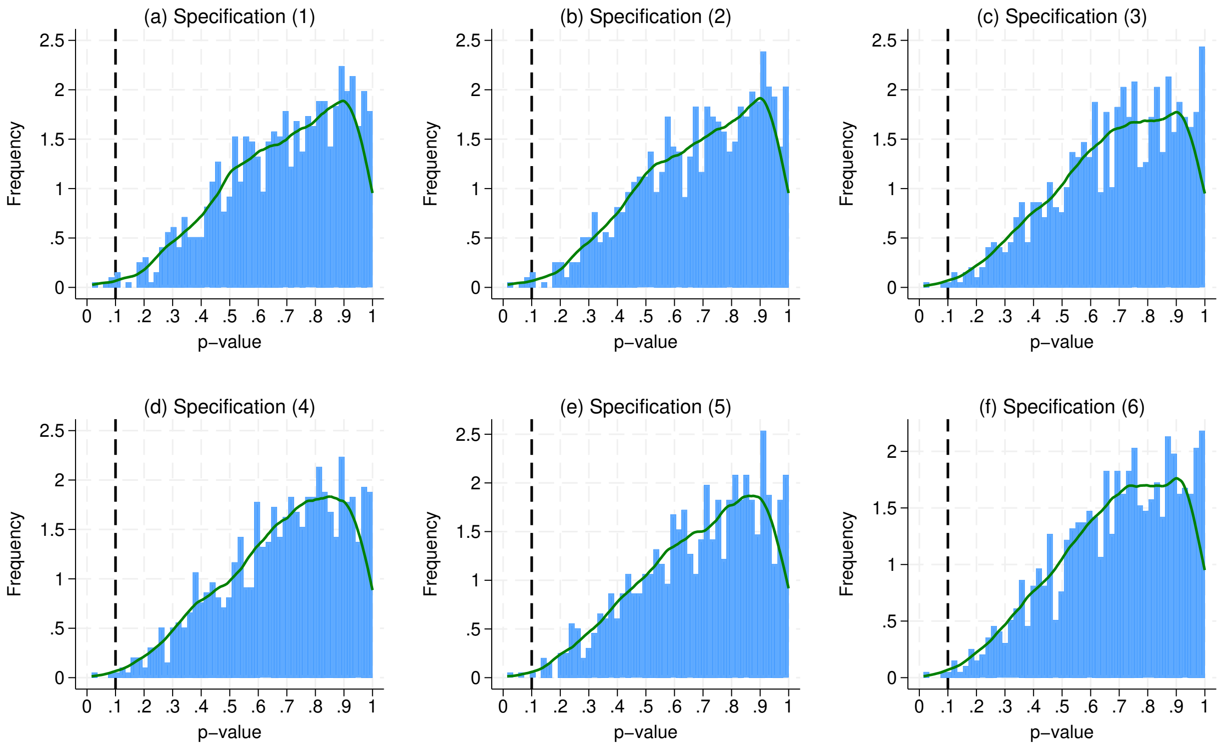

Figure G2: Price discovery shares and price-improving quotes: Placebo test.

This figure displays the results of a placebo test on our 2SLS-IV regressions shown in Table 7. We construct a pseudo instrumental variable $FloorPlacebo_t$ by randomly permuting the floor closure dummy variable ($FloorClose_t$). For each permutation, we estimate the 2SLS-IV regression specifications (1)-(6):

$$ILS^{OPT}_{ijt} = \beta \times \%Price\widetilde{Improve}^{OPT}_{ijt} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt},$$

where $\%Price\widetilde{Improve}^{OPT}_{ijt}$ is the fitted value of the proportion of put-call pair price-improving quotes from the first-stage regression with $FloorPlacebo_t$ as the IV. The figure shows the distributions of p-values of coefficients of $\%Price\widetilde{Improve}^{OPT}_{ijt}$ for each model in panels (a)-(f). The same control variables and fixed effects are used as described in our baseline 2SLS-IV regressions. Standard errors are double clustered by put-call pair. The vertical black line indicates the 10% significance level (i.e., p-value $= 0.1$) and the green lines are the estimated kernel densities.

G.5 ***Robustness to IS as the dependent variable***

Table G3: Price discovery and price-improving quotes: OLS regression.
This table reports the OLS regression results of options information shares (ISs) on the proportion of put-call pair price-improving quotes. The regression specification is

$$IS^{OPT}_{ijt} = \beta \times \%PriceImprove^{OPT}_{ijt} + \boldsymbol{Controls} + \lambda_{ij} + \varepsilon_{ijt},$$

where IS^{OPT}_{ijt} denotes the information share (on a scale of 0–100) of put-call pair i at trading session j on day t. $\%PriceImprove^{OPT}_{ijt}$ 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 $Leverage_{it}$, $Omega_{it}$, $StrikeDistance_{it}$, $Volatility^{FUT}_{jt}$, $VolumeRatio_{it}$, and $TimeMaturity^{OPT}_{it}$. Detailed variable definitions are shown in Table D1 of Appendix D. λ_{ij} denotes put-call-pair (options) × session fixed effects. Standard errors are clustered by put-call pair, and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: IS^{OPT}_{ijt}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\%PriceImprove^{OPT}_{ijt}$	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Leverage_{it}$				0.005***		
				(0.001)		
$Omega_{it}$					0.014***	
					(0.002)	
$StrikeDistance_{it}$						−0.001***
						(0.000)
$Volatility^{FUT}_{jt}$			0.021***	0.022***	0.022***	0.022***
			(0.001)	(0.001)	(0.001)	(0.001)
$VolumeRatio_{it}$		0.001	−0.000	−0.000	−0.001*	−0.003***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$TimeMaturity^{OPT}_{it}$	−0.000*	−0.000*	−0.000**	-0.000	0.000	−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Options × Session FE	Yes	Yes	Yes	Yes	Yes	Yes
N	50576	50576	50576	50576	50576	50576
Adj. R^2	0.312	0.312	0.324	0.327	0.329	0.328