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One contract, two deals: Electronic trading design of exchange-traded calendar spreads*

Richie R. Ma[†], Teresa Serra, Brian G. Peterson, and Scott H. Irwin

Abstract

Electronic trading allows traders to execute calendar spreads simultaneously rather than pairing two outright contracts. Through implied functionality, calendar spreads and outrights are tightly connected, reshaping liquidity provision in outright markets. We examine how the trading architecture of calendar spreads affects the trading outcomes for different groups of agricultural futures market participants. Using Chicago Mercantile Exchange (CME) intraday data, we focus on spread traders who rely on calendar spreads to meet their trading needs, and outright market makers. Counterfactual analyses show that calendar spreads improve execution quality and generate more informative signals about the futures term structure. Implied functionality increases adverse-selection risk borne by market makers, while leaving their gross revenues largely unchanged. Our findings highlight the trade-offs inherent in the current calendar-spread trading design.

Keywords: Calendar spreads, Implied functionality, Term structure, Execution quality, Market makers, Market microstructure
JEL Classification Numbers: G12, G13, G14, Q02, Q13

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1 Introduction

Calendar spreads have been a central trading strategy in agricultural futures markets since the early days of organized commodity exchanges. In futures trading, an "outright" contract refers to a position in a single delivery month—such as December corn. A "calendar spread" involves two delivery months (the "legs" of the spread) for the same commodity, capturing the price difference between contract months (e.g., May–July). A calendar spread therefore manages intertemporal risk across delivery months. Additionally, calendar spreads serve as an informational indicator of the futures term structure. They capture the carrying costs and expected supply–demand conditions, making them useful for marketing decisions across merchandising cycles. Traders use calendar spreads to make physical storage decisions (Hieronymus 1977; DeLong, McKenzie, and Meierotto 2025), to hedge seasonal price fluctuations, and to roll outright positions from an expiring contract into the next for maintaining established long-term exposure (CME 2016).

Electronic trading has fundamentally changed how calendar spreads are executed. In pit trading, a calendar spread was typically constructed synthetically (i.e., leg-by-leg) by a floor trader.[1] Exchange-traded calendar spread contracts make the futures term structure directly tradable, and allow traders to execute two legs simultaneously through a single order in dedicated limit order books.[2] For instance, a $0.25 bid quote represents buying the front-month contract while selling the back-month one at a spread of $0.25. As in pit trading, when this bid order is matched, the trader still receives a long leg for the front-month and a short leg for the back-month with the guaranteed $0.25 price difference. Quotes in calendar spreads can be negative or zero, reflecting contango or flat term structure. Positions executed through calendar spreads can also be used to offset existing outright positions. Hence, exchange-traded calendar spreads substantially enhance the execution of multiple contracts by providing a direct trading mechanism.

Furthermore, calendar spreads and outrights are not isolated. A key feature of CME's electronic trading design is its implied functionality, an automated quoting system that tightly integrates liquidity between calendar spreads and outrights. Through this system, liquidity in calendar spreads generates synthetic and contingent quotes in outrights, providing additional liquidity to outrights and preventing persistent arbitrage opportunities (CME 2007). For example, a $0.25 bid quote of the May–July calendar spread and an ask quote of $4.25 of the May outright can generate an implied $4 bid quote of the July outright. As a result, implied functionality reshapes market liquidity in outrights (Blank 2007) and may alter the nature of market making in those markets.

We study how the CME calendar-spread trading architecture affects trading outcomes for two participant groups. The first group consists of spread traders who use calendar spreads to fulfill their trading demand and gather information from the futures term structure.

[1]Grain pits were typically divided by delivery months, and floor traders could literally turn from one section of the pit to another and execute both legs of a spread. Overdahl (2011) notes that "...in floor-based trading, spread trading was supported by traders who specialized in facilitating spread trading...known as spreaders." Different pits followed different spread quoting conventions, and there is little information in the literature on market dynamics of how spread trades interacted with the broader market.

[2]We use the terms "exchange-traded calendar spreads" and "calendar spreads" interchangeably hereafter.

The second group includes outright market makers[3] who primarily trade outright contracts and seek to earn revenue from liquidity provision. Specifically, we examine whether spread traders benefit from lower execution costs and more informative access to the futures term structure, and whether outright market makers experience changes in their market-making revenues. We do not consider other participant groups such as arbitrageurs, because our evidence suggests that instantaneous arbitrage opportunities between calendar spreads and outrights are rare.

We use CME intraday data from 2015 to 2024 for grain and 2015 to 2019 for livestock futures. Our empirical strategy compares observed outcomes under the current calendar-spread trading design with mechanically constructed counterfactuals. These comparisons help us understand trading outcomes in the absence of exchange-traded calendar spreads. For spread traders, our counterfactuals are synthetic calendar spreads, representing a market in which the term structure is not directly tradable, as in pit trading. We document differences in execution costs and in term-structure informativeness. For outright market makers, our counterfactual is an outright-only liquidity environment without implied quotes.[4] We evaluate whether implied functionality alters market-making conditions in outrights. Specifically, we show how the proportion of implied liquidity is correlated with the difference in market-making revenue between the two liquidity scenarios. Figure 1 summarizes our empirical design.

[Insert Figure 1 here.]

Our results suggest that roughly 40%–70% of total volume in outright markets is driven by spread-related demand, highlighting the quantitative relevance of the calendar-spread market. We find that exchange-traded calendar spreads lower execution costs for spread traders by about half relative to synthetic spreads, provide substantially more executable liquidity at the top of the book, and account for roughly half or more of Hasbrouck (1995)'s information shares in the futures term structure. While synthetic spreads incorporate new information more quickly, calendar spreads remain more informative about futures term structure, delivering more informative pricing signals to spread traders. For market makers, compared to the outright-only liquidity counterfactual, a 10% increase in implied liquidity at the top of the book is associated with an additional increase of \$0.05 (\$0.19) per contract in the adverse-selection cost of market making as measured by price impact, for grains (livestock). These increases represent 17% of the sample mean of price-impact difference for grain futures while 19% for livestock, indicating nontrivial economic meaningfulness. However, gross market-making revenue—the realized spread—remains largely unchanged. Although these additional costs are economically small per contract, they accumulate over time because market makers provide liquidity continuously across multiple futures contracts. Taken together,

[3]We use the term "market makers" to refer to traders who specialize in intraday and continuous market making, such as hedge funds and proprietary trading firms.

[4]Outright market making may also change in the absence of implied functionality. When market makers can quote calendar spreads directly, they may not need to provide liquidity separately on each leg. For example, a market maker may post a bid for 50 contracts in May, an ask for 50 contracts in July, and a bid for 50 May–July calendar spreads. The total liquidity provision is a bid for 100 contracts in May and an ask for 100 contracts in July. However, this effect reflects market makers' own quoting schedules, rather than calendar spread architecture itself. We cannot assess it with our data.

our findings indicate that the current calendar-spread trading design improves execution quality and price informativeness for spread traders, while it is associated with higher adverse selection costs for outright market makers.

The literature documents the risk (e.g., Kawaller, Koch, and Liu 2002), pricing (e.g., Frino and McKenzie 2002; Cuny 2006), performance (e.g., Working 1967; Barrett and Kolb 1995), and market participation (e.g., Ederington and Lee 2002; Robe and Roberts 2019) associated with calendar-spread strategies. Robe and Roberts (2019) report that over one-third of grain and oilseed spread positions was from calendar spreads during 2015–2018. Some studies adopt a trading perspective using intraday data (e.g., Hou and Nordén 2018; Peng, Hu, and Robe 2024; Gousgounis and Onur 2018, 2024). Peng, Hu, and Robe (2024) provide microstructure analysis of calendar-spread market quality by investigating the impact of quadrupling the maximum order size in agricultural futures markets. However, evidence on how calendar-spread trading design affects trading outcomes across different participant groups remains limited. We fill this gap by comparing constructed counterfactual scenarios that capture the differential effects on spread traders and outright market makers. Given the importance of calendar spreads, exploring this question is crucial for improving trading design without disadvantaging any group of participants.

We also contribute to previous studies on implied functionality (e.g., Overdahl 2011; Peng 2022; Arzandeh et al. 2025). Arzandeh et al. (2025) suggest that implied functionality reduces the bid-ask spread and increases market depth in futures markets. Our work differs from theirs by shedding light on the accessibility of implied liquidity at the time of trade execution. We show that while implied functionality enhances liquidity and quote alignment, it is associated with higher adverse selection risk of market-making. Our findings are in line with Overdahl (2011), who suggests that market quality does not deteriorate in the absence of implied functionality, when futures trading relies on sophisticated traders. Furthermore, the institutional history of implied functionality suggests that its benefits are not universally perceived: after its introduction on CME energy markets in 2006 (Blank 2007) and expansion to most markets in 2008, it was periodically turned on and off in specific markets amid dissatisfaction from floor traders,[5] who viewed it as favoring transient liquidity from computerized trading and dwarfing human skill in achieving market efficiency. These disputes further demonstrate the extent to which this trading design remains controversial among different groups of traders.

Our study has implications for exchange design in agricultural futures markets. By making the term structure directly tradable and tightly linking calendar spreads and outrights through implied functionality, the current calendar-spread trading architecture generates trade-offs: gains for spread traders might come at the expense of outright market makers. This suggests that exchange policies governing implied functionality and spread contract specifications can influence how trading benefits and risks are distributed across participant groups. For regulators and exchanges, understanding these allocation outcomes is important when evaluating market pilots intended to enhance liquidity and cross-market integration, particularly in markets where intertemporal linkages are central. For market participants,

[5] For example, CME periodically turned off the implied functionality in corn futures in 2010. See `https://www.cmegroup.com/tools-information/lookups/advisories/electronic-trading/20100616.html`.

since exchanges disseminate outright and implied order books separately, they need to reconstruct the order books locally to monitor real-time market conditions (Arzandeh et al. 2025). This reconstruction entails nontrivial computational and data-subscription costs, potentially increasing both market access and monitoring costs for unsophisticated participants.

2 Data and Institutional details

We use CME Globex intraday Market Depth data for grain futures markets from January 5, 2015, to December 27, 2024, and for livestock futures from January 5, 2015, to December 20, 2019.[6] For grains, we focus on corn and soybeans; for livestock, we focus on live cattle and lean hogs. The two commodities within each group share similar market fundamentals and microstructure characteristics. For outright markets, we analyze the first- to fourth-nearby outright futures series for each trading day. The first-nearby futures series is defined by the most-traded contract, typically the nearest-to-expire contract. We roll to the next most-traded contract when its trading volume exceeds the previous one for two consecutive trading days.[7] All price-limit days are excluded throughout our analyses.

Grain (livestock) outright futures contracts are quoted in cents/bushel (cents/lb.), with quantities in 5,000-bushel (40,000-lb.) contracts. Tick sizes are 0.25 cents/bushel ($12.5/contract) for grains and 0.025 cents/lb. ($10/contract) for livestock commodities. We focus exclusively on day trading sessions, which account for the vast majority of market activity. Calendar spread contracts are quoted similarly to outrights and share identical tick sizes. However, the quoted price represents the price difference between the two legs rather than the absolute price level. Our analysis focuses on six spread pairs, constructed from the four nearby futures series. These pairs span durations ranging from one contract month (e.g., 1st–2nd) to three contract months (e.g., 1st–4th).

CME Market Depth data record incremental updates of the limit order book timestamped to nanosecond precision for both outright and implied quotes. A unique sequence number allows us to sort updates with identical timestamps. We reconstruct consolidated limit order books based on Arzandeh and Frank (2019). Following Easley, de Prado, and O'Hara (2016), we preprocess our data to remove potentially erroneous quotes and those with distorted message sequence numbers.[8]

CME Market Depth data also record trade summaries, including price, size, and direction (buyer- or seller-initiated). Trades are also assigned unique sequence numbers for sorting. In outright markets, CME classifies trades into outright, spread, and other. Outright trades are plain demand for single-month contracts in outright markets and do not involve calendar spreads. Spread trades are leg executions from plain demand for calendar spreads. Spread

[6]We select this sample period because the CME eliminated night trading for livestock futures on October 27, 2014, concentrating all trading activity in the day trading session for all commodities.

[7]By doing so, the May lean hog futures contract and the August and September soybean futures contracts are excluded.

[8]Due to distorted message sequence numbers, we exclude one week of data for livestock and two weeks of data for grains.

trades were counted in outright trading volume by CME until November 20, 2015.[9] Other trades are matched through implied functionality rather than plain market orders. Figure A1 of Appendix A.2 shows examples of outright and spread trades.

According to the trade classification, Figure 2 displays the proportions of the three trade types in outright markets.[10] All commodities exhibit similar patterns. For the first-nearby series, outright trades account for more than 50% of total trading volume, while spread trades constitute about 40% (30%) in grains (livestock). Deferred contracts feature higher spread-trade activity, representing 61.48%–64.15% of total trading volume in grains (51.96%–52.06% in livestock). Other trades only account for 3.09%–19.58% across all commodities, with slightly higher proportions in deferred contracts and livestock markets. Our results indicate that except for the most-traded (first-nearby) contracts, trading volume is primarily from the spreads, suggesting traders mainly use exchange-traded calendar spreads to take multiple contract-month positions rather than execute them separately in outright markets. Overall, consistent with Gousgounis and Onur (2018), our findings suggest that spread trades play a significant role in trading volume along the term structure, especially for deferred futures series.

[Insert Figure 2 here.]

3 Spread traders

Spread traders primarily use calendar spreads for two central purposes. First, they use calendar spreads as a trading strategy to manage intertemporal risk or roll expiring positions. Second, they rely on calendar-spread quotes to extract information about the futures term structure, which guides storage, merchandising, and hedging decisions. Hence, exchange-traded calendar spreads may affect spread traders through two channels: (i) execution quality and (ii) information efficiency. In this section, we examine these channels in turn. Section 3.1 evaluates whether exchange-traded calendar spreads improve execution conditions relative to synthetic spreads constructed from separate outright executions. Section 3.2 studies where price discovery in the futures term structure occurs by comparing exchange-traded calendar spreads with synthetic spreads.

3.1 Execution quality

Under pit trading, a calendar-spread strategy had to be constructed synthetically by executing two separate outright contracts, exposing spread traders to slippage[11] and execution delays. Exchange-traded calendar spreads allow both legs to be executed simultaneously in

[9] See Table A1 of Appendix A.1. After November 20, 2015, CME discontinued the dissemination of spread trades, requiring us to recover the data. Technical details of the recovery procedure are provided in Appendix A.3.

[10] This analysis accounts for spread trades from all exchange-traded calendar spread contracts, rather than limiting to the six spread pairs mentioned in section 2.

[11] Slippage refers to the difference between the intended execution price of a spread position and the realized execution price that arises when the two legs are executed separately and prices move between executions.

a dedicated order book. If calendar spreads provide tighter quoted spreads and deeper liquidity than synthetic spreads, spread traders should face lower transaction costs and reduced execution risk when establishing or rolling intertemporal positions. We test this hypothesis by comparing execution quality in calendar spreads with counterfactual synthetic spreads constructed from corresponding legs.[12]

We construct the leg-implied best bid and offer (BBO) prices for counterfactual synthetic spreads. Buying a calendar spread entails buying the front-month contract and selling the back-month contract. The leg-implied bid and ask prices are

$$\begin{aligned} \text{leg-implied bid} &= \text{front bid} - \text{back ask}, \\ \text{leg-implied ask} &= \text{front ask} - \text{back bid}. \end{aligned} \tag{1}$$

where *front* and *back* denote the front-month and the back-month legs. Because executing a synthetic spread requires trading both legs separately, its quoted spread equals the sum of the quoted spreads of the front-month and back-month contracts.

The BBO depth of a synthetic spread is limited by the less liquid leg. For example, if the best bid depth of the front-month leg is 5 contracts and that of the back-month leg is 3, the maximum number of spread positions that can be executed is 3. Formally, the leg-implied best bid and ask depths are given by

$$\begin{aligned} \text{Leg-implied best bid depth} &= \min\left(\text{front bid depth}, \text{back ask depth}\right), \\ \text{Leg-implied best ask depth} &= \min\left(\text{front ask depth}, \text{back bid depth}\right). \end{aligned} \tag{2}$$

We measure volatility as the daily standard deviation of the midpoint price (the arithmetic mean of the best bid and offer prices) returns, annualized using $\sqrt{252}$.[13] All liquidity cost measures are computed from 1-second resampled data, using the last observation in each interval.

Figure 3 displays the quoted spreads for calendar and synthetic spreads. The median calendar spreads are 0.27–0.48 cents lower than synthetic spreads in grain markets and 0.012–0.066 cents lower in livestock. This implies that execution costs in calendar spreads are about one-tick lower than those for synthetic spreads. Unreported Wilcoxon signed-rank tests confirm these median differences are significant at the 1% level. The decline is larger for pairs with shorter inter-leg distances: quoted spreads drop by 0.27–0.33 (0.050–0.053) cents for the 1st–2nd pair, but only by 0.27–0.29 (0.012–0.027) cents for the 1st–4th pair in grains (livestock).

[Insert Figure 3 here.]

Accounting for market size, Figure 4 displays the daily cumulative dollar trading costs, cal-

[12] As the counterfactual, the leg-by-leg synthetic spreads are assumed to be executed simultaneously. However, this represents a frictionless scenario without slippage, whereas actual trading would involve slippage. Accordingly, our estimated trading costs for synthetic spreads should be viewed as a lower bound.

[13] Because calendar spread quotes can be negative during contango, log returns are not feasible.

culated by multiplying per unit quoted spreads by trading volume.[14] Compared to synthetic spreads, calendar spreads reduce trading costs by $194,100–$223,870 ($56,690–$69,700) for the 1st–2nd pair in grains (livestock), the largest cost reduction among all pairs. Unreported Wilcoxon signed-rank tests confirm that all median differences in costs are significant at the 1% level. Consistent with Figure 3, cost reductions decline with the inter-leg distance. The cost reduction for the 1st–4th pair in grains (livestock) is $8,055–$18,860 ($520–$2,095). This smaller reduction likely reflects the relatively low trading volume of long-distance pairs, despite sizable per-unit cost differences.

[Insert Figure 4 here.]

Though calendar spreads offer lower trading costs, it remains unclear whether this reflects price-level differences or superior market liquidity. To answer this, we examine pricing conditions between calendar spreads and synthetic spreads. We classify them into three cases (Tomio 2017): included, overlapped, and crossed. In the first two cases, the BBO of the synthetic spread lies inside that of the calendar spread, implying no difference in price levels across markets. In the last case, the synthetic quotes lie entirely outside the calendar spread quotes, suggesting that one market offers strictly better prices than the other. Visualization examples are shown in Figure B1 of Appendix B.1. Figure B2 of Appendix B.2 confirms that the crossed case is the least frequent pricing condition, suggesting that prices across venues remain closely aligned. This implies that cost differences primarily reflect liquidity conditions, rather than price-level misalignments.

Figure 5 displays time-weighted average BBO depths. Calendar spreads consistently offer greater executable depth than synthetic spreads for both grains and livestock, with the largest gains in the 1st–2nd pair. In livestock, calendar spreads post 12–28 additional contracts at the BBO for the 1st–2nd pair. In grains, additional BBO depth ranges from 1,902–6,419 contracts, in line with Peng, Hu, and Robe (2024). This indicates that calendar spreads provide greater executable liquidity and lower execution risk than synthetic spreads. Unreported Wilcoxon signed-rank tests confirm the differences are significant at the 1% level. Depth improvements are more pronounced for short-distance pairs and diminish for long-distance ones. Figure 6 shows the annualized return volatility. Consistent with Working (1967), calendar spreads are systematically less volatile than synthetic spreads: volatility is 2.5%–4% lower in grain markets and around 1% lower in livestock. These differences are also statistically significant at the 1% level. The reduction in volatility is larger for short-distance pairs than for long-distance ones.

[Insert Figures 5 and 6 here.]

Additionally, our results indicate that execution quality is more closely related to inter-leg distance than to the liquidity of the underlying legs: though the 2nd- and 3rd-nearby contracts have less liquidity than the 1st-nearby contract, calendar spreads still provide better execution quality than synthetic spreads. This feature particularly benefits spread traders with longer trading horizons, as it allows them to avoid the less liquid conditions typically found in deferred outright markets. Taken together, these findings provide microstructure

[14] We use trading volume generated from plain demand for calendar spreads, as defined in section 2.

evidence that calendar spreads offer lower liquidity costs and execution risk than synthetic spreads from separate outright trades.

3.2 Price discovery of term structure

Calendar spreads are designed to allow the term structure to be traded directly, which may promote a transparent process of price discovery through calendar spreads. To serve this informational role, calendar spreads must incorporate new information about the term structure in a timely and reliable manner. At the same time, synthetic spreads may also react to incoming news as outright markets experience higher volatility. We examine whether the price discovery of the term structure occurs primarily in calendar spreads or in synthetic spreads.

According to Lehmann (2002), price discovery entails both efficient and timely incorporation of new information into market prices. Efficiency concerns which market contributes more to revealing the efficient price, whereas timeliness indicates which market adjusts first to new information. Putniņš (2013) notes that these two dimensions of price discovery may not necessarily occur in the same market. Hence, we analyze the two dimensions separately using different price discovery measures, following Vollmer, Herwartz, and von Cramon-Taubadel (2019).

Following Hasbrouck (1995), we use a vector error correction model (VECM) in which cointegrated market prices share a common efficient price. For each spread pair on each day, we estimate a VECM of calendar spread midpoint returns (Δp_t^{spd}) and leg-implied (synthetic) spread midpoint returns (Δp_t^{leg}).[15] Midpoint returns capture information incorporation driven by both quote and trade activities (Ma and Serra 2025). Midpoint returns also reduce the effects of bid-ask bounce introduced by trades (e.g., Hansen and Lunde 2006), which is not directly related to price discovery. All price series are resampled at a 1-second frequency.[16] Our VECM is defined as:

$$\Delta \boldsymbol{p}_t = \boldsymbol{\alpha} z_{t-1} + \boldsymbol{B}_1 \Delta \boldsymbol{p}_{t-1} + \boldsymbol{B}_2 \Delta \boldsymbol{p}_{t-2} + \cdots + \boldsymbol{B}_M \Delta \boldsymbol{p}_{t-M} + \boldsymbol{\varepsilon}_t, \tag{3}$$

where $\Delta \boldsymbol{p}_t = \left[\Delta p_t^{spd}, \Delta p_t^{leg}\right]'$ and $\boldsymbol{B}_i \in \mathbb{R}^{2\times 2}$ denotes the coefficient matrix associated with lag i. The error-correction term is set to $z_{t-1} = \left(p_{t-1}^{spd} - p_{t-1}^{leg}\right)$. In microstructure price discovery analysis, the normalized cointegrating vector is set to $[1, -1]'$, ensuring that all price series share a common efficient price.[17] $\boldsymbol{\alpha} \in \mathbb{R}^{2\times 1}$ represents the adjustment coefficient matrix, indicating the speed at which each market adjusts to deviations from the long-run

[15] Note that the midpoint return of a synthetic spread is the sum of returns of each leg. We do not calculate log returns as quotes in calendar spreads may be negative, indicating contango.

[16] 1-second resampling has been used by, for example, Hasbrouck (2003), Chakravarty, Gulen, and Mayhew (2004), and Comerton-Forde and Putniņš (2015). Our results are qualitatively similar to 100-millisecond, 500-millisecond, and 5-second resampling, as discussed in Appendix C.3.

[17] Hasbrouck (2007, sec. 10.3.3) notes that "In microstructure analysis...The bids, asks, trade prices, and so on, even from multiple trading venues, for a single security cannot reasonably diverge without bound." We also estimate the unrestricted cointegrating beta and its average is -0.9989 across commodities.

cointegrating relationship. $\boldsymbol{\varepsilon}_t$ represents a vector of error terms with zero mean and variance–covariance matrix $\boldsymbol{\Omega}$. We select the number of lags (M) based on the Schwarz Information Criterion (SIC), with a maximum lag of 60. The VECM is estimated for each commodity on each trading day using OLS.[18]

To extract the common efficient price, Hasbrouck (1995) transforms the VECM into a vector moving-average (VMA) process:

$$\Delta \boldsymbol{p}_t = \boldsymbol{\Psi}(L)\varepsilon_t = \boldsymbol{\Psi}_0 \boldsymbol{\varepsilon}_t + \boldsymbol{\Psi}_1 \boldsymbol{\varepsilon}_{t-1} + \boldsymbol{\Psi}_2 \boldsymbol{\varepsilon}_{t-2} + \cdots , \tag{4}$$

where $\boldsymbol{\Psi}(L)$ denotes the polynomial of the lag operator. Here, $\boldsymbol{\Psi}(L) = \boldsymbol{\Psi}_0 + \boldsymbol{\Psi}_1(L) + \boldsymbol{\Psi}_2(L^2) + \cdots$. Hasbrouck (1995) demonstrates that all rows of $\boldsymbol{\Psi}(1)$ are identical, given the normalized cointegrating vector is set to $[1, -1]'$, ensuring each price reflects the same long-run efficient price. We denote the variance of the common efficient price returns as $\mathsf{Var}(\boldsymbol{\psi}\boldsymbol{\varepsilon}_t) = \boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}'$, where $\boldsymbol{\psi} = (\psi_1, \psi_2)$ is a common row vector of $\boldsymbol{\Psi}(1)$. Gonzalo and Granger (1995) derive the component share (CS) based on a permanent-transitory framework. It is calculated by normalized weights of each market in the common efficient price:

$$CS_i = \frac{\psi_i}{\sum_i \psi_i}. \tag{5}$$

Hasbrouck (1995)'s information share (IS) is defined as the proportion of variance in the efficient price attributed to each price series:

$$IS_i = \frac{\psi_i^2 \boldsymbol{\Omega}_{ii}}{\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}'}, \tag{6}$$

where $\boldsymbol{\Omega}_{\boldsymbol{ii}}$ is the i-th diagonal element of variance–covariance matrix $\boldsymbol{\Omega}$. Considering that $\boldsymbol{\Omega}$ is often non-diagonal and price innovations are correlated across markets, Hasbrouck (1995) applies a Cholesky factorization to $\boldsymbol{\Omega}$ such that $\boldsymbol{\Omega} = \boldsymbol{M}\boldsymbol{M}'$ to eliminate contemporaneous correlations. Thus, the IS measure can be expressed as

$$IS_i = \frac{([\psi \boldsymbol{M}]_i)^2}{\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}'}. \tag{7}$$

However, the factorization does not derive a unique IS measure, which is dependent on the ordering of prices in the VECM. We thus calculate the average IS by taking all possible orderings, which is common practice in the literature (e.g., Hasbrouck 2003; Baillie et al. 2002; Putniņš 2013; Janzen and Adjemian 2017; Hu et al. 2020). Each IS measure lies in the range between 0 and 1, and together they sum to one.

Yan and Zivot (2010) document that both the IS and CS measures are adequate to capture timeliness only when market prices exhibit similar noise levels because they tend to be biased toward the market with less noise but potentially more staleness. Putniņš (2013) suggests the inconsistency of the two perspectives is likely to be more pronounced in analyses between

[18] We confirm the choice of a maximum lag of 60 is generally not a binding constraint on the lag length. 99.71% of our estimated VECMs have fewer than 60 lags.

different types of markets (e.g., electronic vs. pits) or different asset classes (e.g., futures vs. options). Overall, the IS and CS are more reliable measures for assessing price discovery from the perspective of efficiency instead of timeliness.[19] Hence, we use the IS to measure which market price is more informative.[20]

To measure the timeliness of price discovery, Putniņš (2013) proposes an information leadership share (ILS) based on Yan and Zivot (2010), which mitigates the influence of noise when capturing timeliness:

$$ILS_i = \frac{\left| \frac{IS_i}{IS_{-i}} \cdot \frac{CS_{-i}}{CS_i} \right|}{\left| \frac{IS_i}{IS_{-i}} \cdot \frac{CS_{-i}}{CS_i} \right| + \left| \frac{IS_{-i}}{IS_i} \cdot \frac{CS_i}{CS_{-i}} \right|}. \tag{8}$$

Each ILS also lies in the range $[0, 1]$, and together they sum to one. We use ILSs to measure which market is the first to incorporate information.
Figure 7 shows the ISs and ILSs of calendar spreads and synthetic spreads.[21] In terms of timeliness, the ILSs of synthetic spreads are 65.26%–75.97% (64.09%–72.88%) in grain (livestock) markets, significantly higher than those of calendar spreads for all pairs. Unreported Wilcoxon signed-rank tests confirm that synthetic spreads are the first to incorporate new information. This is consistent with the higher volatility observed in synthetic spreads (Figure 6), where frequent changes in midpoint prices reflect a noisier but faster adjustment to efficient prices. Nearby spread pairs incorporate information slightly faster and do so more consistently than longer-distance pairs. Although the microstructure characteristics are distinct across grain and livestock markets (e.g., Hu et al. 2020), our results suggest similar speeds of information incorporation across both commodity groups.

We observe distinct patterns in informativeness across markets, as measured by ISs. Calendar spreads contribute more to the common efficient price than synthetic spreads, as indicated by higher IS values. The median IS values of calendar spreads exceed 50% across all pairs and are significantly higher than those of the synthetic spreads, as confirmed by unreported Wilcoxon signed-rank tests. Calendar spreads in grains have substantially higher pricing efficiency (79.77%–96.85%) than those in livestock (53.34%–77.26%). A possible reason is that livestock commodities are non-storable and thus have limited ability to absorb shocks through inventories. We find that calendar spreads are more informative for short-distance pairs, and their informativeness declines as inter-leg distance increases.

[Insert Figure 7 here.]

We validate our price discovery results by examining return frequency and noise. We calculate the log frequency of non-zero returns from 1-second resampled data. Markets that

[19] This choice is also supported by Putniņš (2013, p. 78), who mentions that "...The influence of noise on IS is only biased if the view of price discovery is 'who moves first.'"

[20] The results for CSs are qualitatively similar to those for ISs. For brevity, the CSs are not reported but available upon request.

[21] On a small number of trading days, exchange-traded calendar spreads in grain markets exhibit nearly zero midpoint returns, preventing VECM estimation. We therefore drop 4.98% (2.44%) of pair-day observations for corn (soybean).

incorporate information more rapidly exhibit more frequent midpoint updates. The results shown in Figure C1 of Appendix C.1 indicate that synthetic spreads exhibit a higher frequency of non-zero returns, consistent with more frequent midpoint price updates than calendar spreads. This effect is more pronounced in short-distance pairs. We define noise as the mean absolute deviation between each price series and the estimated common efficient price. Following Gonzalo and Granger (1995) and Harris, McInish, and Wood (2002), we estimate the efficient price as the weighted average of the synthetic spread midpoint price and the calendar spread midpoint price, using their respective component shares as weights. We present noise ratios in Figure C2 of Appendix C.2. Consistent with Figure 6, synthetic spreads are noisier than calendar spreads, with median noise ratios approximately twice as high. This effect is more pronounced in shorter-duration pairs. These findings support our choice of ILS to measure timeliness.

Our analysis complements previous studies on price discovery in agricultural derivatives by showing, for the first time, how futures term structure responds to new information. A related study is Hu et al. (2020) who measure price discovery between nearby and deferred outright futures contracts in grain and livestock markets across the contract lifecycle. We differ from them by exploiting the informational role of "tradable" term structure (i.e., calendar spreads) through comparisons with counterfactual synthetic spreads. Our findings suggest that tradable calendar spreads allow spread traders to obtain informative pricing signals, while also benefiting from lower trading costs and reduced execution risk.

We conduct two robustness checks for our price discovery analysis. We first assess whether our price discovery shares are sensitive to different sampling frequencies and the results are presented in Appendix C.3. Second, we follow Hagströmer (2021), who proposes a weighted midpoint price measure that considers depth imbalance, which may better capture market fundamental values. We re-estimate our VECMs using weighted midpoint prices, and we present the results in Appendix C.4. Both exercises indicate that our main findings remain robust.

4 Outright market makers

Section 3 shows that exchange-traded calendar spreads improve execution and information efficiency for spread traders. We now examine how the same trading architecture affects outright market makers who engage intensively in liquidity provision for profit. Under the current design of electronic trading, implied liquidity generated from calendar spreads reshapes the limit order books in outrights, thereby altering the risks and benefits faced by market makers. We focus on the CME implied functionality introduced earlier in the paper, which provides additional liquidity automatically (see Figure D1 of Appendix D).

Market makers earn revenues by continuously posting bids and asks and capturing bid–ask spreads, but they bear the risk that prices move against their inventory when trading with better-informed or faster counterparts. By injecting implied quotes into outright order books, implied functionality alters both the depth available at the BBO and the likelihood that resting quotes are executed against informed trades. This can change market makers' gross revenues and adverse-selection exposure, even in grain futures markets where outright liquidity is already abundant (e.g., Hu, Serra, and Garcia 2020). To quantify these effects, we compare trading outcomes under consolidated liquidity, which includes implied quotes with those under a counterfactual outright-only liquidity scenario, which excludes them. We capture these differences using standard market quality measures that map directly into market-making revenues and risks.

4.1 Implied liquidity and market-making outcomes

4.1.1 *Implied liquidity ratio*

In each outright market, we measure implied quotes' contribution to liquidity provision using the share of implied BBO depth relative to consolidated BBO depth ($Implied\ ratio$):

$$Implied\ ratio = \left(\frac{BBO\ depth^I}{BBO\ depth^I + BBO\ depth^O} \right) \mathbb{1} \left\{ BBO\ price^I = BBO\ price^C \right\}, \quad (9)$$

where $BBO\ depth^I$ $\left(BBO\ depth^O\right)$ denotes the implied (outright) BBO depth. The consolidated BBO depth $\left(BBO\ depth^C\right)$ is their sum. Because implied and outright order books are disseminated separately, we count implied depth only when its quote matches the consolidated best price. The indicator function $\mathbb{1}\{\cdot\}$ ensures that off-best implied quotes, which do not contribute to executable liquidity at the top of the book, are excluded.

Figure 8 shows the proportions of implied liquidity. Distinct patterns emerge across the term structure. For the first-nearby futures, implied liquidity contributes 16.00%–17.97% to consolidated liquidity, rising to 50.97%–52.48% for second-nearby futures. For more deferred contracts, implied liquidity constitutes about 68.92%–72.09% of consolidated depth in grain markets and 52.00%–54.86% in livestock markets. These results suggest that implied liquidity plays a more important role in deferred futures, where outright liquidity is typically thinner, compared with nearby contracts.

[Insert Figure 8 here.]

4.1.2 *Market making outcomes*

Following Hendershott, Jones, and Menkveld (2011), we consider three spread market-quality indicators reflecting market-making outcomes: effective spread, realized spread, and price impact. From the market maker's perspective, the effective spread is the gross compensation for supplying immediacy to market takers. From the market taker's perspective, it measures the immediate cost of execution. The effective spread is defined as a function of the difference between the transaction price and the prevailing midpoint price.

$$\text{effective spread}_t = 2 \times \frac{q_t(p_t - m_t)}{m_t}, \quad (10)$$

where q_t equals $+1$ for buyer-initiated trades and -1 for seller-initiated trades, as identified directly by the trade aggressor flag in our data. p_t is the trade price and m_t is the prevailing midpoint price at the time of the trade. We focus on outright trades, as defined in section 2, because these are from plain outright position demand and exclude those arising from calendar spread demand or implied functionality. All outright trades have a trading direction assigned by the CME.

The realized spread measures the gross revenue of market-making, calculated as a function of the difference between the trade price and the midpoint price 5 seconds later (m_{t+5s}) (O'Hara 2015), a horizon commonly used to approximate inventory unwinding by market makers. For each trade t, the realized spread is defined as

$$\text{realized spread}_t = 2 \times \frac{q_t(p_t - m_{t+5s})}{m_t}. \tag{11}$$

Traders with information or speed advantages may place market orders to exploit stale quotes posted by market makers. When such orders execute against quotes that have not yet been updated to new information, market makers incur losses due to adverse selection (Kyle 1985; Glosten and Milgrom 1985). Price impact measures these losses and is defined as a function of the change in the midpoint price from the time of the trade to 5 seconds afterward:

$$\text{price impact}_t = 2 \times \frac{q_t(m_{t+5s} - m_t)}{m_t}. \tag{12}$$

The arithmetic relationship between the effective spread, the realized spread, and price impact is:

$$\text{effective spread}_t = \text{realized spread}_t + \text{price impact}_t, \tag{13}$$

which decomposes market-making revenues into market takers' trading costs and adverse-selection costs borne by market makers. For each trade, we calculate the three spread measures and summarize them using trading-volume-weighted averages for each session. We complement our analysis with quoted spreads.[22] Table 1 reports summary definitions.

[Insert Table 1 here.]

Table 2 presents median market quality measures under consolidated and outright-only liquidity. In bold, we present the consolidated values that are statistically different based on the Wilcoxon rank-sum test. Across all commodities, consolidated liquidity is generally associated with higher trading costs for market takers and lower revenues for market makers than outright-only liquidity. Price impact accounts for at least 80% of the effective spread under consolidated liquidity, reducing market-making revenues to 0.02–1.35 bps in grains and −0.29–1.48 bps in livestock. Under outright-only liquidity, realized spreads are generally higher, while price impacts are lower across commodities, indicating greater net revenues and lower adverse-selection exposure for market makers. These differences are statistically significant for spread measures in most futures series across commodities. Market-making performance varies along the term structure: deferred futures exhibit lower price impacts and higher realized spreads under both liquidity scenarios, consistent with thinner trading

[22] The quoted spread here refers to the bid–ask spread in outright markets and should not be confused with the one used in section 3. We complement our analysis with this measure because it is the most commonly used in the previous literature (e.g., Arzandeh et al. 2025).

activity and reduced market monitoring intensity.

[Insert Table 2 here.]

4.1.3 *Regression analysis*

To assess the impact of implied liquidity on market makers, we regress differences in market-making outcomes on the share of implied liquidity. We estimate the following OLS regression:

$$\begin{aligned}\left(MQ^C_{i,j,m,t} - MQ^O_{i,j,m,t}\right) =& \beta \times Implied\ ratio_{i,j,m,t} + \boldsymbol{Controls}_{i,j,m,t} + \\ & \delta_j + \gamma_m + \theta_t + \varepsilon_{i,j,m,t}\end{aligned}, \tag{14}$$

where $MQ^C_{i,j,m,t}$ $\left(MQ^O_{i,j,m,t}\right)$ denotes the market quality measures under the consolidated (outright) scenario for an individual futures contract i of nearby futures series j for commodity m on day t. Our variable of interest is the proportion of implied liquidity ($Implied\ ratio$, on a scale of 0–1), computed at each quote update and then aggregated within each day using time-weighted averages. We pool corn and soybeans (live cattle and lean hog) to enhance statistical power while controlling for contract position along the term structure, commodity-specific, and day characteristics through fixed effects. Following previous literature (e.g., Comerton-Forde and Putniņš 2015; Foley and Putniņš 2016; Chung, Lee, and Rösch 2020; Shkilko and Sokolov 2020), we include log dollar trading volume and inverse price as controls ($\boldsymbol{Controls}_{i,j,m,t}$). Trading volume captures variation in market activity that may independently affect market quality, while inverse price accounts for contract price-level differences that mechanically affect proportional spread and price impact measures.[23] We include nearby-futures-contract fixed effects (δ_j), commodity fixed effects (λ_m), and day fixed effects (θ_t) to capture time-invariant term-structure characteristics, commodity, and day conditions, respectively. Standard errors are double clustered by individual futures and day. We keep trading days for which market quality measures can be constructed for all nearby futures series in both grain and livestock markets, thereby constructing a balanced panel. We winsorize all variables at the 2.5 and 97.5 percentiles by commodity for each nearby futures series to mitigate outlier influence. Table E1 of Appendix E.1 presents summary statistics for the dependent and independent variables, which are consistent with the market-level statistics reported in Table 2.

A potential concern in our regression is that traders may adjust their trading behavior in response to changes in liquidity, making these differences reflect both behavioral changes and mechanical liquidity effects. We argue that such endogeneity is unlikely for several reasons. First, trading demand in agricultural futures is primarily driven by fundamentals—hedging needs, capital constraints, and market expectations—which are plausibly exogenous to implied liquidity. Major market participants, such as hedgers and portfolio managers, are likely to trade based on their existing positions and portfolios rather than marginal liquidity improvements. Conversations with market participants indicate that implied liquidity does not alter traders' fundamental trading demand. We also examine whether dollar trading volume changes monotonically with our market quality measures by grouping observations

[23] Our findings are robust to excluding these controls.

into three quantile ranges: <P25, P25–P75, and >P75. Our unreported results show no such monotonic relationship.

Our analysis assumes that market makers do not adjust their outright quoting to compete with implied quotes. The operation of implied functionality supports this assumption. First, because outright quotes have matching priority over implied quotes (CME 2007), market makers have little incentive to adjust quoting strategies in response to implied liquidity. Second, manipulating implied functionality would require coordinated quoting across multiple outright markets, as implied quotes are generated from all calendar spreads. Such behavior is algorithmically complex, costly to implement, and prohibited under CME rules.

Our measure of implied liquidity proportion is not subject to classical measurement error. Because CME separately disseminates outright and implied order books, both components are directly observed, thereby limiting attenuation bias from mismeasured explanatory variables.[24] Although these assumptions cannot be empirically tested with our data, they reflect institutional features and motivate a cautious interpretation of our results. Accordingly, we do not interpret our findings as evidence of causal inference.

Table 3 presents the OLS regression estimates for grain markets. Compared to outright-only liquidity, a 1% increase in implied liquidity is associated with a statistically significant 0.0044 bps increase in price impact, a significant increase in effective spread of 0.0041 bps, and an insignificant 0.0002 bps decrease in realized spread. Moreover, implied liquidity is also related to a significant narrowing of quoted spreads (0.0121 bps), indicating tighter posted prices despite higher execution costs. Similar patterns are observed in livestock commodities (Table 4), but with larger coefficients than in grains. A 1% increase in implied liquidity proportion is associated with a significant 0.0092 bps increase in price impact, a 0.0106 bps increase in effective spread. However, the 0.0015 bps increase in realized spread is statistically insignificant. Implied liquidity is associated with a significant 0.1019 bps decrease in the quoted spread, though adverse-selection costs rise at execution.

[Insert Tables 3 and 4 here.]

To assess economic significance, we convert the estimates into dollar terms.[25] Using the sample average day-session trading volumes of \$296.78 million, a 10% increase in implied liquidity indicates an additional \$1,305.83 in daily adverse-selection cost for market makers. Given the average trading volume of 24,958 contracts, this corresponds to roughly \$0.05 per contract.[26] Since the sample mean price-impact difference is 0.248 bps (\$0.30 per contract, see Table E1), our estimate is about 17% of sample mean price-impact difference, indicating a nontrivial economic magnitude. Following similar logic, in livestock markets, per-contract cost is roughly \$0.19, representing about 19% of the sample mean difference in price impact.

We next discuss mechanisms potentially underlying our results. Implied functionality typically adds the BBO depth (Figure 8) and alters the availability of midpoint price movements.

[24] Robustness checks using lagged consolidated depth as the denominator yield qualitatively similar results (Table E4 of Appendix E.3).

[25] This dollar-term calculation is different from that in Figure 4, where we report daily cumulative (aggregated) statistics. Here, the measures are daily volume-weighted averages.

[26] For example, the per-contract amount is: $\$296{,}780{,}000 \times 0.044$ bps $\times\, 0.0001 \div 24{,}958$ contracts $\approx \$0.05$.

Thus, implied liquidity's effect is likely to vary with trade size. For small trades, which primarily result in transitory price pressure (e.g., Kyle 1985; Hendershott and Menkveld 2014), additional liquidity from implied functionality may anchor prices more tightly at execution by reducing midpoint movements. In this case, market makers earn positive realized spreads and bear minimal price impacts. For large trades that create permanent price changes, the midpoint price may move against market makers, resulting in lower or even negative realized spreads and higher price impacts.[27] Because our market quality measures are volume-weighted averages, large trades typically trigger larger price impacts and receive greater weights, causing their adverse-selection component to dominate the aggregated averages. Following this logic, Table E2 of Appendix E.2 replicates Table 2 across three trade-size groups. The results are consistent with our interpretation: under consolidated liquidity, large trades in both grain and livestock commodities are associated with higher price impacts and lower realized spreads. Furthermore, effective spreads increase more for small trades than for large trades, and the differences are statistically significant. This suggests that although small trades receive lower weights, their cost increases for market takers dominate the aggregated averages. Overall, implied liquidity appears to redistribute costs toward small trades while having limited ability to mitigate the price impacts of large trades.

Robustness checks with different fixed effects and lagged consolidated depth confirm that our main findings remain unchanged (Appendix E.3). We also conduct heterogeneity analyses across nearby futures series and individual commodities, with results presented in Appendix E.4. Commodity-level results (Table E5) show that market makers' revenues slightly increase for soybeans (by 0.0017 bps) but not for corn. Both livestock commodities exhibit patterns similar to our pooled results. For both commodities (Tables E6 and E7), implied liquidity is more strongly associated with market-making outcomes for deferred contracts (e.g., 3rd-, 4th-nearby) than for nearby contracts. For first-nearby futures, realized spreads increase slightly but significantly (0.0069 bps for soybeans and 0.0026 bps for livestock). However, their magnitudes are still smaller than those of price impacts. Extending spread calculations beyond a 5-second horizon (Table E8), we find price impacts are significantly higher (lower) at the 1-second (10-second) horizon. Although realized spreads rise for livestock, their magnitudes remain below those of price impacts. Overall, our heterogeneity results are qualitatively similar to our main results.

Our results are qualitatively similar to Overdahl (2011), indicating that implied liquidity is not correlated with gross market-making revenue, but is positively related to the adverse-selection risk borne by market makers. Although market takers may face higher immediate trading costs, as reflected in higher effective spreads, their costs appear to arise almost entirely through price impacts rather than changes in realized spreads under consolidated liquidity. Furthermore, while implied liquidity is associated with tighter quoted spreads, market takers do not necessarily benefit from this improvement when they trade, as reflected in higher effective spreads.

[27] Unreported results show implied quotes are often withdrawn following trades, suggesting limited ability to buffer price impacts.

5 Conclusions

This paper examines how the trading design of exchange-traded calendar spreads affects trading outcomes for spread traders and outright market makers in agricultural futures markets. Exchange-traded calendar spreads make the term structure directly tradable and link outright markets through implied functionality. Using CME intraday market data from 2015 to 2024 for grains and 2015–2019 for livestock, we compare observed outcomes under the current spread-market architecture with constructed counterfactuals.

For spread traders, our findings suggest that exchange-traded calendar spreads improve execution quality and price informativeness about futures term structure. Calendar spreads offer more executable liquidity and lower execution costs than synthetic spreads constructed from separate leg executions, particularly for the 1st–2nd spread pair, where daily cost reductions are about \$200,000 for grains and \$60,000 for livestock. In terms of term-structure informativeness, calendar spreads play the primary role in revealing the efficient term structure information, while outright markets lead in information incorporation speed.

For outright market makers, implied liquidity alters the risk–return profile of market making in outright markets. While quoted spreads tighten, higher price impacts increase effective spreads, leaving realized spreads largely unchanged, indicating greater adverse-selection exposure for market makers. A 10% increase in implied liquidity at the top of the book is associated with about \$0.05 (\$0.19) higher adverse-selection cost per contract, representing 17% (19%) of the sample mean of price-impact differences. These additional costs are economically small at the contract level but accumulate over time because market makers continuously provide liquidity across multiple futures contracts. Heterogeneity analyses show that these impacts are more pronounced for deferred contracts, where outright liquidity is thinner and implied functionality accounts for a larger share of executable depth.

Taken together, our findings suggest that the current calendar-spread trading design improves execution and information efficiency for spread traders while reallocating adverse-selection risk to outright market makers. This redistribution helps explain why implied functionality can coexist with tighter quoted spreads yet higher execution costs at the time of trade execution.

Our results have implications for exchange-trading design. Since exchange-traded calendar spreads are cost-effective and informative instruments for managing intertemporal risk, exchanges may introduce volume-based incentive programs to promote their use. Moreover, the benefits of implied functionality appear concentrated in less liquid contracts. Considering that implied functionality is currently implemented for all contract months in agricultural futures markets, exchanges may reconsider the conditions under which implied functionality is operated, giving priority to long-dated and thinly traded contracts where outright liquidity is genuinely scarce.

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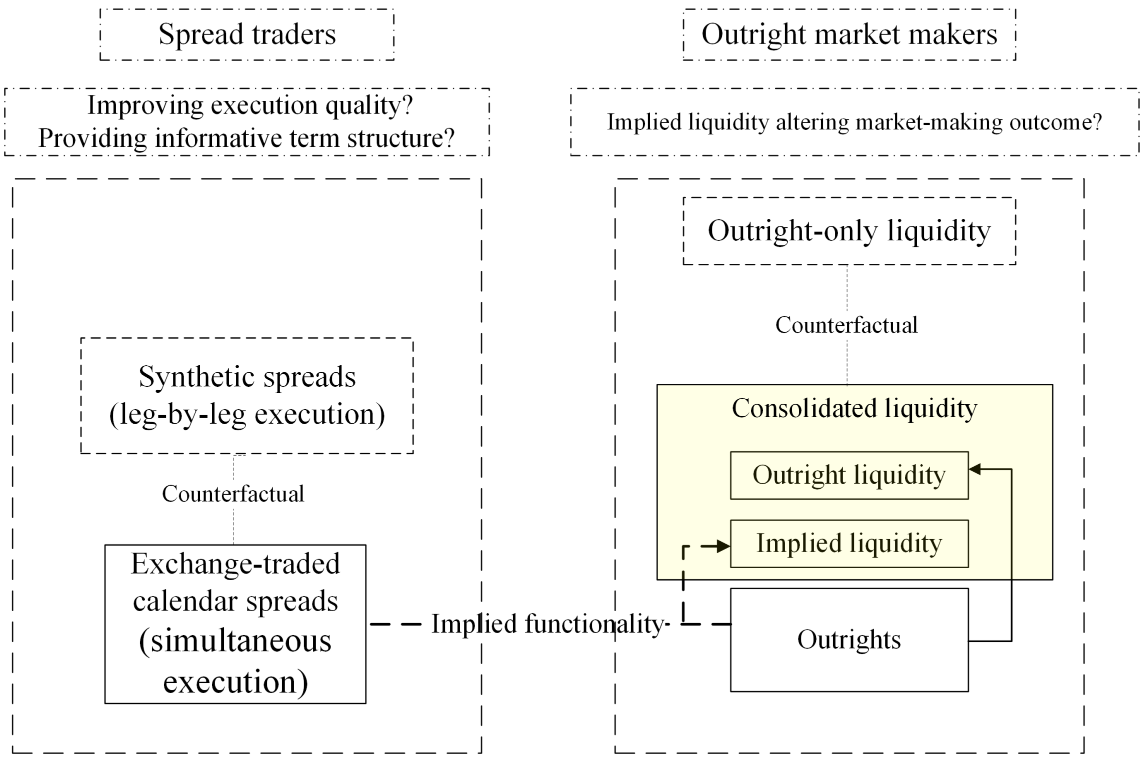

Figure 1: Empirical design.

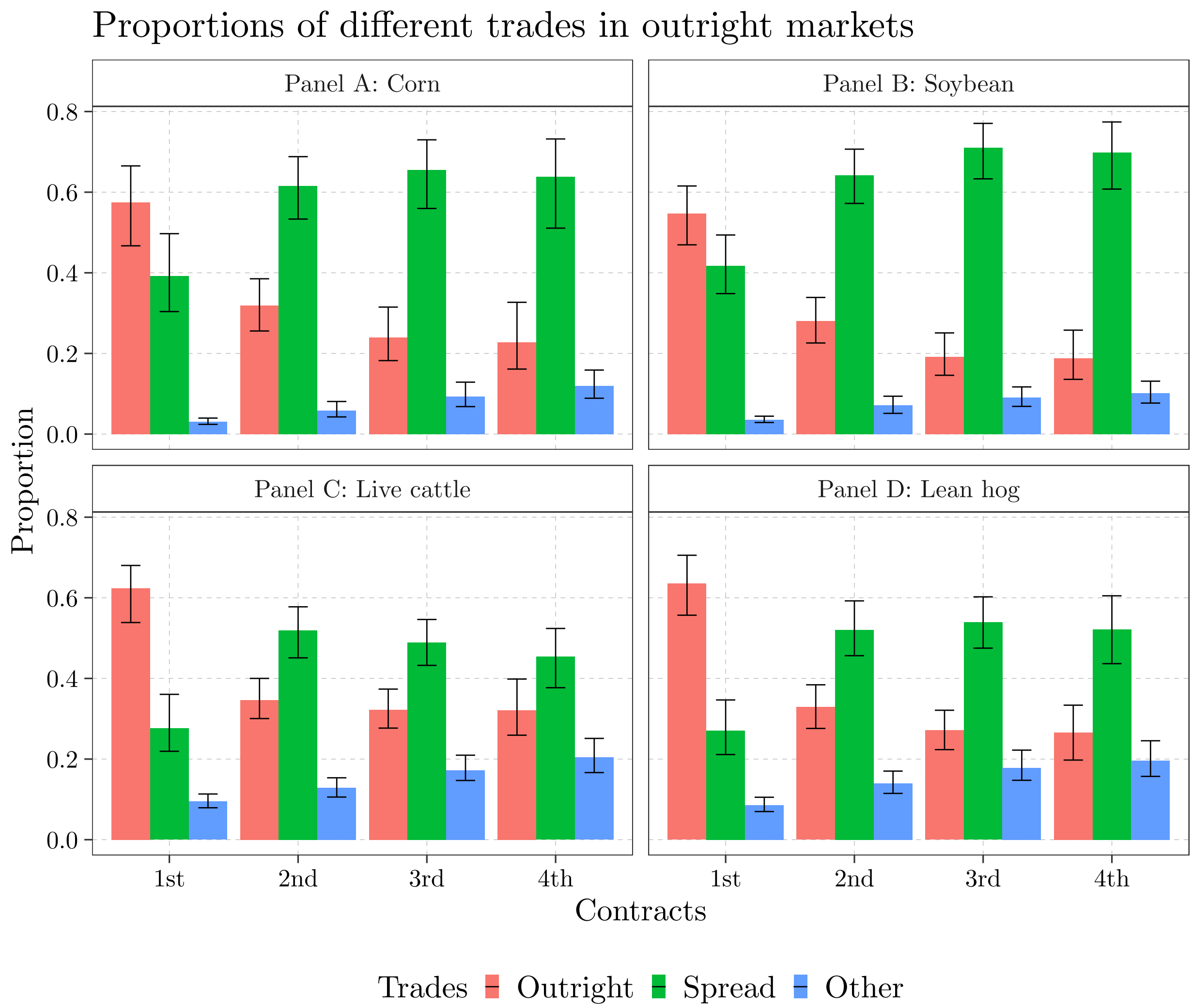

Figure 2: The proportion of trades in outright markets: Outright, spread, and others.

This figure displays the interquartile ranges of three trade categories in CME grain outright markets (Panels A and B) and livestock outright markets (Panels C and D). We measure the proportion of trades as the trading volume in each category divided by total trading volume. The four nearby series are organized by column. We consider three trade categories: outright, spread, and other. Outright trades are those that are not driven by spread demand. Spread trades are those executed as the legs of a calendar spread. Other trades primarily include executions generated by implied functionality. We identify spread trades only after November 20, 2015, because CME did not disseminate spread trades directly to outright markets before that date. Our sample period spans January 5, 2015, to December 20, 2019, for livestock, and January 5, 2015, to December 27, 2024, for grains. Price-limit days are excluded.

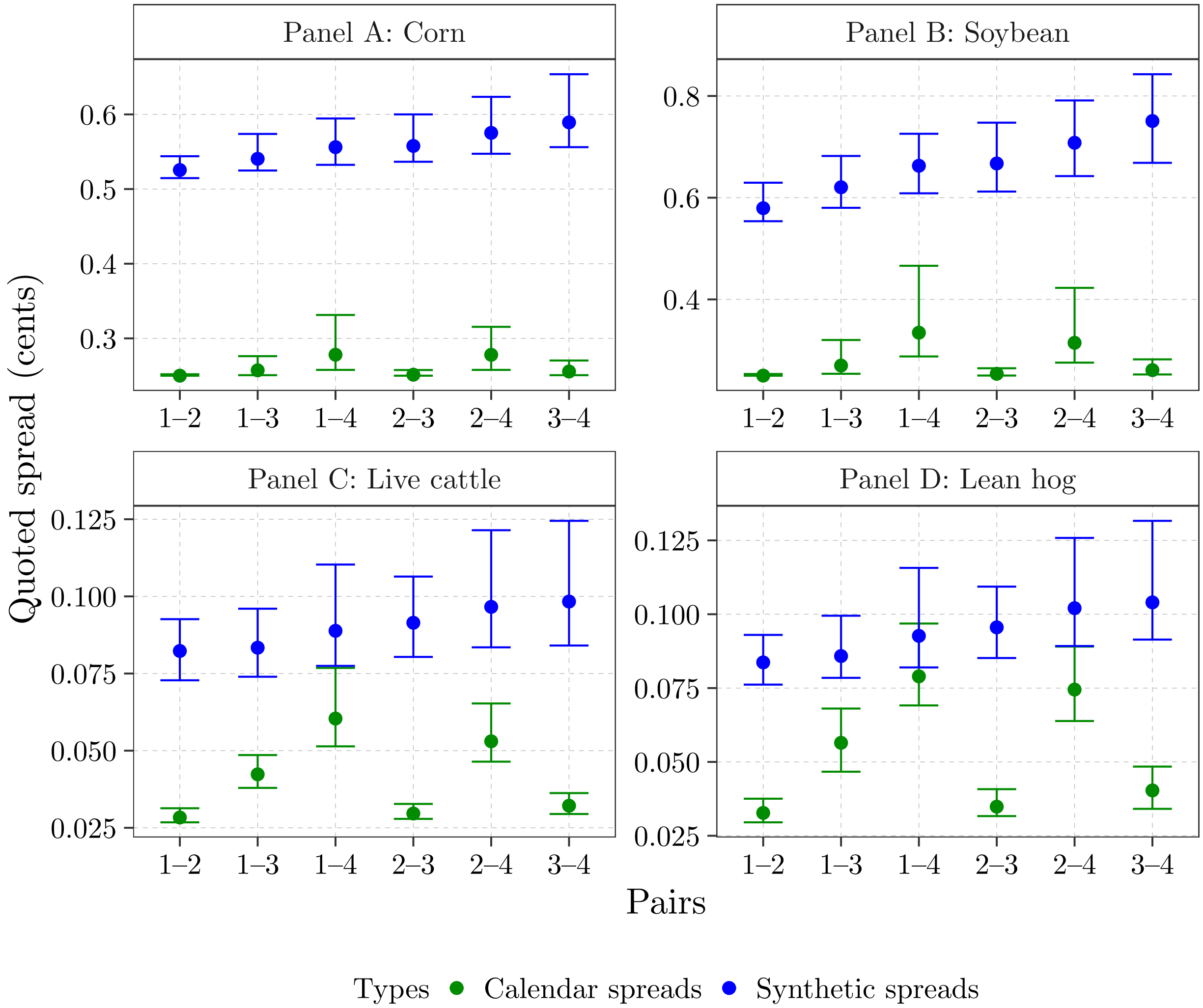

Figure 3: Quoted spread: Exchange-traded calendar spreads and synthetic spreads.

This figure displays the interquartile ranges of daily quoted spreads (in cents) for exchange-traded calendar spreads and synthetic spreads in CME grain markets (Panels A and B) and livestock markets (Panels C and D). The quoted spread is defined as the difference between the best bid and best ask prices. For synthetic spreads, the implied bid (ask) price is calculated as the best bid (ask) price of the front-month leg minus the best ask (bid) price of the back-month leg. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded.

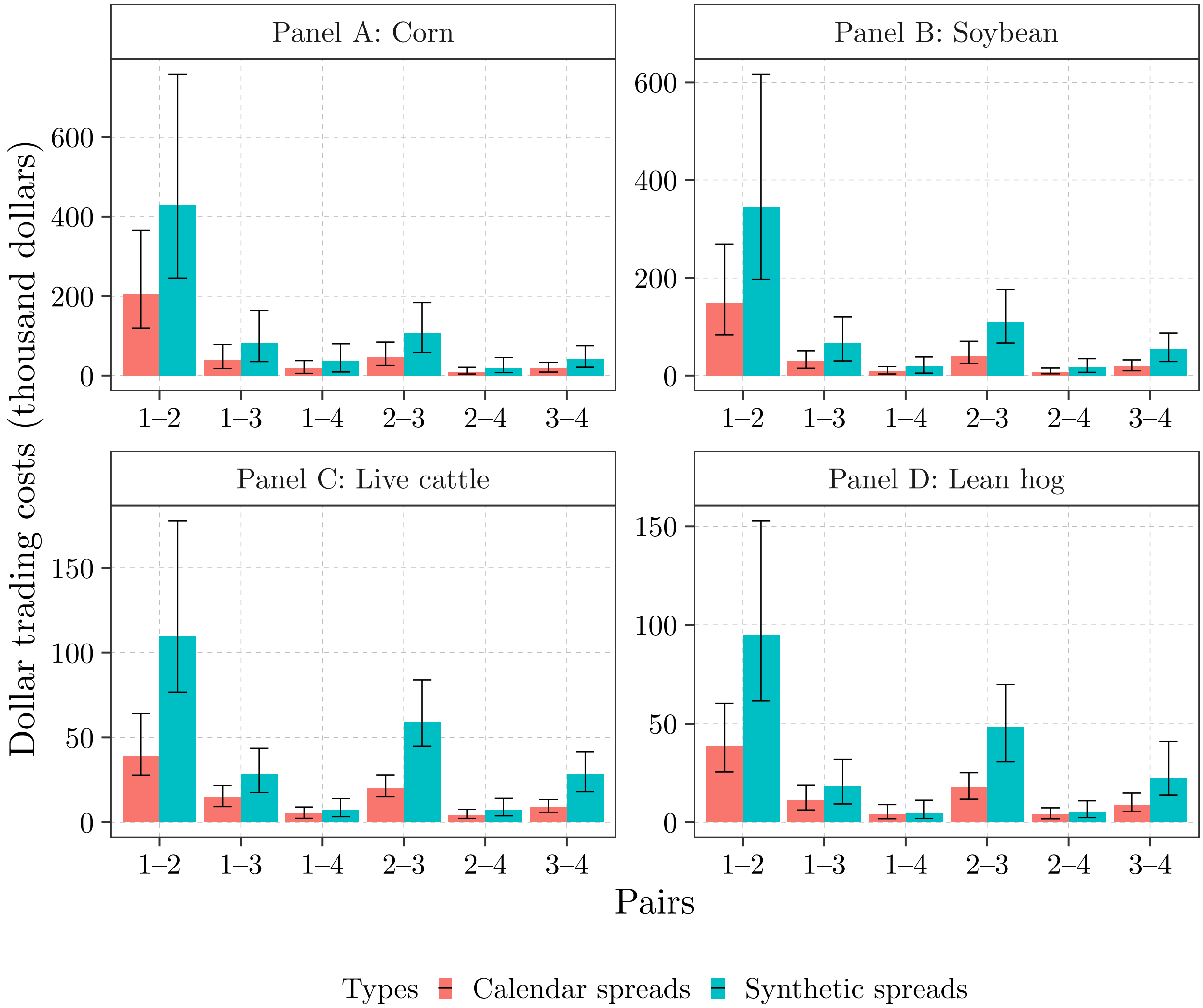

Figure 4: Dollar trading costs: Exchange-traded calendar spreads and synthetic spreads.

This figure displays the interquartile ranges of daily dollar trading costs (in thousand dollars) for exchange-traded calendar spreads and synthetic spreads in CME grain markets (Panels A and B) and livestock markets (Panels C and D). Dollar trading costs are measured as daily trading volume multiplied by the quoted spread (in cents). Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded.

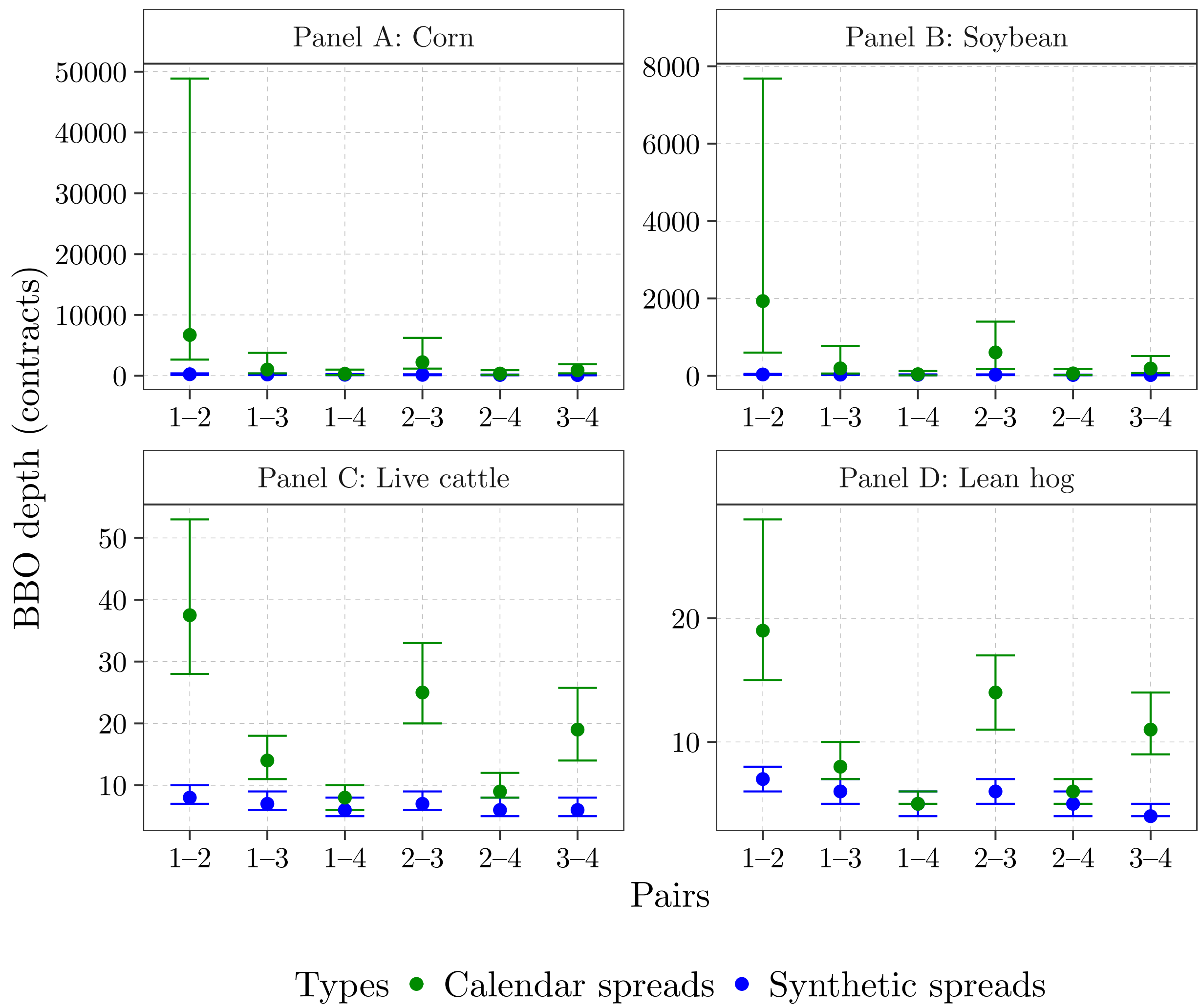

Figure 5: BBO depth: Exchange-traded calendar spreads and synthetic spreads.

This figure displays the interquartile ranges of daily BBO depth (in number of contracts) for exchange-traded calendar spreads and synthetic spreads in CME grain markets (Panels A and B) and livestock markets (Panels C and D). We calculate daily time-weighted average BBO depth using quotes resampled at the 1-second frequency. For synthetic spreads, implied bid (ask) depth is defined as the minimum available quantity between the front-month bid (ask) depth and the back-month ask (bid) depth. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded.

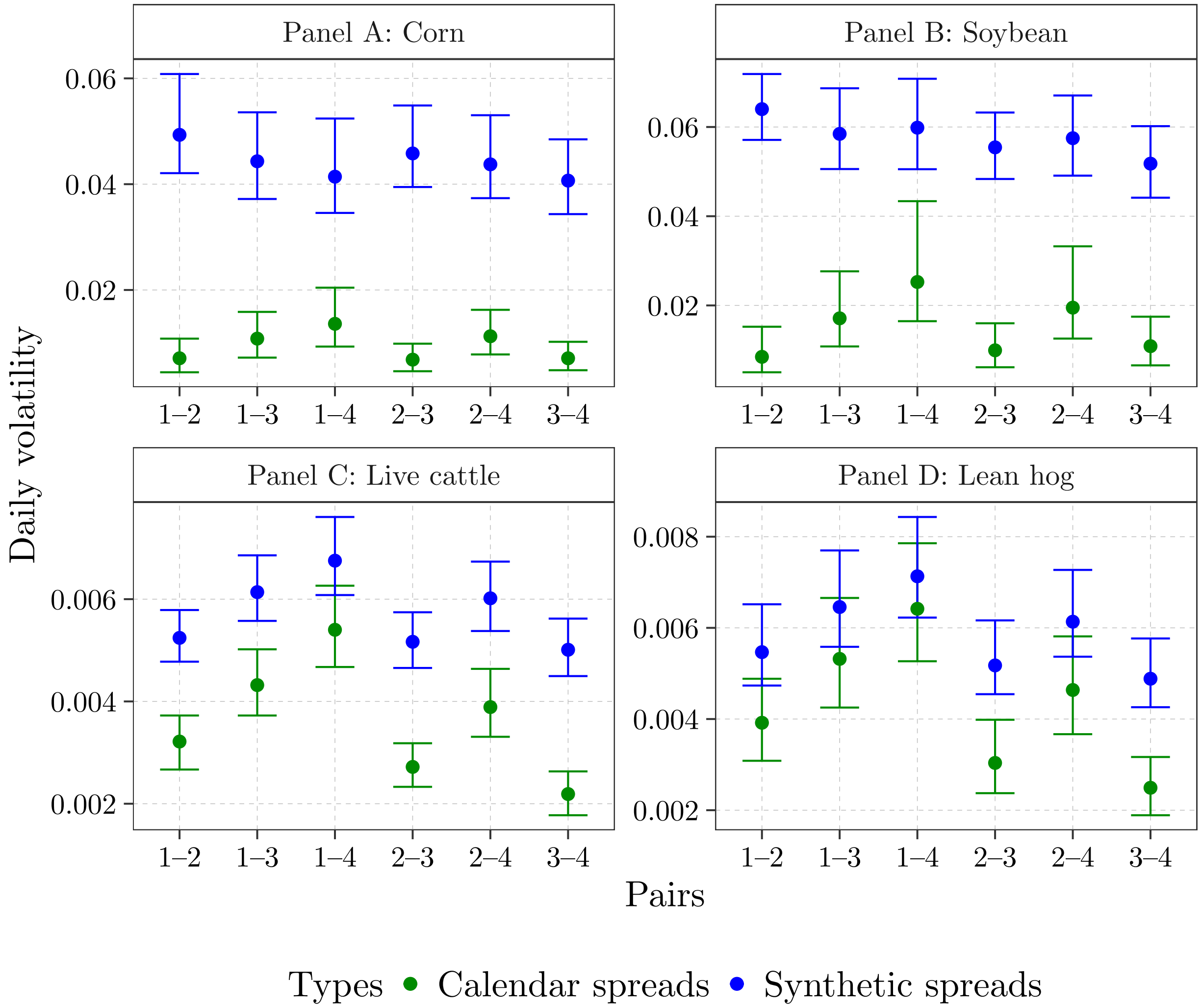

Figure 6: Volatility: Exchange-traded calendar spreads and synthetic spreads.

This figure displays the interquartile ranges of daily annualized volatility for exchange-traded calendar spreads and synthetic spreads in CME grain markets (Panels A and B) and livestock markets (Panels C and D). Volatility is defined as the standard deviation of midpoint returns and is annualized by multiplying by $\sqrt{252}$. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded.

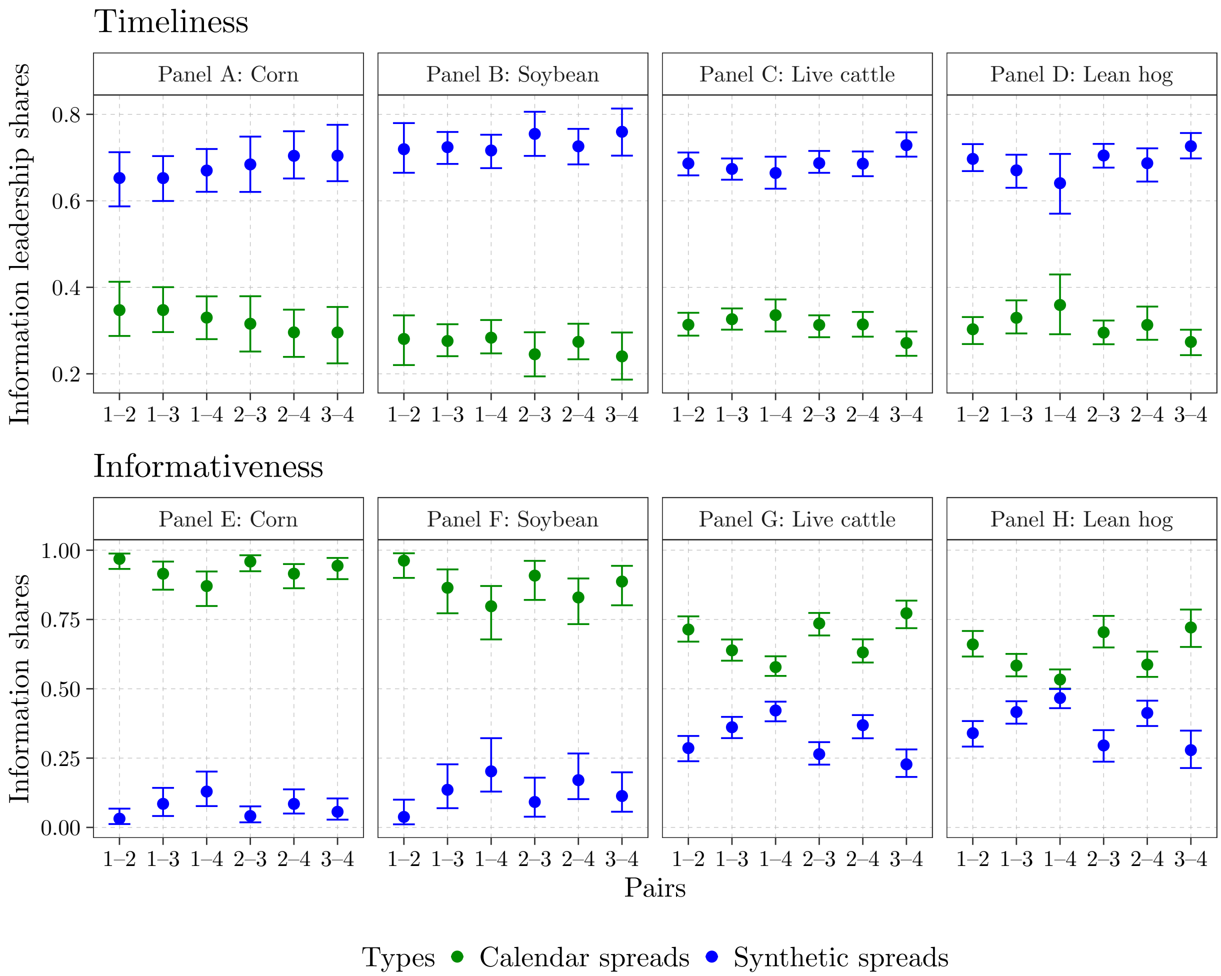

Figure 7: Price discovery shares: Exchange-traded calendar spreads and synthetic spreads.

This figure displays the interquartile ranges of the daily price discovery shares of exchange-traded calendar spreads and synthetic spreads in CME grain and livestock markets, from the perspectives of timeliness (upper panel) and informativeness (lower panel). Timeliness refers to which market moves first to incorporate new information and is measured by the information leadership share (ILS), whereas informativeness refers to which market contributes more to the efficient price and is measured by Hasbrouck's (1995) information share (IS). The ILSs and ISs are estimated from a bivariate vector error correction model (VECM) between exchange-traded spread midpoint returns ($\Delta p^{spd}t$) and leg-implied midpoint returns ($\Delta p^{leg}t$), estimated for each pair on each trading day. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded.

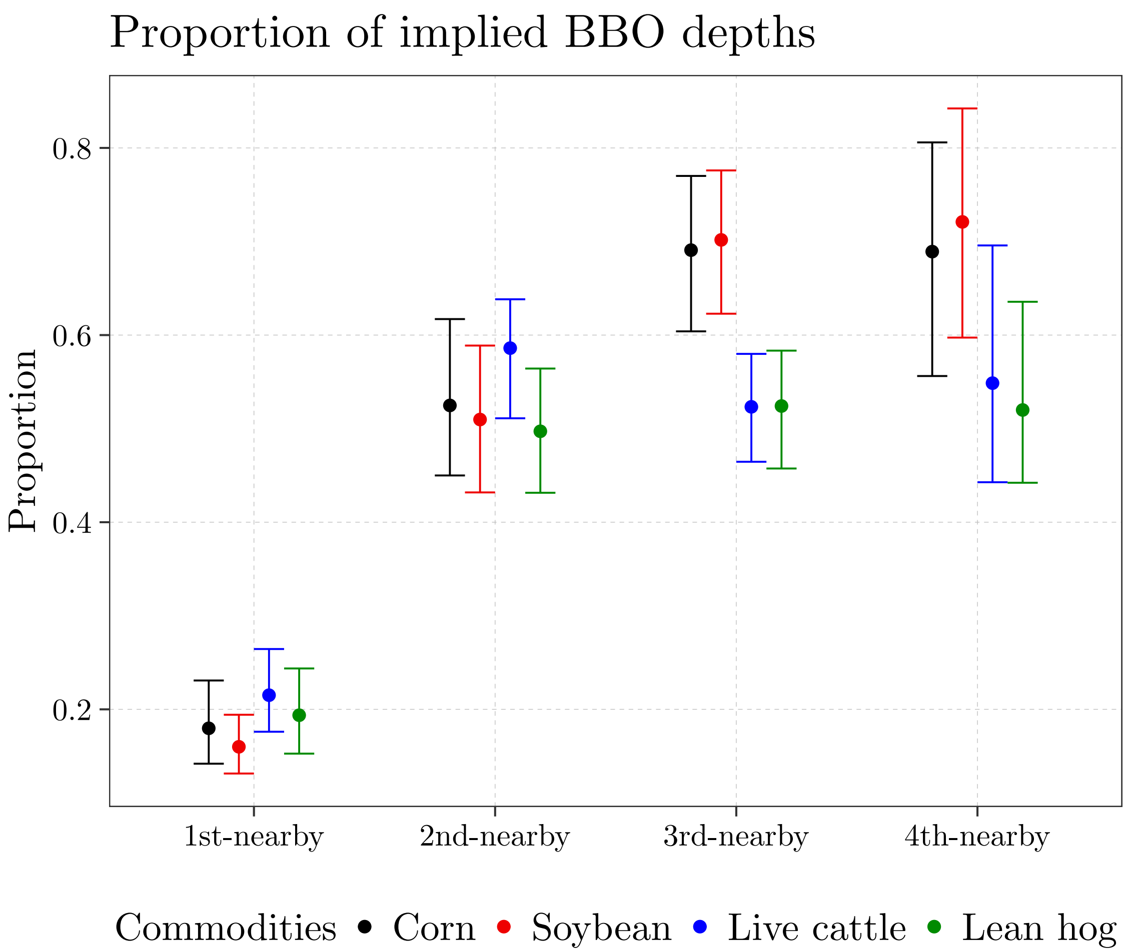

Figure 8: Implied BBO ratio.

This figure displays the interquartile ranges of the proportion of implied BBO depth relative to total (consolidated) BBO depth in CME grain and livestock futures markets. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded.

Table 1: Variable descriptions: Market quality.

Variable	Description
Quoted spread (bps)	Time-weighted quoted spread, calculated for a trading session as the difference between the best bid and best ask prices divided by the midpoint price, expressed in basis points.
Effective spread (bps)	Trading-volume-weighted effective spread, calculated for a trading session and expressed in basis points. It measures the immediate trading cost faced by market takers and is defined as $2q_t \left(p_t - mid_t\right)/mid_t$, where p_t is the trade price, mid_t is the prevailing midpoint price at the time of the trade, and q_t equals +1 (−1) for buyer- (seller-)initiated trades.
Realized spread (bps)	Trading-volume-weighted realized spread, calculated for a trading session and expressed in basis points. It measures gross market-making revenue and is defined as $2q_t \left(p_t - mid_{t+5s}\right)/mid_t$, where p_t is the trade price, mid_{t+5s} is the midpoint price 5 seconds after the trade, and q_t equals +1 (−1) for buyer- (seller-)initiated trades.
Price impact (bps)	Trading-volume-weighted price impact, calculated for a trading session and expressed in basis points. It captures adverse selection costs and is defined as $2q_t \left(mid_{t+5s} - mid_t\right)/mid_t$, where mid_t is the prevailing midpoint price at the time of the trade, mid_{t+5s} is the midpoint price 5 seconds after the trade, and q_t equals +1 (−1) for buyer- (seller-)initiated trades.

Table 2: Market quality under two liquidity scenarios: Consolidated and outright.

This table reports the median market quality measures in CME grain (Panels A and B) and livestock markets (Panels C and D) under consolidated and outright liquidity. The columns are sorted by futures series expiration. Detailed variable definitions are provided in Table 1. Wilcoxon rank-sum tests assess whether the medians of the market quality measures differ statistically between consolidated and outright liquidity. Bold values indicate statistical significance at the 5% or 1% level. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded from the analysis.

	Consolidated liquidity				Outright liquidity			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Panel A: Corn market.								
Quoted spread (bps)	6.49	6.69	6.85	6.89	6.49	6.68	6.86	6.94
Effective spread (bps)	6.65	**6.49**	**6.45**	**6.41**	6.61	6.30	6.06	5.92
Realized spread (bps)	0.21	**0.55**	**0.93**	**1.35**	0.21	0.60	1.01	1.47
Price impact (bps)	6.05	**5.56**	**5.10**	**4.70**	6.02	5.30	4.64	4.02
Panel B: Soybean market.								
Quoted spd. (bps)	2.62	2.98	**3.33**	**3.62**	2.63	2.97	3.44	3.93
Effective spread (bps)	**2.90**	**2.86**	**3.04**	**3.28**	2.87	2.72	2.79	2.97
Realized spread (bps)	0.02	0.22	**0.50**	**0.79**	0.02	0.21	0.45	0.67
Price impact (bps)	2.80	**2.59**	**2.49**	**2.42**	2.77	2.46	2.28	2.22
Panel C: Live cattle market.								
Quoted spread (bps)	**3.06**	**3.78**	**3.98**	**4.46**	3.19	4.37	4.52	5.66
Effective spread (bps)	**3.37**	**3.54**	**3.65**	**4.05**	3.27	3.34	3.39	3.64
Realized spread (bps)	−0.14	**0.27**	**0.62**	**0.90**	−0.10	0.37	0.72	0.97
Price impact (bps)	**3.55**	**3.24**	**2.94**	**3.08**	3.42	2.92	2.59	2.55
Panel D: Lean hog market.								
Quoted spread (bps)	**5.34**	**6.40**	**6.50**	**7.40**	5.55	7.13	7.45	9.45
Effective spread (bps)	**6.08**	**5.83**	**5.80**	**6.16**	5.93	5.46	5.31	5.56
Realized spread (bps)	**−0.29**	**0.41**	**0.93**	**1.48**	−0.18	0.61	1.23	1.67
Price impact (bps)	**6.43**	**5.44**	**4.73**	**4.40**	6.18	4.85	3.92	3.48

Table 3: Market quality and implied liquidity: Grain markets.

This table reports OLS regression results for the relationship between the proportion of implied liquidity and differences in market quality in grain markets (corn and soybeans). The regression specification is as follows:

$$\left(MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}\right) = \beta \times Implied\ ratio_{i,j,m,t} + \boldsymbol{Controls}_{i,j,m,t} + \delta_j + \gamma_m + \theta_t + \varepsilon_{i,j,m,t},$$

where $\left(MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}\right)$ denotes the difference in market quality measures between consolidated and outright liquidity for individual futures contract i in nearby futures series j for commodity m on day t. $Implied\ ratio_{i,j,m,t}$ denotes the proportion of implied BBO depth relative to consolidated BBO depth. Control variables include the log dollar trading volume and inverse price. To mitigate the influence of outliers, we winsorize all variables at the 2.5 and 97.5 percentiles by commodity and nearby futures series. Detailed variable definitions are provided in Table 1. δ_j, γ_m, and θ_t denote nearby futures series, commodity, and day fixed effects, respectively. Standard errors are double clustered by contract and day, and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Our sample spans January 5, 2015, to December 27, 2024. Price-limit days are excluded.

	Dependent Variable: $MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}$.			
	(1)	(2)	(3)	(4)
	Quoted spread.	Effective spread.	Realized spread.	Price impact
Implied ratio	−1.209***	0.409***	−0.020	0.437***
	(0.232)	(0.105)	(0.064)	(0.082)
Log volume	0.200***	−0.057***	−0.021	−0.030
	(0.062)	(0.015)	(0.016)	(0.018)
Inverse price	−39.767	−139.988***	−108.278***	−31.049
	(137.093)	(36.464)	(27.464)	(52.935)
Series FE	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
N	19,832	19,832	19,832	19,832
Adj. R^2	0.371	0.400	0.057	0.280

Table 4: Market quality and implied liquidity: Livestock markets.

This table reports OLS regression results for the relationship between the proportion of implied liquidity and differences in market quality in livestock (live cattle and lean hogs) markets. The regression specification is as follows:

$$\left(MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}\right) = \beta \times Implied\ ratio_{i,j,m,t} + \boldsymbol{Controls}_{i,j,m,t} + \delta_j + \gamma_m + \theta_t + \varepsilon_{i,j,m,t},$$

where $\left(MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}\right)$ denotes the difference in market quality measures between consolidated and outright liquidity for individual futures contract i in nearby futures series j for commodity m on day t. $Implied\ ratio_{i,j,m,t}$ denotes the proportion of implied BBO depth relative to consolidated BBO depth. Control variables include log dollar trading volume and inverse price. To mitigate the influence of outliers, we winsorize all variables at the 2.5th and 97.5th percentiles by commodity and nearby futures series. Detailed variable definitions are provided in Table 1. δ_j, γ_m, and θ_t denote nearby futures series, commodity, and day fixed effects, respectively. Standard errors are double-clustered by contract and day, and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Our sample spans January 5, 2015, to December 20, 2019. Price-limit days are excluded.

	Dependent Variable: $MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}$.			
	(1)	(2)	(3)	(4)
	Quoted spread	Effective spread	Realized spread	Price impact
Implied ratio	−10.189***	1.059***	0.150	0.918***
	(0.757)	(0.123)	(0.105)	(0.106)
Log volume	1.067***	0.003	0.084***	−0.121***
	(0.206)	(0.026)	(0.029)	(0.026)
Inverse price	−120.389**	−1.611	−6.832	5.427
	(56.393)	(6.882)	(6.156)	(6.318)
Series FE	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
N	8,376	8,376	8,376	8,376
Adj. R^2	0.671	0.118	0.060	0.235

Online Appendices

A CME institutional details

A.1 CME trade summary recording prior to November 20, 2015

Table A1: An example of CME live cattle trade summary data prior to November 20, 2015.
This table presents sample trade-summary data from the live cattle outright futures market on April 6, 2015. It shows only limited information extracted from the raw data. All trade records are timestamped to the millisecond (the `Time` column), and prices are reported in cents per pound. In the `Code` column, LE denotes live cattle, M denotes the June futures contract, and 5 denotes the 2015 contract year. `Quantity` indicates trade size in number of contracts. `Aggressor` identifies the trade initiator as either buyer-initiated or seller-initiated. `TradeID` indicates the chronological order of trades. `TradeCon` is an indicator variable equal to 1 if the trade is a spread-leg trade and 0 otherwise. `Seq.#` stands for sequence number. We therefore classify trades into three categories. Outright trades, identified by the presence of trade aggressors and the absence of `TrdCon` tags, are denoted by blue rows. Other trades, identified by the absence of trade aggressors, are denoted by red rows. Spread trades, identified by the presence of both `TrdCon` tags and trade aggressors, are denoted by green rows.

Date	Time	Code	Price	Quantity	Aggressor	TradeID	TrdCon	Seq. #
2015-04-06	2015-04-06 09:09:08.808	LEM5	154.425	1	—	1950	—	9154
2015-04-06	2015-04-06 09:09:08.808	LEM5	154.425	1	—	1951	—	9155
2015-04-06	2015-04-06 09:09:08.810	LEM5	154.400	1	—	1952	—	9169
2015-04-06	2015-04-06 09:09:08.883	LEM5	154.425	1	Buy	1953	1	9196
2015-04-06	2015-04-06 09:09:13.111	LEM5	154.425	1	—	1954	—	9245
2015-04-06	2015-04-06 09:09:13.151	LEM5	154.425	1	Sell	1955	—	9260
2015-04-06	2015-04-06 09:09:13.218	LEM5	154.400	1	Buy	1956	1	9270
2015-04-06	2015-04-06 09:09:13.218	LEM5	154.425	1	Sell	1957	1	9273
2015-04-06	2015-04-06 09:09:13.220	LEM5	154.425	1	Sell	1958	1	9279
2015-04-06	2015-04-06 09:09:13.221	LEM5	154.425	1	Sell	1959	1	9280
2015-04-06	2015-04-06 09:09:13.224	LEM5	154.425	1	Sell	1960	1	9287
2015-04-06	2015-04-06 09:09:13.727	LEM5	154.400	1	Sell	1961	—	9293
2015-04-06	2015-04-06 09:09:13.727	LEM5	154.400	1	Sell	1962	—	9294

A.2 Examples of trade types

In Panel A of Figure A1, outright trades occur when market orders submitted to outright markets hit standing quotes and consume liquidity, with the corresponding trade direction assigned by CME. In Panel B of Figure A1, market orders submitted to exchange-traded calendar spreads directly match standing quotes in those same markets. Because both counterparties receive two outright positions (i.e., LEG5 and LEJ5), the resulting trading volume is recorded in outright futures contracts but does not consume liquidity in outright markets. CME also assigns trade directions to the corresponding outright contracts accordingly.

Panel A: Outright trades.

LEG5			
Depth	Price	Depth	
	241.850	~~2~~ 1	**1**
1	**241.825**		
Vol +1 buy			

Panel B: Spread trades.

LEG5			LEJ5			LEG5–LEJ5			
Depth	Price	Depth	Depth	Price	Depth	Depth	Price	Depth	
	241.850	**2**		**237.575**	**1**		**4.300**	~~12~~ 11	**1**
1	**241.825**		**1**	**237.525**		**7**	**4.250**		
Vol +1 buy			**Vol +1 sell**			**Vol +1 buy**			

Figure A1: Examples of outright and spread trades.

This figure displays examples of outright trades (Panel A) and spread trades (Panel B) using hypothetical limit order books in live cattle futures markets. In Panel A, a market buy order (green cell) for one contract hits the best ask quote at 241.850 in the LEG5 outright. Following the trade, depth at the best ask decreases by one contract, and trading volume increases by one contract. CME classifies this trade as buyer-initiated. In Panel B, a market buy order for one contract hits the best ask quote at 4.300 in the LEG5–LEJ5 exchange-traded calendar spreads, which means buying the LEG5 contract (the front leg) and selling the LEJ5 contract (the back leg). Accordingly, CME records a buy trade in both LEG5 and LEG5–LEJ5, and a sell trade in the LEJ5 contract. However, this trade does not consume liquidity in the outright markets.

A.3 Spread trade recovery since November 20, 2015

Following the CME Globex platform upgrade, the exchange discontinued dissemination of detailed trade records for spread trades on November 23, 2015, replacing them with cumulative trading-volume updates whenever spread trades occurred (see Table A2 in Appendix A.3). After this change, only outright and other trades are explicitly recorded in the trade summary data (see Table A3 in Appendix A.3). This change in reporting rules limits traders' ability to directly obtain spread-execution details from CME market data, such as the assigned price of each leg.

To recover the execution details of spread trades after this reporting change, we assign leg prices based on CME's procedure. First, the exchange determines the "anchor" leg of a calendar spread trade according to which leg has the most recent trade-price update. If neither leg has a recent price update, the front-month leg is designated as the anchor leg. The price of the back-month (front-month) leg then equals the anchor-leg price minus (plus) the calendar spread trade price when the front-month (back-month) leg is the anchor. If an assigned leg price falls outside its price limits, that leg price is set at the corresponding limit price, and the anchor-leg price is recalculated. Our recovery procedure considers all calendar spread trades from all exchange-listed spreads.[1] To link the recovered trade data to CME's official trade summary, we assign each recovered trade a sequence number corresponding to the cumulative trading-volume updates in Table A3.

[1]To keep the recovery procedure manageable, we do not consider butterfly spreads or inter-commodity spreads between live cattle and lean hogs. These trades account for only about 3% of total trading volume, on average, in our sample commodities.

Table A2: An example of CME live cattle trade summary data since November 20, 2015.

This table presents sample trade-summary data from the live cattle outright futures market on June 10, 2016. It shows only limited information extracted from the raw data. All trade records are timestamped in nanoseconds (the `Time` column), and prices are reported in cents per pound. In the `Code` column, LE denotes live cattle, Q denotes the August futures contract, and 6 denotes the 2016 contract year. `Quantity` indicates trade size in number of contracts. `Aggressor` identifies the trade initiator as either buyer-initiated or seller-initiated. `Seq.#` stands for sequence number, and `MsgSeq` stands for message number. CME does not disseminate trade aggressor information for implied trades. We therefore classify trades into two categories: outright trades, identified by the presence of trade aggressors, are denoted by blue rows; and other trades, identified by the absence of trade aggressors, are denoted by red rows.

Date	Time	Seq. #	Code	Price	Quantity	Aggressor	MsgSeq
2016-06-10	2016-06-10 09:09:16.800664497	490341	LEQ6	118.975	2	Buy	5353264
2016-06-10	2016-06-10 09:09:16.804221059	490358	LEQ6	118.975	1	Sell	5353338
2016-06-10	2016-06-10 09:09:16.811576342	490371	LEQ6	118.975	1	—	5353424
2016-06-10	2016-06-10 09:09:19.588043586	490400	LEQ6	118.950	1	Sell	5353922
2016-06-10	2016-06-10 09:09:23.606578040	490412	LEQ6	118.950	2	Sell	5354192
2016-06-10	2016-06-10 09:09:23.606578040	490413	LEQ6	118.925	1	Sell	5354192
2016-06-10	2016-06-10 09:09:30.971801653	490439	LEQ6	118.950	1	Sell	5355200
2016-06-10	2016-06-10 09:09:31.264424355	490449	LEQ6	118.950	1	—	5355260
2016-06-10	2016-06-10 09:09:37.397757834	490465	LEQ6	118.950	2	Sell	5355665
2016-06-10	2016-06-10 09:09:37.400356431	490481	LEQ6	118.950	1	Sell	5355701
2016-06-10	2016-06-10 09:09:37.400535830	490486	LEQ6	118.950	1	Sell	5355704
2016-06-10	2016-06-10 09:09:39.854236727	490495	LEQ6	118.950	1	—	5355793

Table A3: An example of CME live cattle cumulative electronic trading volume since November 20, 2015.

This table presents sample cumulative electronic volume data from the live cattle outright futures market on June 10, 2016. It shows only limited information extracted from the raw data. All cumulative electronic trading-volume records are timestamped in nanoseconds (the `Time` column). In the `Code` column, LE denotes live cattle, Q denotes the August futures contract, and 6 denotes the 2016 contract year. `Cumulative electronic volume` reports the cumulative trading volume, in number of contracts, since the beginning of the trading session. `Seq.#` stands for sequence number, and `MsgSeq` stands for message number. Since November 20, 2015, spread trades have no longer been disseminated to outright markets with assigned leg prices.

Date	Time	Code	Seq. #	Cumulative electronic volume	MsgSeq
2016-06-10	2016-06-10 11:19:01.091012273	LEQ6	531164	7454	5770846
2016-06-10	2016-06-10 11:19:01.091224921	LEQ6	531167	7457	5770848
2016-06-10	2016-06-10 11:19:01.091562889	LEQ6	531172	7458	5770853
2016-06-10	2016-06-10 11:19:13.093073910	LEQ6	531212	7459	5771511
2016-06-10	2016-06-10 11:19:13.093503988	LEQ6	531215	7461	5771513
2016-06-10	2016-06-10 11:19:26.136658916	LEQ6	531243	7464	5772334
2016-06-10	2016-06-10 11:19:26.197863057	LEQ6	531269	7468	5772407
2016-06-10	2016-06-10 11:19:33.583649187	LEQ6	531287	7469	5772609
2016-06-10	2016-06-10 11:19:33.584164729	LEQ6	531290	7470	5772612
2016-06-10	2016-06-10 11:20:04.990959981	LEQ6	531310	7477	5773494
2016-06-10	2016-06-10 11:20:14.287565759	LEQ6	531347	7480	5774469
2016-06-10	2016-06-10 11:20:14.287749804	LEQ6	531350	7481	5774473
2016-06-10	2016-06-10 11:20:14.325638177	LEQ6	531375	7482	5774556

B Pricing conditions

B.1 Example

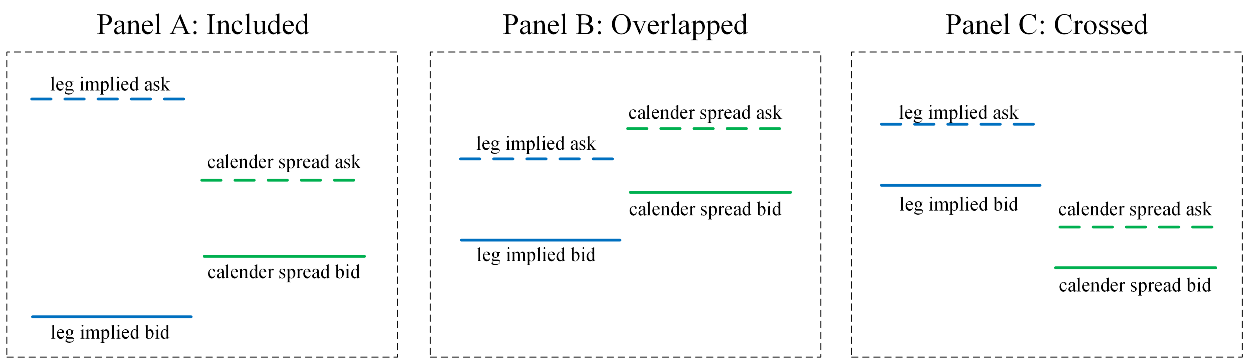

Figure B1: Pricing conditions between calendar spreads and corresponding outrights.

This figure illustrates three pricing conditions between calendar spreads and the corresponding outright contracts based on their BBO quote condition. The *included* (*overlapped*) condition indicates that the BBO quotes of synthetic spreads (i.e., leg-implied bid and ask quotes) lie completely within (partially within) those of calendar spreads. The *crossed* condition indicates that the BBO quotes of synthetic spreads lie completely outside those of calendar spreads. Only under the crossed condition can arbitrageurs engage in instantaneous arbitrage using two market orders.

B.2 Frequency of pricing conditions

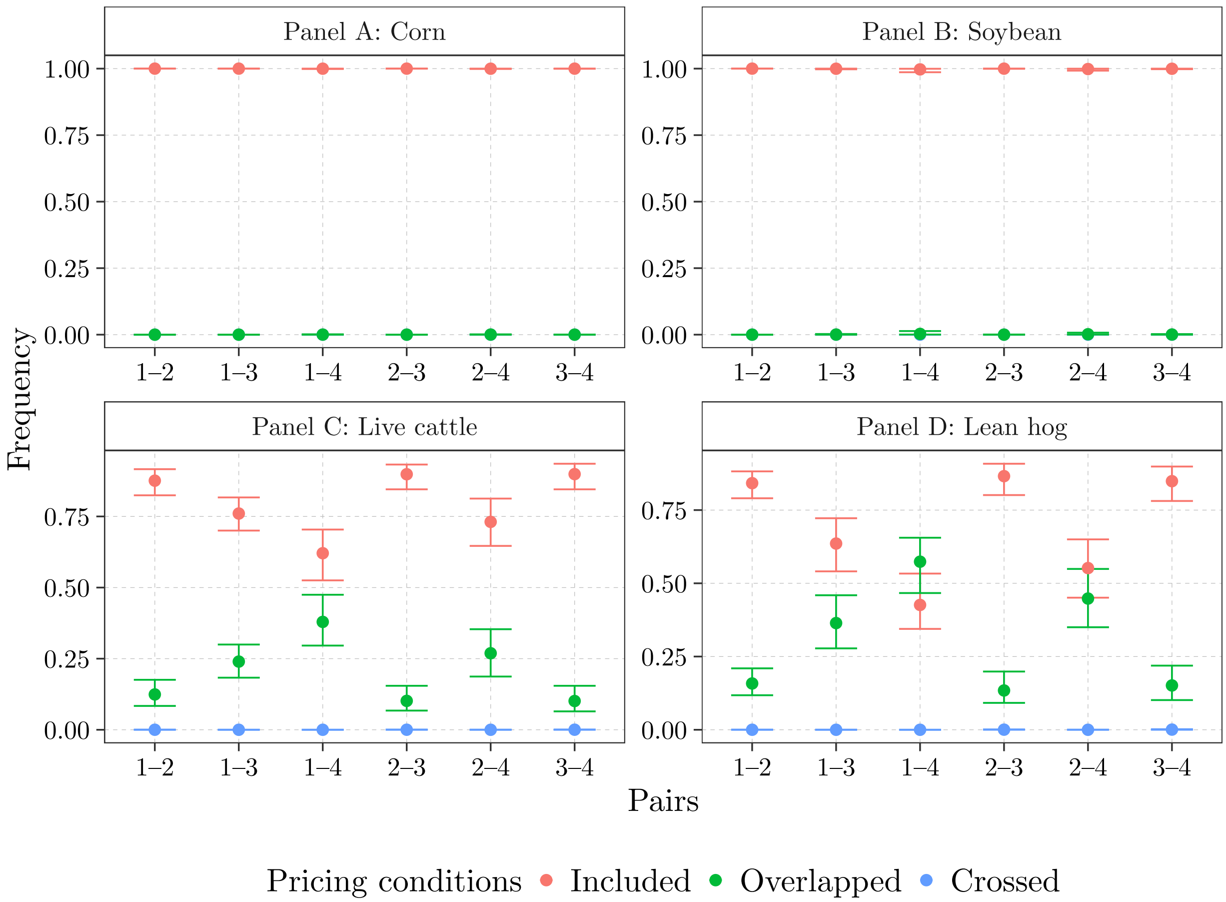

Figure B2: Frequency of pricing conditions between calendar spreads and corresponding outrights.

This figure displays the interquartile ranges of the frequencies of three pricing conditions between calendar spreads and their synthetic counterparts in grain markets (Panels A and B) and livestock markets (Panels C and D) under two liquidity scenarios. "Included" ("overlapped") indicates that the leg-implied BBO quotes lie completely within (partially within) the calendar spread BBO quotes. "Crossed" indicates that the leg-implied BBO quotes lie completely outside the calendar spread BBO quotes. No instantaneous arbitrage opportunities exist under either the included or overlapped condition. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded from this analysis.

C Price discovery

C.1 Non-zero returns

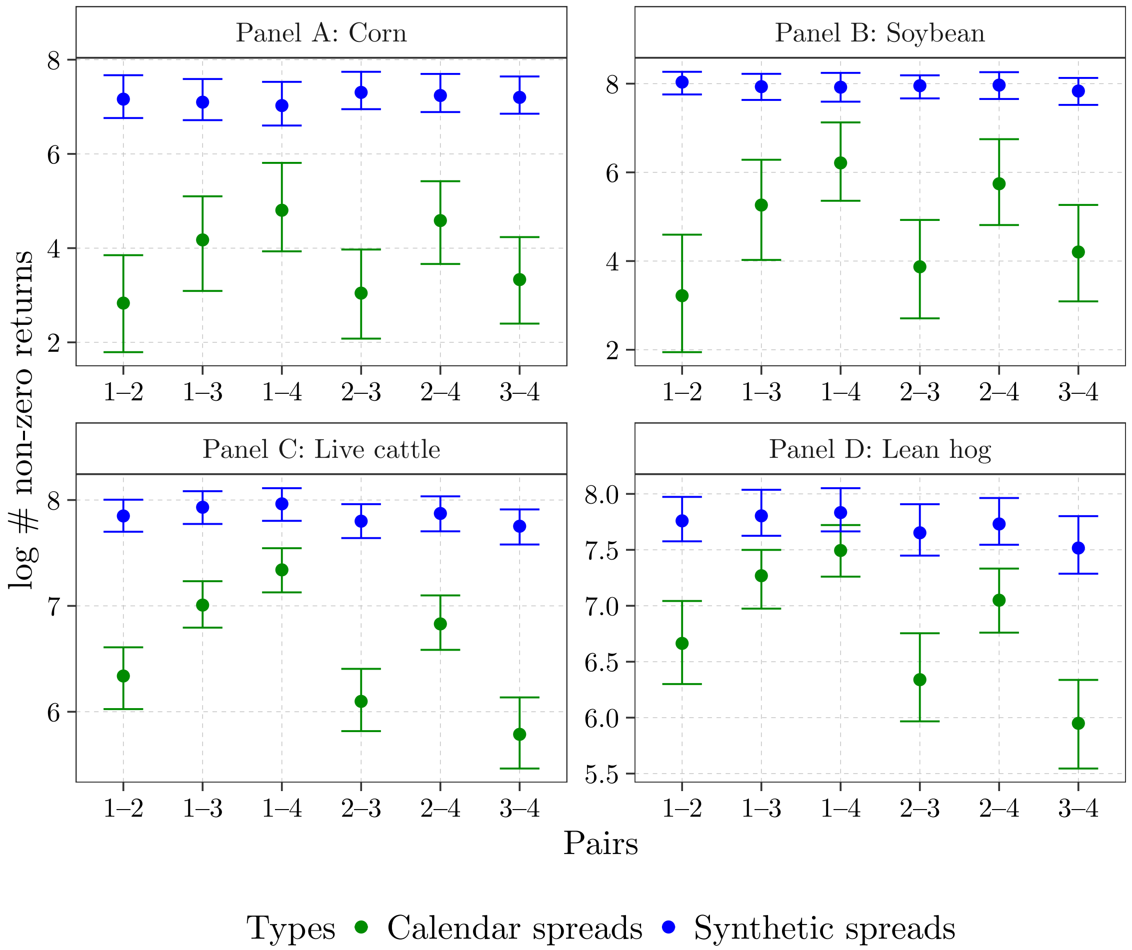

Figure C1: Log number of non-zero returns: Exchange-traded calendar spreads vs. synthetic spreads.

This figure displays the interquartile ranges of the logarithmic numbers of non-zero returns for calendar spread midpoint prices and their synthetic counterparts in CME grain markets (Panels A and B) and livestock markets (Panels C and D). Midpoint returns are calculated as the log differences between two consecutive midpoint prices.

C.2 Noise ratio

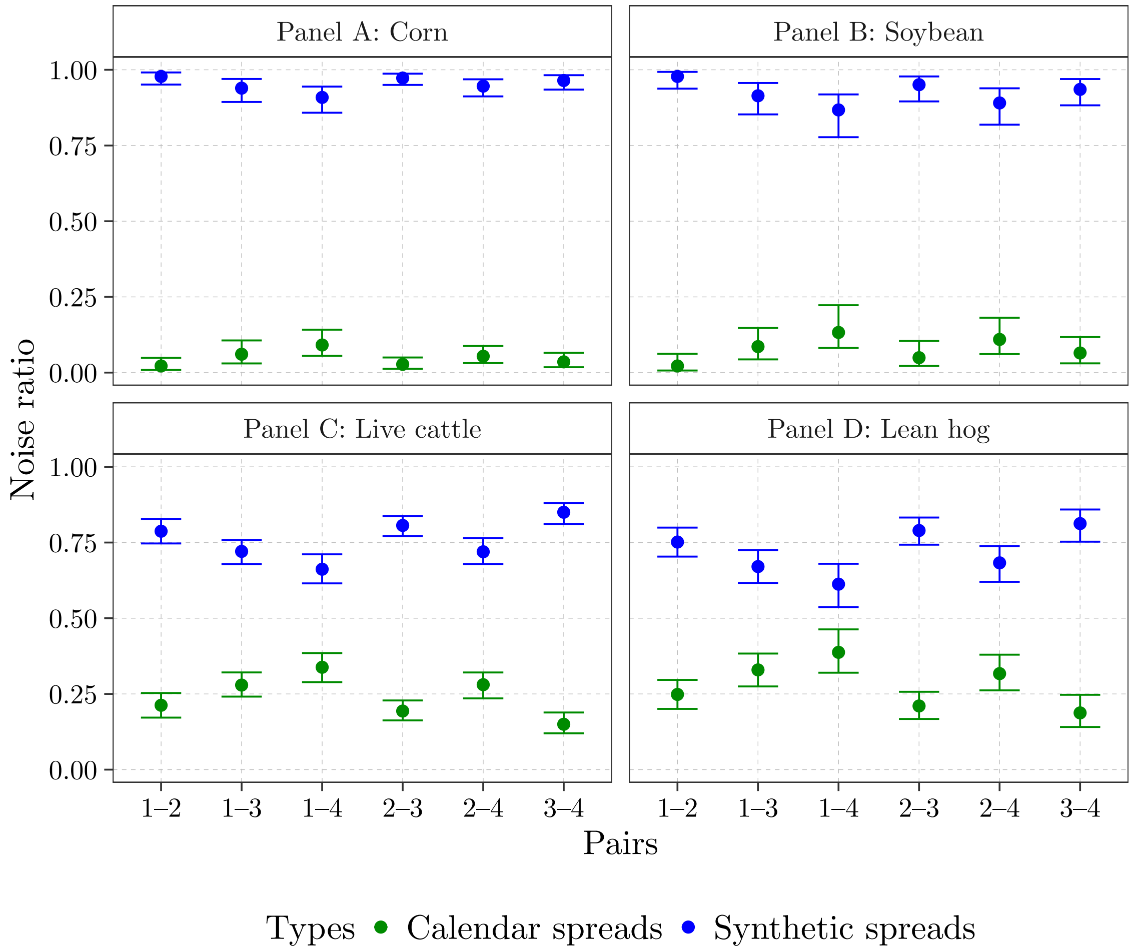

Figure C2: Noise ratio: Exchange-traded calendar spreads vs. synthetic spreads.

This figure displays the interquartile ranges of noise ratios for calendar spreads and synthetic spreads in CME grain markets (Panels A and B) and livestock markets (Panels C and D). We define the noise of a calendar spread (synthetic spread) as the mean absolute deviation of its midpoint price from the estimated common efficient price. The noise ratio for an exchange-traded spread (synthetic spread) is defined as its noise relative to the sum of the two noise measures. Following Gonzalo and Granger (1995), the common efficient price is constructed as the weighted average of the two midpoint prices, using their respective component shares as weights.

C.3 Robustness: Sampling frequency

One potential concern is that a 1-second sampling frequency may introduce staleness, as electronic trading typically operates at much higher speeds. We therefore assess whether our price-discovery measures are sensitive to alternative sampling frequencies.

We consider three alternative sampling frequencies: 100 milliseconds, 500 milliseconds, and 5 seconds. The results are reported in Figure C3 of Appendix C.3. Consistent with our main results based on 1-second resampling, synthetic spreads remain faster in responding to new information, whereas calendar spreads remain more informative about the efficient price. We find that the ILSs of synthetic spreads increase slightly as the sampling frequency becomes lower. For example, for the 1st–2nd pair, the median ILSs increase from 59.79%–66.96% (65.56%–67.80%) to 67.32%–72.55% (71.27%–72.27%) in grains (livestock) as the sampling interval increases from 100 milliseconds to 5 seconds. This effect is more pronounced for shorter-duration pairs.

However, the ISs of synthetic spreads also increase at lower sampling frequencies, possibly because lower-frequency sampling reduces noise. For the 1st–2nd pair, the ISs increase from 1.48%–1.68% (23.26%–29.56%) at 100 milliseconds to 5.89%–7.46% (36.33%–39.78%) at 5 seconds in grains (livestock). We find that these increases in ISs are pronounced across all pairs. Overall, our main findings are robust to alternative sampling frequencies.

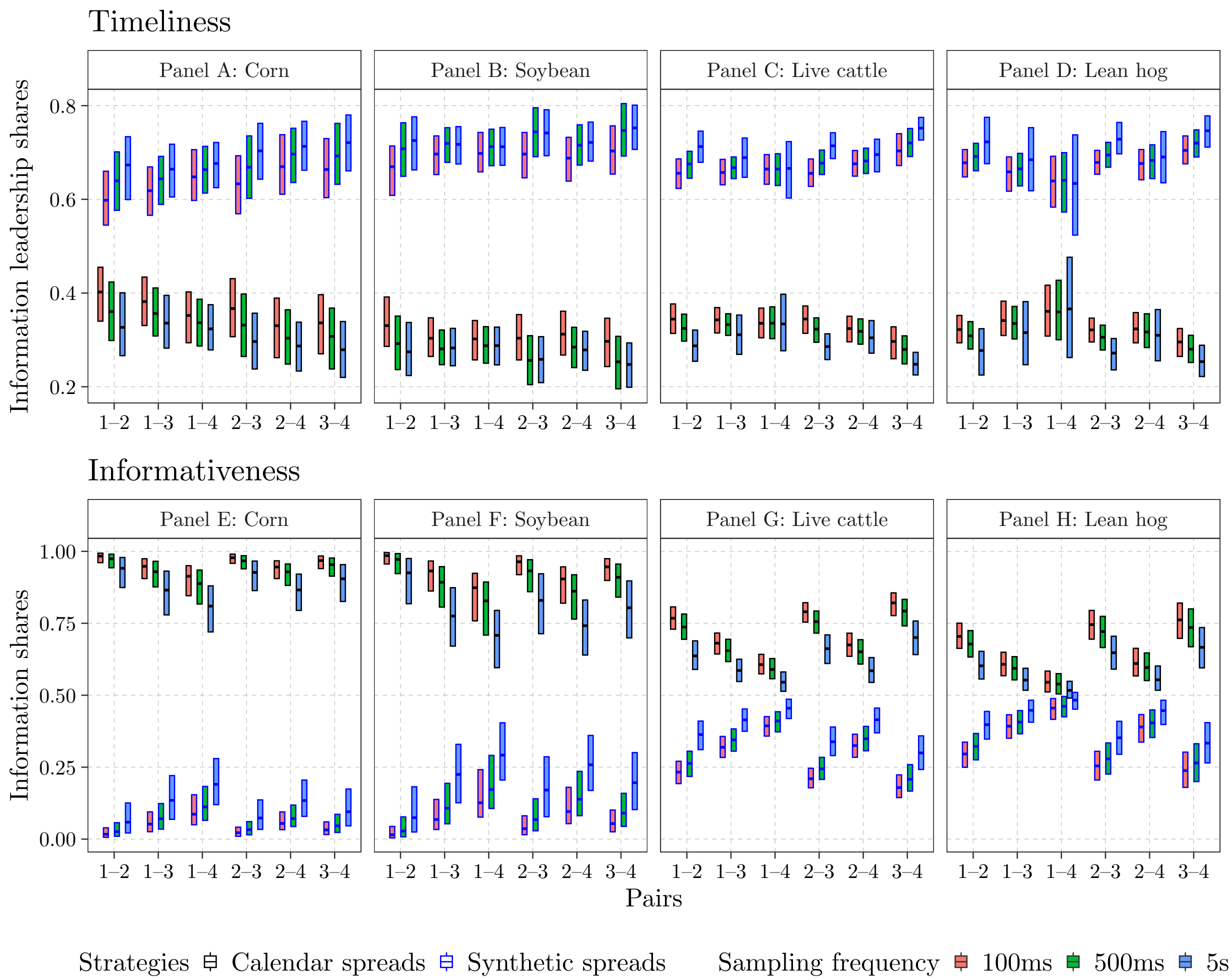

Figure C3: Price discovery shares: Robustness to sampling frequency.

This figure displays the interquartile ranges of the daily price discovery shares of exchange-traded calendar spreads and synthetic spreads in CME grain and livestock futures markets, from the perspectives of timeliness (Panels A and B) and informativeness (Panels C and D), under three alternative sampling frequencies. Timeliness refers to which market moves first to incorporate new information and is measured by the information leadership share (ILS), whereas informativeness refers to which market contributes more to the efficient price and is measured by Hasbrouck's (1995) information share (IS). The ILSs and ISs are estimated from a bivariate vector error correction model (VECM) between exchange-traded spread midpoint returns ($\Delta p^{spd}t$) and leg-implied midpoint returns ($\Delta p^{leg}t$), constructed for each pair on each trading day. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded from the analysis.

C.4 Robustness: Hagströmer (2021)'s weighted midpoint price

Hagströmer (2021) notes that the midpoint price implicitly assumes symmetry between the best bid and best ask quotes in the limit order book. However, a greater number of quotes on the bid (ask) side suggests that the fundamental value is closer to the ask (bid) side (Glosten 1994). We therefore calculate the weighted midpoint price, p^{wm}, proposed by Hagströmer (2021), which accounts for quote imbalances between the bid and ask sides:

$$p^{wm} = \frac{p^{bid}q^{ask} + p^{ask}q^{bid}}{q^{bid} + q^{ask}}, \tag{15}$$

where p^{bid} (p^{ask}) and q^{bid} (q^{ask}) denote the best bid (ask) price and best bid (ask) depth, respectively. We calculate weighted midpoint prices for both the leg-implied spread market (p^{wm_leg}) and the actual spread market ($p^{wm_{spd}}$).

Figure C4 in Appendix C.4 reports the ILSs and ISs based on weighted midpoint prices for four sampling frequencies. The results are qualitatively similar to those in Figure 7. Synthetic spreads retain their lead in timeliness. At the 1-second frequency, the median ILSs for synthetic spreads range from 66.57% to 82.42% in grains and from 58.25% to 84.15% in livestock. These values are somewhat higher than those in our main results, but they also exhibit slightly greater variation, suggesting that synthetic spreads display even stronger timeliness in incorporating information when depth imbalances are taken into account. As in the main results, this effect is more pronounced for shorter-duration pairs. In terms of informativeness, calendar spreads continue to outperform synthetic spreads, although the ISs exhibit greater variation than in the main results. The median ISs range from 93.69% to 99.54% in grains and from 55.58% to 94.83% in livestock. The largest increases in ISs are again observed for shorter-duration pairs. Similar patterns emerge across all sampling frequencies. Overall, our findings remain robust to using alternative midpoint price measures.

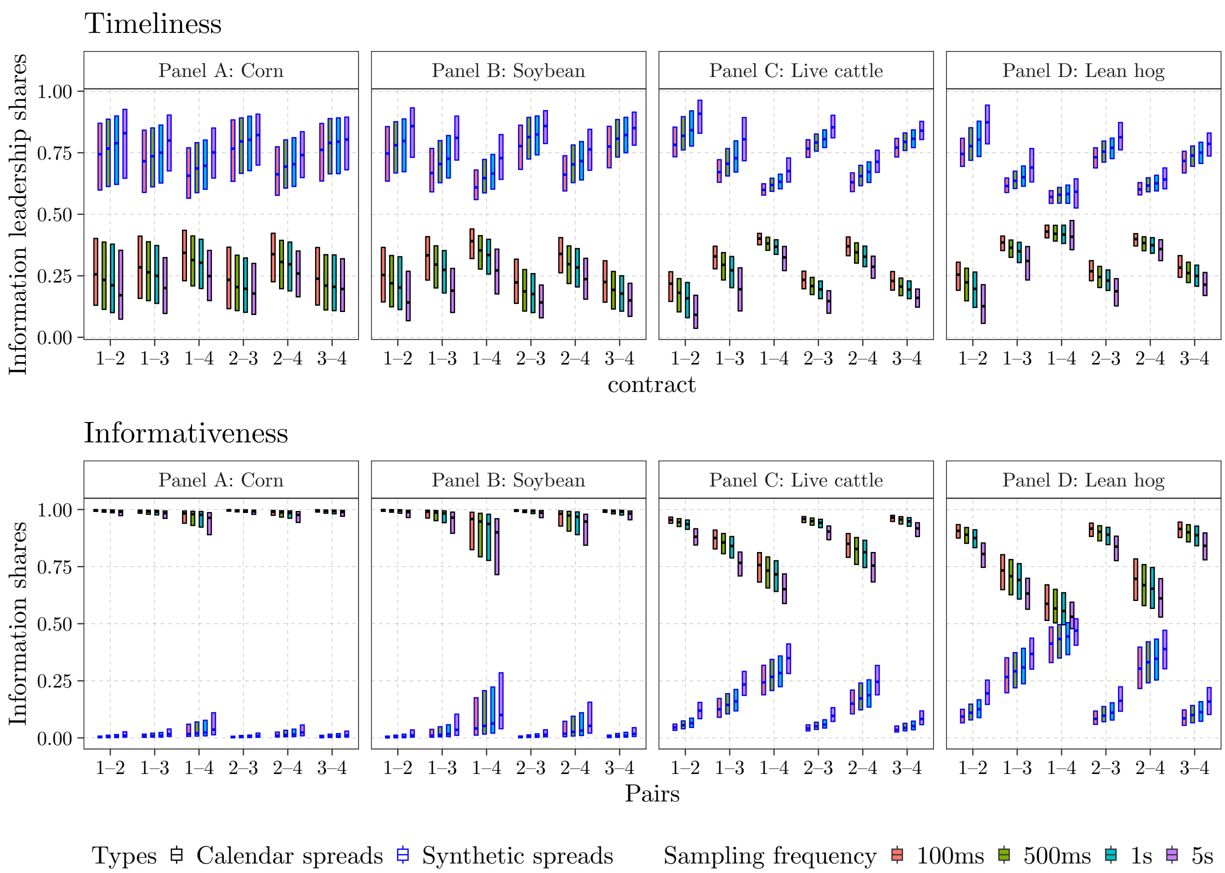

Figure C4: Price discovery shares: Robustness to weighted midpoint price.

This figure displays boxplots of the daily price discovery shares of calendar spreads and synthetic spreads in CME grain and livestock markets, from the perspectives of timeliness (Panels A and B) and informativeness (Panels C and D), using Hagströmer (2021)'s weighted midpoint prices. Timeliness refers to which market moves first to incorporate new information and is measured by the information leadership share (ILS), whereas informativeness refers to which market contributes more to the efficient price and is measured by Hasbrouck's (1995) information share (IS). The ILSs and ISs are estimated from a bivariate vector error correction model (VECM) between the weighted midpoint price of the exchange-traded spread and that of the synthetic spread, constructed for each spread on each trading day. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded from the analysis.

D CME implied functionality

Outright contract V1

Bid price	Bid Qty.	Ask price	Ask Qty.
500	1		

Spread trading V1–V2

Bid price	Bid Qty.	Ask price	Ask Qty.
		2	1

Implied out

Outright contract V2

Bid price	Bid Qty.	Ask price	Ask Qty.
498	1i		

i: implied order

Figure D1: An example of CME implied functionality.

This figure displays an example of the CME implied functionality using a hypothetical outright and a calendar spread. An implied-out order is a synthetic outright quote generated from calendar spread quotes. In our example, a bid at 500 (1 contract) in outright market V1 and an ask (1 contract) in spread V1-V2 can create an implied-out bid in outright market V2 at price 498 with quantity 1 as there is no available outright ask order at quoted price 498 with quantity 1. More details on CME implied functionality are in https://cmegroupclientsite.atlassian.net/wiki/spaces/EPICSANDBOX/pages/457095346/Implied+Orders.

E Implied liquidity and market quality

E.1 Summary statistics

Table E1: Summary statistics.

This table reports summary statistics for the pooled regression samples in grain and livestock markets. The dependent variables are the differences in market quality measures between consolidated and outright liquidity (i.e., $MQ^C - MQ^O$). The main independent variable is the proportion of implied best-bid-offer (BBO) depth relative to consolidated BBO depth, measured on a scale from 0 to 1. Control variables include log trading volume (in million dollars) and inverse price. Variable definitions are provided in Table 1. To mitigate the influence of outliers, we winsorize all variables at the 2.5 and 97.5 percentiles by commodity and nearby futures series. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded from the analysis.

Variables	Mean	Std	P25	Med	P75	N
Panel A: Grain markets.						
Dependent variables						
Quoted spread diff (bps)	−0.179	0.749	−0.090	−0.004	0.049	19,832
Effective spread diff (bps)	0.227	0.295	0.043	0.137	0.316	19,832
Realized spread diff (bps)	−0.021	0.322	−0.047	0.001	0.046	19,832
Price impact diff (bps)	0.248	0.415	0.035	0.128	0.340	19,832
Independent variable						
Implied ratio	0.517	0.243	0.289	0.558	0.716	19,832
Control variables						
Log volume	5.693	1.621	4.478	5.607	7.185	19,832
Inverse price	0.0016	0.0008	0.0010	0.0013	0.0025	19,832
Panel B: Livestock markets.						
Dependent variables						
Quoted spread diff (bps)	−1.493	2.587	−1.307	−0.469	−0.176	8,376
Effective spread diff (bps)	0.299	0.519	0.110	0.214	0.387	8,376
Realized spread diff (bps)	−0.186	0.617	−0.276	−0.085	0.011	8,376
Price impact diff (bps)	0.493	0.619	0.166	0.336	0.635	8,376
Independent variable						
Implied ratio	0.456	0.174	0.325	0.482	0.583	8,376
Control variables						
Log volume	4.622	1.224	3.776	4.634	5.516	8,376
Inverse price	0.011	0.003	0.009	0.011	0.014	8,376

E.2 Summary statistics by trade size groups

We classify trades into three size groups: fewer than 10 (5) contracts, 10–99 (5–10) contracts, and at least 100 (more than 10) contracts for grains (livestock). We compute market quality measures as volume-weighted averages within each trade-size group, and report the median values in Table E2.

Consistent with our argument, we find that in grain markets, realized spreads decrease and price impacts increase when consolidated liquidity is used, with the magnitudes positively associated with trade size. For example, in the corn market, price impact increases by 0.32 bps for trades of at least 100 contracts, compared with 0.25 bps for trades between 10 and 99 contracts. In contrast, differences in effective spreads decline as trade size increases, suggesting that implied liquidity has little effect on large trades. For example, in the corn market, the effective spread increases by 0.45 bps for trades smaller than 10 contracts, but by only 0.17 bps for trades between 10 and 99 contracts. Thus, large trades tend to generate greater price impacts while leaving effective spreads largely unchanged, resulting in lower realized spreads. One-sided Wilcoxon rank-sum tests confirm that these patterns are generally statistically significant, although there are some exceptions. Livestock markets exhibit a similar pattern.

Table E2: Market quality under two liquidity scenarios by trade sizes.

This table reports the median values of effective spreads, realized spreads, and price impacts calculated using both consolidated and outright liquidity in grain markets (Panels A and B) for three trade-size groups: fewer than 10 contracts, 10–99 contracts, and at least 100 contracts. We consider all nearby futures series. All market quality measures are summarized as volume-weighted averages within each trade-size group. Corresponding summary statistics are also reported for livestock markets (Panels C and D), using three trade-size groups: fewer than 5 contracts, 5–10 contracts, and more than 10 contracts. We conduct several Wilcoxon rank-sum tests to assess whether the medians of effective spreads, realized spreads, and price impacts are, respectively, greater, lower, and greater under consolidated liquidity than under outright liquidity. *, **, and *** denote statistical significance at the 1% level. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded from the analysis.

	Consolidated liquidity			Outright liquidity		
	< 10	10–99	≥ 100	< 10	10–99	≥ 100
Panel A: Corn market.						
Effective spread (bps)	6.22***	6.53***	7.16	5.77	6.36	7.17
Realized spread (bps)	1.21	0.74***	−1.21***	1.23	0.81	−0.90
Price impact (bps)	4.36***	5.41***	8.78***	4.00	5.16	8.46
Panel B: Soybean market.						
Effective spread (bps)	2.67***	3.67***	5.00	2.45	3.62	5.01
Realized spread (bps)	0.41	0.15	−1.43	0.37	0.14	−1.40
Price impact (bps)	2.13***	3.38**	6.51	1.97	3.34	6.48

	Consolidated liquidity			Outright liquidity		
	< 5	5–10	> 10	< 5	5–10	> 10
Panel C: Live cattle market.						
Effective spread (bps)	2.96***	4.28	5.99	2.69	4.30	5.97
Realized spread (bps)	0.46	0.40***	−0.67***	0.46	0.57	−0.23
Price impact (bps)	2.46***	3.83***	6.55***	2.16	3.57	6.08
Panel D: Lean hog market.						
Effective spread (bps)	4.98***	7.26	9.52	4.52	7.31	9.60
Realized spread (bps)	0.65***	0.27***	−1.33***	0.71	0.71	−0.37
Price impact (bps)	4.25***	6.84***	11.10***	3.69	6.43	10.16

E.3 Robustness checks

Table E3: Market quality and implied liquidity: Robustness to commodity-nearby futures interacted fixed effect.

This table reports the OLS regression results for the relationship between the proportion of implied liquidity and differences in market quality in grain markets (Panel A) and livestock markets (Panel B). The regression specification is as follows:

$$\left(MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}\right) = \beta \times Implied\ ratio_{i,j,m,t} + \boldsymbol{Controls}_{i,j,m,t} + \eta_{jm} + \theta_t + \varepsilon_{i,j,m,t},$$

where $\left(MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}\right)$ denotes the difference in market quality measures between consolidated and outright liquidity for individual futures contract i in nearby futures series j for commodity m on day t. $Implied\ ratio_{i,j,m,t}$ denotes the proportion of implied BBO depth relative to consolidated BBO depth. Control variables include log dollar trading volume and inverse price. To mitigate the influence of outliers, we winsorize all variables at the 2.5 and 97.5 percentiles by commodity and nearby futures series. Detailed variable definitions are provided in Table 1. η_{jm} and θ_t denote series-by-commodity and day fixed effects, respectively. Standard errors are double clustered by individual futures contract and day, and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded from the analysis.

	Dependent Variable: $MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}$.			
	(1)	(2)	(3)	(4)
	Quoted spread	Effective spread	Realized spread	Price impact
Panel A: Grain markets.				
Implied ratio	−1.067***	0.462***	−0.088	0.558***
	(0.225)	(0.055)	(0.054)	(0.071)
Log volume	0.202***	−0.056***	−0.022	−0.029*
	(0.061)	(0.015)	(0.015)	(0.016)
Inverse price	42.651	−108.096***	−150.472***	42.528
	(142.179)	(33.707)	(25.926)	(46.224)
N	19,832	19,832	19,832	19,832
Adj. R^2	0.397	0.423	0.094	0.344
Panel B: Livestock markets.				
Implied ratio	−10.544***	1.101***	0.153	0.959***
	(0.745)	(0.124)	(0.095)	(0.104)
Log volume	0.968***	0.009	0.069**	−0.099***
	(0.197)	(0.027)	(0.027)	(0.025)
Inverse price	−195.576***	−1.557	−17.529***	17.398***
	(56.714)	(7.320)	(6.322)	(6.419)
N	8,376	8,376	8,376	8,376
Adj. R^2	0.693	0.122	0.067	0.244
Commodity × Series FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

Table E4: Market quality and implied liquidity: Robustness to lagged denominator of implied BBO ratio.

This table reports OLS regression results on the relationship between the proportion of implied liquidity, measured using lagged consolidated depth, and differences in market quality. The regression specification is as follows:

$$\left(MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}\right) = \beta \times \left(\frac{BBO\ depth^{I}_{i,j,m,t}}{BBO\ depth^{C}_{i,j,m,t-1}}\right) + \boldsymbol{Controls}_{i,j,m,t} + \delta_j + \gamma_m + \theta_t + \varepsilon_{i,j,m,t},$$

where $\left(MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}\right)$ denotes the difference in market quality measures between consolidated and outright liquidity for individual futures contract i in nearby futures series j for commodity m on day t. $\left(\frac{BBO\ depth^{I}_{i,j,m,t}}{BBO\ depth^{C}_{i,j,m,t-1}}\right)$ denotes the proportion of implied BBO depth relative to lagged consolidated BBO depth. Control variables include log dollar trading volume and inverse price. To mitigate the influence of outliers, we winsorize all variables at the 2.5 and 97.5 percentiles by commodity and nearby futures series. Detailed variable definitions are provided in Table 1. δ_j, γ_m, and θ_t denote nearby futures series, commodity, and day fixed effects, respectively. Standard errors are double clustered by individual futures contract and day, and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. Price-limit days are excluded from the analysis.

	Dependent Variable: $MQ^{C}_{i,j,m,t} - MQ^{O}_{i,j,m,t}$.			
	(1)	(2)	(3)	(4)
	Quoted spread	Effective spread	Realized spread	Price impact
Panel A: Grain markets.				
$\left(\frac{BBO\ depth^{I}_{i,j,m,t}}{BBO\ depth^{C}_{i,j,m,t-1}}\right)$	−0.199**	0.190***	−0.047	0.247***
	(0.092)	(0.028)	(0.032)	(0.037)
Log volume	0.298***	−0.078***	−0.024	−0.048***
	(0.064)	(0.014)	(0.016)	(0.033)
Inverse price	−27.789	−139.559***	−108.428***	−30.170
	(142.810)	(35.398)	(27.557)	(51.823)
N	19,741	19,741	19,741	19,741
Adj. R^2	0.347	0.391	0.056	0.277
Panel B: Livestock markets.				
$\left(\frac{BBO\ depth^{I}_{i,j,m,t}}{BBO\ depth^{C}_{i,j,m,t-1}}\right)$	−4.852***	0.603***	0.084	0.484***
	(0.473)	(0.083)	(0.082)	(0.077)
Log volume	1.588***	−0.041	0.077**	−0.162***
	(0.239)	(0.028)	(0.032)	(0.029)
Inverse price	−71.170	−5.190	−7.725	2.241
	(61.498)	(7.176)	(5.963)	(6.342)
N	8,313	8,313	8,313	8,313
Adj. R^2	0.595	0.103	0.060	0.225
Series FE	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

E.4 Heterogeneity analyses

Table E5: Market quality and implied liquidity: Individual commodity.

This table reports the OLS regression results for the relationship between the proportion of implied liquidity and differences in market quality for each commodity. The regression specification is as follows:

$$\left(MQ^{C}_{i,j,t} - MQ^{O}_{i,j,t}\right) = \beta \times \mathit{Implied\ ratio}_{i,j,t} + \boldsymbol{Controls}_{i,j,t} + \delta_j + \theta_t + \varepsilon_{i,j,t},$$

where $\left(MQ^{C}_{i,j,t} - MQ^{O}_{i,j,t}\right)$ denotes the difference in market quality measures between consolidated and outright liquidity for individual futures contract i in nearby futures series j on day t. $\mathit{Implied\ ratio}_{i,j,t}$ denotes the proportion of implied BBO depth relative to consolidated BBO depth. Control variables include log dollar trading volume and inverse price. To mitigate the influence of outliers, we winsorize all variables at the 2.5 and 97.5 percentiles by commodity and nearby futures series. Detailed variable definitions are provided in Table 1. δ_j and θ_t denote nearby futures series and day fixed effects, respectively. Standard errors are double clustered by individual futures contract and day, and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. To save space, we report only the estimates of the variable of interest.

	Dependent Variable: $MQ^{C}_{i,j,t} - MQ^{O}_{i,j,t}$.			
	(1)	(2)	(3)	(4)
	Quoted spread	Effective spread	Realized spread	Price impact
Panel A: Corn market.				
Implied ratio	−0.570***	0.336***	−0.116	0.460***
	(0.199)	(0.074)	(0.080)	(0.095)
N	9,916	9,916	9,916	9,916
Adj. R^2	0.262	0.514	0.085	0.361
Panel B: Soybean market.				
Implied ratio	−2.336***	0.274***	0.174**	0.112
	(0.528)	(0.103)	(0.082)	(0.083)
N	9,916	9,916	9,916	9,916
Adj. R^2	0.430	0.315	0.089	0.161
Panel C: Live cattle market.				
Implied ratio	−7.414***	0.844***	−0.056	0.917***
	(0.612)	(0.118)	(0.105)	(0.103)
N	4,188	4,188	4,188	4,188
Adj. R^2	0.685	0.275	0.030	0.273
Panel D: Lean hog market.				
Implied ratio	−13.535***	1.153***	0.161	1.003***
	(0.961)	(0.169)	(0.199)	(0.195)
N	4,188	4,188	4,188	4,188
Adj. R^2	0.717	0.073	0.061	0.170
Controls	Yes	Yes	Yes	Yes
Series FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

Table E6: Market quality and implied liquidity by nearby contract series: Grain markets.

This table reports the OLS regression results for the relationship between the proportion of implied liquidity and differences in market quality in grain markets, estimated separately for each nearby contract series. The regression specification is as follows:

$$\left(MQ^{C}_{i,m,t} - MQ^{O}_{i,m,t}\right) = \beta \times \mathit{Implied\ ratio}_{i,m,t} + \boldsymbol{Controls}_{i,m,t} + \lambda_i + \gamma_m + \theta_t + \varepsilon_{i,m,t},$$

where $\left(MQ^{C}_{i,m,t} - MQ^{O}_{i,m,t}\right)$ denotes the difference in market quality measures between consolidated and outright liquidity for individual futures contract i for commodity m on day t. $\mathit{Implied\ ratio}_{i,m,t}$ denotes the proportion of implied BBO depth relative to consolidated BBO depth. Control variables include log dollar trading volume and inverse price. To mitigate the influence of outliers, we winsorize all variables at the 2.5 and 97.5 percentiles by commodity and nearby futures series. Detailed variable definitions are provided in Table 1. λ_i, γ_m, and θ_t denote individual futures contract, commodity, and day fixed effects, respectively. Standard errors are double clustered by individual futures contract and day, and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Our sample spans January 5, 2015, to December 27, 2024. Price-limit days are excluded from the analysis. To save space, we report only the estimates of the variable of interest.

	Dependent Variable: $MQ^{C}_{i,m,t} - MQ^{O}_{i,m,t}$.			
	(1)	(2)	(3)	(4)
	Quoted spread	Effective spread	Realized spread	Price impact
Panel A: First-nearby.				
Implied ratio	−0.005	0.197***	0.018	0.179***
	(0.006)	(0.013)	(0.013)	(0.020)
N	4,958	4,958	4,958	4,958
Adj. R^2	0.510	0.566	0.066	0.250
Panel B: Second-nearby.				
Implied ratio	−0.373*	0.308***	0.069*	0.226***
	(0.102)	(0.042)	(0.041)	(0.058)
N	4,958	4,958	4,958	4,958
Adj. R^2	0.659	0.605	0.213	0.475
Panel C: Third-nearby.				
Implied ratio	−2.063***	0.431***	0.076	0.331***
	(0.420)	(0.105)	(0.129)	(0.124)
N	4,958	4,958	4,958	4,958
Adj. R^2	0.755	0.473	0.184	0.373
Panel D: Fourth-nearby.				
Implied ratio	−3.287***	0.574***	−0.182	0.771***
	(0.412)	(0.113)	(0.174)	(0.201)
N	4,958	4,958	4,958	4,958
Adj. R^2	0.844	0.374	0.183	0.327
Controls	Yes	Yes	Yes	Yes
Contract FE	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

Table E7: Market quality and implied liquidity by nearby contract series: Livestock markets.

This table reports the OLS regression results for the relationship between the proportion of implied liquidity and differences in market quality in livestock markets, estimated separately for each nearby contract series. The regression specification is as follows:

$$\left(MQ^{C}_{i,m,t} - MQ^{O}_{i,m,t}\right) = \beta \times Implied\ ratio_{i,m,t} + \boldsymbol{Controls}_{i,m,t} + \lambda_i + \gamma_m + \theta_t + \varepsilon_{i,m,t},$$

where $\left(MQ^{C}_{i,m,t} - MQ^{O}_{i,m,t}\right)$ denotes the difference in market quality measures between consolidated and outright liquidity for individual futures contract i for commodity m on day t. $Implied\ ratio_{i,m,t}$ denotes the proportion of implied BBO depth relative to consolidated BBO depth. Control variables include log dollar trading volume and inverse price. To mitigate the influence of outliers, we winsorize all variables at the 2.5 and 97.5 percentiles by commodity and nearby futures series. Detailed variable definitions are provided in Table 1. λ_i, γ_m, and θ_t denote individual futures contract, commodity, and day fixed effects, respectively. Standard errors are double clustered by individual futures contract and day, and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Our sample spans January 5, 2015, to December 20, 2019. Price-limit days are excluded from the analysis. To save space, we report only the estimates of the variable of interest.

	Dependent Variable: $MQ^{C}_{i,m,t} - MQ^{O}_{i,m,t}$.			
	(1)	(2)	(3)	(4)
	Quoted spread	Effective spread	Realized spread	Price impact
Panel A: First-nearby.				
Implied ratio	−1.163***	0.660***	0.263**	0.399***
	(0.108)	(0.050)	(0.107)	(0.115)
N	2,094	2,094	2,094	2,094
Adj. R^2	0.795	0.663	0.223	0.440
Panel B: Second-nearby.				
Implied ratio	−5.115***	0.636***	−0.086	0.763***
	(0.663)	(0.134)	(0.201)	(0.193)
N	2,094	2,094	2,094	2,094
Adj. R^2	0.851	0.310	0.113	0.265
Panel C: Third-nearby.				
Implied ratio	−8.071***	0.899***	0.356	0.494
	(1.105)	(0.198)	(0.290)	(0.297)
N	2,094	2,094	2,094	2,094
Adj. R^2	0.886	0.239	0.127	0.297
Panel D: Fourth-nearby.				
Implied ratio	−12.650***	1.716***	0.787	0.920*
	(1.237)	(0.534)	(0.636)	(0.529)
N	2,094	2,094	2,094	2,094
Adj. R^2	0.897	0.148	0.034	0.187
Controls	Yes	Yes	Yes	Yes
Contract FE	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

Table E8: Market quality and implied liquidity: Different time horizons.

This table reports OLS regression results on the relationship between the proportion of implied liquidity and differences in market quality using alternative time horizons (1 and 10 seconds) in grain markets (Panel A) and livestock markets (Panel B). The regression specification is as follows:

$$\left(MQ^C_{i,j,m,t} - MQ^O_{i,j,m,t}\right) = \beta \times Implied\ ratio_{i,j,m,t} + \boldsymbol{Controls}_{i,j,m,t} + \delta_j + \gamma_m + \theta_t + \varepsilon_{i,j,m,t},$$

where $\left(MQ^C_{i,j,m,t} - MQ^O_{i,j,m,t}\right)$ denotes the difference in market quality measures between consolidated and outright liquidity for individual futures contract i in nearby futures series j for commodity m on day t. $Implied; ratio_{i,j,m,t}$ denotes the proportion of implied BBO depth relative to consolidated BBO depth. Control variables include the log of dollar trading volume and inverse price. To mitigate the influence of outliers, we winsorize all variables at the 2.5th and 97.5th percentiles by commodity and nearby futures series. Detailed variable definitions are provided in Table 1. δ_j, γ_m, and θ_t denote nearby futures series, commodity, and day fixed effects, respectively. Standard errors are double-clustered by contract and day, and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Our sample period spans January 5, 2015, to December 27, 2024, for grains, and January 5, 2015, to December 20, 2019, for livestock. To save space, we report only the estimates of the variable of interest.

	Dependent variable: $MQ^C_{i,j,m,t} - MQ^O_{i,j,m,t}$.			
	$t+1s$		$t+10s$	
	Realized spread	Price impact	Realized spread	Price impact
Panel A: Grain markets.				
Implied ratio	−0.464***	0.873***	0.101*	0.316***
	(0.120)	(0.111)	(0.052)	(0.072)
N	19,832	19,832	19,832	19,832
Adj. R^2	0.040	0.209	0.034	0.221
Panel B: Livestock markets.				
Implied ratio	0.284	1.020***	0.290**	0.769***
	(0.237)	(0.176)	(0.115)	(0.098)
N	8,376	8,376	8,376	8,376
Adj. R^2	0.017	0.063	0.042	0.180