Limit orders and price discovery: Evidence from agricultural futures markets

Abstract

This paper examines the dynamics of limit orders and their contribution to price discovery in CME corn, soybean, and wheat futures markets from January 2019 to June 2020 using order-level data. We find that 25%-28% of limit orders submitted are executed, while around 75-79% are deleted and 7%-8% revised. Latency of limit orders is low, with half of the limit orders being deleted within 2-5 seconds after their placement. Most market messages represent limit orders that do not affect mid-quote returns contemporaneously, while the remaining messages are composed by aggressive trades and limit orders. The latter have major roles in corn, soybean, and wheat market price discovery, while non-aggressive trades and limit orders play a marginal role. We find an increased role of trades in price discovery while a decreased role of aggressive limit orders, following announcements. Our results suggest that most limit orders in grain futures markets continue to play the traditional role of uninformed liquidity provision, which challenges previous research results that point at limit orders far down the book being highly relevant for price discovery.

Keywords: Price discovery; Limit orders; Microstructure; Futures markets; Liquidity

JEL Classification Numbers: G12, G13, G14

1 Introduction

During the first decade of the 21st century, CME futures markets transitioned into order-driven electronic trading featuring an open limit order book. Electronic trading allows traders to easily monitor markets and respond to changes in real time by submitting new market or limit orders or updating existing limit orders through revisions and cancellations. This has changed the nature of trading which is now characterized by fast limit order changes and a high quote-to-trade ratio (Hagströmer and Nordén 2013). The speed at which limit orders are submitted, canceled, and revised, has become a concern for some market participants. The changing nature of trading has revived the interest in assessing how liquidity is provided in electronic futures markets and how information is impounded into prices in the new trading environment.

Electronic trading blurs the distinction between informed and uninformed traders. While informed traders essentially demanded liquidity by placing market orders in the traditional trading floor (Kyle 1985), electronic platforms have prompted these traders to also use limit orders, conditional upon their strategies and the state of the market (e.g., Bloomfield, O'Hara, and Saar 2005; Harris and Panchapagesan 2005; Kaniel and Liu 2006). For example, informed traders may use limit orders whenever volatility is high to reduce execution costs (Goettler, Parlour, and Rajan 2009) and reveal information to the market. Consistently, empirical research has shown that limit orders are at least as informative as trades (e.g., Chaboud, Hjalmarsson, and Zikes 2021).

Informative limit orders should contribute to price discovery. Lehmann (2002)'s well known definition of price discovery refers to efficient and timely incorporation of information into market prices. Efficient refers to the market price reflecting the permanent price movements without transitory pricing errors. The latter could be caused, for example, by the tick size that forces prices to move in minimum price increments as opposed to continuously, or imperfect liquidity that may discourage market participants from incorporating information into the market. Timely is related to the relative speed with which prices reflect new fundamental values.

In the framework of a security traded in a single market, the shape of the limit order book (LOB) provides a picture of the security demand and supply. The microstructure literature has relied on the market equilibrium price represented by the midpoint price, as the random walk permanent price movement observed with transitory pricing errors and discovered through both trades and limit orders (e.g. Fleming, Mizrach, and Nguyen 2018; Brogaard, Hendershott, and Riordan 2019; Chaboud, Hjalmarsson, and Zikes 2021). To quantify the contribution of trades and limit orders to price discovery, these studies have used a structural vector autoregressive (SVAR) model. Fleming, Mizrach, and Nguyen (2018) measure both the permanent price impacts and information shares of trades and limit order flows in the U.S. Treasury markets. They show that trades have the largest permanent price impact, followed by limit order submissions and cancellations, which have similar permanent price impacts and jointly contribute more than trades to price discovery. Brogaard, Hendershott, and Riordan (2019) focus on the Toronto Stock Exchange (TSX). They find that while trades have larger individual impacts than limit orders, the latter are usually much more numerous which results in limit orders having larger overall contribution to price discovery. Chaboud, Hjalmarsson, and Zikes (2021) assess how price discovery evolved over a 10-year period in the foreign exchange (FX) markets. They identify a sharp decline in the relevance of trades, which they attribute to the decline in manual trading. In contrast, limit orders play an increasing role, consistent with lower information advantage of informed traders under the new trading environment and their higher reliance on limit orders.

In the spirit of Harris and Panchapagesan (2005), some studies have also considered price discovery in the limit order book of a single market from a different perspective. These studies rely on a series of prices, as opposed to limit orders and trades. Based on a vector error correction model (VECM), they investigate the co-movement between trade prices and volume-weighted midpoint prices calculated down the LOB (Cao, Hansch, and Wang 2009; Arzandeh and Frank 2019). They identify the common stochastic trend between these variables using relatively frequent snapshots of the LOB.[1] Following the literature on price discovery shares, they quantify how volume-weighted bid and ask prices down the LOB contribute to this common stochastic trend, which is assumed to represent the efficient price. While Cao, Hansch, and Wang (2009) focus on stock markets in Australia, Arzandeh and Frank (2019) study CME corn, soybean, wheat, live cattle, lean hogs and the E-mini S&P 500 futures markets.

Arzandeh and Frank (2019) is to our knowledge the only article that sheds light on the informativeness of the LOB in commodity futures markets. Our analysis adds to the literature by departing from Arzandeh and Frank (2019). Our objective is to identify whether trades and limit orders incorporate information in agricultural futures markets and what is their corresponding price discovery share. Specifically, we shed light on the contribution of trades and limit order submissions, revisions, and cancellations, classified by their aggressiveness, to price discovery. We concentrate on CME corn, soybean, and wheat futures markets. We provide, for the first time, a descriptive analysis of liquidity provision in these markets. Specifically, we identify the proportion of submitted limit orders that are executed, revised, and deleted, along with their respective latencies. Then, we investigate price discovery through permanent price impacts and information shares using a SVAR model. Moreover, we also quantify how limit orders and trades affect the transitory pricing errors (noises).

Findings from our descriptive analysis suggest that for the period from January 7, 2019, to June 26, 2020, 75%-79% of the limit orders submitted are finally deleted, which contrasts with a much smaller proportion of these orders getting executed (25%-28%) or revised (7%-8%). Consistent with Jarnecic and Snape (2014), the latency of limit orders is low: around 50% of limit orders are deleted within 2 to 5 seconds after submission, placing human traders

[1] These studies summarize the information at different depths of the LOB by averaging the bid and ask prices at these depths, weighted by their respective volumes. Notice that as one moves farther down the LOB, these prices represent the weighted midpoint between demand and supply prices that are far apart. Volume-weighted midpoint prices at different LOB depths are correlated with each other due to the mechanics of the LOB. These analyses do not establish what is the relationship of the common stochastic trend between these midpoint prices and the efficient market price.

at a clear disadvantage. We find price discovery to be different in the least liquid market (wheat) relative to the most liquid markets (corn and soybean). While aggressive trades represent around 30% of price discovery in corn and soybean markets, they contribute 43% in the wheat market. Aggressive limit orders contribute around 60% to price discovery in corn and soybean markets and around 50% in the wheat market. In contrast, limit orders that do not change best quotes, have a marginal role in price discovery though they represent most of the limit orders coming into the market. Our findings that most limit orders in grain futures markets continue to play the traditional role of uninformed liquidity provision contrasts with previous research results in futures markets (Arzandeh and Frank 2019), that point at limit orders beyond the best-bid-offer being highly relevant in price discovery. Our results, however, are consistent with current research in the finance literature that focuses on how information is incorporated into the market through trades and limit orders.

2 Data and institutional details

Corn, soybean, and wheat futures contracts trade in the CME Globex platform from Sunday to Friday, with two continuous (day and night) trading sessions preceded by two pre-open (batch auction) sessions. Figure A1 in Appendix A shows the details of the trading sessions in terms of timing as well as the order functionality allowed in each of these sessions. We consider all orders that are submitted during the continuous trading sessions. Our sample includes all trading days from January 7, 2019, to June 26, 2020 for CME corn, soybean, and Chicago soft red winter (SRW) wheat futures markets. Following standard methods (e.g. Couleau, Serra, and Garcia 2019), we focus on the most-traded futures contract that usually coincides with the first-to-expire contract and we roll over to the next most-traded contract, usually the second-to-expire contract, when the latter has higher trading volumes than the former for two consecutive trading days.

As discussed, price discovery refers to efficient and timely incorporation of information

(Putniņš 2013). As high-frequency financial data have become more accessible, researchers have been able to better measure the time dimension of price discovery by using highly granular data. We rely on event-time data which reflect incremental LOB updates originated by a trade or a limit order. More importantly, since we intend to assess the contribution of trades and limit orders to price discovery, we use, for the first time in agricultural futures markets, the CME Market by Order (MBO) data, a message-based *order-level* data that records complete details of all marketable and limit orders, allowing to reconstruct the LOB.

Our approach contrasts with previous literature that has studied the role of market depth in price discovery using the Market by Price (MBP) data (e.g. Arzandeh and Frank 2019). Aside from the fact that MBO data allow to reconstruct the complete LOB, while the MBP data only allows to reconstruct the LOB up to ten depths, the MBO offers important advantages for a more precise measurement of price discovery. First, MBO informs on the origins of each change in the LOB as opposed to offering snapshots of the book. Hence, MBO allows us to clearly identify limit order submissions, revisions, and deletions. These can only be indirectly and imprecisely inferred from MBP. Also, LOB updates via MBP are sometimes slower than MBO updates. This occurs, for example, during intensive sequences of limit order inflows which are timely and incrementally reflected in the MBO, but instead are aggregated into a single update in the MBP. Given the relevance of speed in price discovery measures, the latter can introduce distortions during periods of intensive market activity.

In MBO, limit order messages are classified into submission, revision, execution, and deletion with complex orders, such as Fill-or-Kill (FOK) decomposed as corresponding limit orders and trades. While every trader's identity is confidential, every limit order submitted is assigned a unique order ID so that future revisions and cancellations can be traced back to the original submission. Most trades are classified as either buy or sell-initiated with a few exceptions discussed below in footnote 2. All data are timestamped to the nanosecond precision with a unique message number which allows sorting events with identical timestamps. An order revision implies a quantity and/or price change of an existing limit order, whose details are specified in the MBO revision message. Trade summary messages provide details on the aggregated executed quantity and aggressors. Each trade summary message is followed by order execution messages that specify the limit orders matched and the quantity executed for each order.[2] A limit order disappears from the LOB with an order deletion message. Not all revision and deletion messages originate from limit order traders. For example, when a limit order gets partially executed, the MBO records an execution message to show the traded price and matched quantity, and a revision message to indicate the rest unmatched quantity. Similarly, when a limit order is fully executed in a trade, a deletion message is also sent after the execution message. We remove all deletion and revision messages initiated by trades in our analysis to avoid double counting.[3]

In Figure B1 in Appendix B we report the daily prices (in U.S. cents per bushel), realized volatilities (calculated as squared intraday log returns), and trading volumes (in hundred thousand contracts) of the markets considered. Prices and especially realized volatilities show the markets experienced two highly volatile periods around July 2019, when the U.S.-China trade war started, and from 2020, when the COVID-19 pandemic spread worldwide. The corn and wheat markets are more volatile than the soybean market based on average values (dashed lines) during the sample period. The corn market is the most liquid, with a daily average trading volume of 191,663 contracts, while this number is about 109,420 and 65,800 contracts in soybean and wheat markets, respectively. Table C1 in Appendix C offers the distribution of continuous trading session messages into trades, limit order submissions, executions, revisions, and deletions. Submission messages represent, according to median values, around 29%-30% in the soybean and wheat futures market and 26% in the corn futures market. Deletion messages constitute a similar proportion of total messages (27%-28%) in the three markets. This suggests traders finally delete most limit order submissions. We

[2]Order details (e.g., order ID, matched quantity, aggressor) are not provided for those market orders that are executed against implied order(s). If a market order is executed against both outright and implied limit order(s), only matched outright order details are recorded.

[3]Traders might submit a limit order that crosses the quoted spread, which is similar to a pure market(able) order. The MBO data classifies a cross-spread limit order as a trade (execution) and only an execution message will be sent rather than a submission message.

shed further light on deletions in the next section. Revisions represent around 12%-13% of messages in corn and wheat, and 22% in soybean. The latter may be related to soybean being highly affected by the uncertainty derived from the U.S.-China trade war. Execution messages are either the second or third most relevant category in the corn (34%) and wheat (29%) markets and the least relevant in the soybean market (22%). Our results are qualitatively similar to Nikolsko-Rzhevska, Nikolsko-Rzhevskyy, and Black (2020), though the relevance of execution messages is substantially higher in agricultural futures markets than in the Nasdaq market.

3 Empirical design and results

In subsections 3.1 and 3.2 we assess limit order activity by providing further detail on the limit order submission, execution, revision and deletion rates, and more importantly, the latency of limit orders. The latter sheds lights on the nature of the current trading environment characterized by fleeting liquidity (e.g., Hasbrouck and Saar 2009). Subsection 3.3 presents the empirical design and results of price discovery.

3.1 Limit order submission, execution, revision, and deletion

Panel A of Table 1 reports the percentage of limit orders executed, revised, and deleted over total number of limit orders submitted in a day during continuous trading sessions. Notice that a limit order may be both revised and fully or partially executed; thus, the three rates are not necessarily mutually exclusive. Deletions are predominant, with median rates around 75%-79% across markets which are substantially below those in equity markets with reported values above 95% (SEC 2013; McInish et al. 2020). Median execution rates are 25%-28% during the sample period, indicating that slightly over one-fourth of submitted orders get executed partially or fully. Median revision rates are the lowest and only account for about 7%-8%.

Consistent with past literature suggesting that most trades occur during the day trading session (e.g., Lehecka, Wang, and Garcia 2014), Figure D1 in Appendix D shows this is also applicable to limit order submission, execution, deletion and revision. In Figure D2 in Appendix D, we show the intra-session distribution of market activity is specially concentrated at the market open and close for both the day and night trading sessions, leading to the well-known 'U' shape activity pattern (e.g., McInish and Wood 1992; Lehecka, Wang, and Garcia 2014). A similar 'U' pattern for trades and limit order activities is also identified in Fong and Liu (2010) for stocks traded in the Australian Securities Exchange (ASX) and Nikolsko-Rzhevska, Nikolsko-Rzhevskyy, and Black (2020) in the Nasdaq market. Given the reduced trade and limit order activity during the night session, the 'U' shape characterizing the day session may be strongly related to the inventory management of liquidity providers who do not hold significant overnight positions and thus unwind their positions before the end of day (e.g., Glosten and Milgrom 1985). This is consistent with Shang, Mallory, and Garcia (2018), who show that inventory costs are significantly lower by the end of the day trading session than during other intraday periods in the corn futures market. Interestingly, the night session activity reaches a minimum at around 12 a.m., and subsequently increases reaching peaks at around 7:30 a.m., i.e., 15 minutes before the night session closes. Increased activity after 12:00 a.m. may be related to traders responding to information from overseas markets as they start trading.

We next study order submission, execution, deletion, and revision by order aggressiveness. Aggressive limit orders are more likely to be executed than less aggressive ones, which may impact order revision and cancellation. We consider two levels of order aggressiveness that we denote as 'BBO' and 'Non-BBO'. 'BBO' represents aggressive limit orders that either improve the BBO, or are priced at the current BBO, while 'Non-BBO' represents less aggressive limit orders submitted behind the best bid and offer quotes. We group the orders based on the aggressiveness when they are initially submitted, though some may be revised or canceled. Panel B in Table 1 shows the distribution of the orders by aggressiveness level.

The submissions are expressed as percentages over all submitted orders at BBO and Non-BBO. The executions, deletions, and revisions are expressed as a percentage of submissions at the same level of aggressiveness. Median results suggest that 67% to 73% of the limit orders submitted during the continuous trading sessions are placed at the BBO in the three markets. About 30%-37% of limit orders submitted at the BBO are executed, while the number is around 10% for Non-BBO limit orders. This suggests that more aggressive limit orders are around three times more likely to be executed than the Non-BBO limit orders. Not surprisingly and in contrast to executions, deletions and revisions are relatively more important among orders placed at Non-BBO. Deletion (revision) rates of Non-BBO limit orders are around 90% (10%-14%) across markets, relative to 68%-74% (4%-7%) for BBO limit orders.

Nikolsko-Rzhevska, Nikolsko-Rzhevskyy, and Black (2020) argue that order revisions or deletions represent how traders respond to new information, and one of the major reasons limit orders get revised is to increase the likelihood of execution. We calculate whether revised orders are more likely to be executed and find results consistent with this argument. We show results in Table 2 for the two continuous trading sessions (day and night). Median results suggest that 43%, 38%, and 42% of limit orders revised in the continuous trading sessions are executed in corn, soybean, and wheat markets, respectively. As expected, orders revised at the BBO (Non-BBO) have better (worse) prospects of being executed, with median executions ranging from 43%-68% (24%-33%). Disparities between the BBO and the Non-BBO appear to be smaller the more liquid the market is (e.g., corn or soybean vs. wheat). Our pairwise t-statistics show that the mean differences between BBO and Non-BBO are statistically significant at the 1% level.

Since a deletion is defined as the full disappearance of the unmatched quantity of a limit order, an order may be deleted with partial or no execution. To further understand deletion in the markets, we measure the percentage of canceled orders with partial execution. The results are also reported in Table 2. Median results suggest that only 8%, 4%, and 4% of canceled orders are partially executed in corn, soybean, and wheat markets, respectively. As expected, BBO orders are from five to six times more likely to be partially executed before deletion than Non-BBO, and the differences are statistically significant at the 1% level. In summary, our results show that most deleted orders are not (partially) executed during their whole life.

3.2 Latency of limit order activities

Fast order cancellation has been associated with fleeting market liquidity and raised questions about its pervasiveness on the market. Evidence from equity markets suggests that over one-third of non-marketable limit orders in Nasdaq-listed stocks were canceled within 2 seconds (s, hereafter) of placement on October 2004 (Hasbrouck and Saar 2009). Overseas markets show similar patterns (e.g., Jarnecic and Snape 2014; Jain and Jordan 2017). Here we document, for the first time in the literature of commodity futures markets, the latency of all order activities, rather than only cancellations. Results are reported in Table 3. We define latency as the time difference between order execution, revision, or deletion, and its submission. We also show the results based on order aggressiveness.

As expected, latency is highly right-skewed. Panel A in Table 3 shows that half of the limit orders get their first executions in 11.53s, 5.46s, and 7.54s in corn, soybean, and wheat markets, respectively. BBO limit orders get executed faster than Non-BBO orders whose median execution time is at least 26 times longer than BBO limit orders. Interestingly, we find the minimum execution latency is zero, which we attribute to complex orders.[4] The deletion latency is reported in Panel B. Half of the limit orders are canceled within 4.33s, 2.00s, and 4.74s of placement in the corn, soybean, and wheat markets, respectively. The BBO limit orders are deleted at least 13 times faster than those at Non-BBO. Our results are

[4]Specific types of complex orders such as market-limit and stop-limit orders, generally get their quantity partially executed and leave the unexecuted quantity at the LOB simultaneously. Thus, an execution message and a submission message may be sent with identical timestamps. Information on complex orders is, however, limited and not observable from MBO. For more details about complex orders, refer to https://www.cmegroup.com/confluence/display/EPICSANDBOX/Order+Types+for+Futures+and+Options.

qualitatively similar to those obtained in past studies. The minimum deletion latency reaches microsecond and even nanosecond levels, with few exceptions where orders are submitted and deleted simultaneously. The latency of order revisions reported in Panel C is lower than executions, but higher than deletions, based on median values. Half of the limit orders are revised, for the first time, within 8.29s, 2.92s, and 8.01s of placement in corn, soybean, and wheat markets, respectively, with BBO limit orders being revised faster than Non-BBO orders. The minimum revision latency also reaches the nanosecond level. Figure E1 in Appendix E offers the cumulative distribution of limit order duration, with duration being the time a limit order sits in the LOB. Half of the limit orders last for only about 10s since they are posted in the LOB and 90% of limit orders last for at most 15 minutes. The longer the limit orders remain in the book, the smaller proportion of total orders they represent, which results in the concave shape of the distribution curve. Overall, results are indicative of fast-moving liquidity in the electronic grain futures markets.

3.3 Price discovery: Trades vs. limit orders

We assess price discovery by measuring how trades and limit orders affect mid-quote returns. We take the midpoint price as the best indicator of the efficient price observed with noise (e.g., Hasbrouck 1991; Hansen and Lunde 2006; Couleau, Serra, Garcia, 2018). We use event-time message data as opposed to regularly resampled data, which allows us better measure the time dimension of price discovery. Following Brogaard, Hendershott, and Riordan (2019), we sign and categorize our trade and limit order variables based on their impacts on the midpoint price. We consider both implied and outright liquidity in our analyses. The trade variables are signed as +1 (−1) if they are buy (sell)-initiated. Limit order variables increasing (decreasing) liquidity at the bid side are signed as +1 (−1). Similarly, limit orders increasing (decreasing) the liquidity at the ask side are signed as −1 (+1). Orders are separated into those that effectively change the BBO quotes from those that do not. For example, *Trades – change price* ($Trades^{change}$) includes both buy-initiated and sell-initiated trades that consume all liquidity at the BBO, thus changing the midpoint price. Otherwise, trades are assigned to category *Trades – same price* ($Trades^{same}$). Similarly, the submission of a bid or an ask limit order is classified into three categories: *Improving submission* ($Submit^{improve}$), *Submission at BBO* ($Submit^{BBO}$), and *Submission at Non-BBO* ($Submit^{Non-BBO}$) if it is placed inside the spread thus improving the midpoint price, adds liquidity at BBO, or adds liquidity down the book, respectively. Revision messages that add liquidity are considered as (re)submission messages and classified according to their aggressiveness level. Cancellations include both deletion messages and revision messages that reduce liquidity. We classify cancellations into *Worsening cancellation* ($Cancel^{worsen}$), *Cancellation at BBO* ($Cancel^{BBO}$) and *Cancellation at Non-BBO* ($Cancel^{Non-BBO}$), depending on whether they worsen the midpoint price, reduce liquidity at the BBO or reduce liquidity down the book. A summary of the order categories is presented in Table 4. All variables are measured in million-dollar values and mid-quote returns are calculated as log midpoint price changes, expressed in basis points. In terms of trade variables, we follow Fleming, Mizrach, and Nguyen (2018) and consider the trade summary messages that aggregate matched order(s) as a single trade in our price discovery.[5] Aggregation avoids artificially inflated serial correlation in the trade flow and allows us to better measure the price impact of trades by considering their total size. Our observations include both day (from 8:30:00 to 13:19:59 U.S. Central Time) and night (from 19:00:00 to 7:44:59) trading sessions.[6] Results are reported separately for each session.

The following SVAR model is estimated daily for each market and each trading session

[5]As discussed, the trade summary message that aggregates the matched limit orders does not provide the aggressor indicator if implied liquidity is involved in the match. If a trade is matched against outright limit order(s), we assign the aggressor of this trade to the opposite side of the matched outright limit orders, i.e., if the matched order(s) stand at the bid (ask) side, we consider the aggressor to be the seller (buyer). If the entire trade is executed against implied liquidity, we delete the trade. On average, 0.03%, 0.01%, and 0.01%, of total number of trades are deleted in the corn, soybean, and wheat markets, respectively, in each trading day.

[6]The closing time of CME Globex is 12:04:59, U.S. Central Time in some national holidays.

using OLS:

$$\boldsymbol{A}\boldsymbol{y}_t = \sum_{i=1}^{p} \boldsymbol{B}_i \boldsymbol{y}_{t-i} + \boldsymbol{\epsilon}_t, \tag{1}$$

where $\boldsymbol{\epsilon}_t \sim i.i.d.(\mathbf{0}, \boldsymbol{I})$, with $\boldsymbol{I}$ being the 9×9 identity matrix and $\mathbf{0}$ a 9×1 vector of zeros. The 9×1 endogenous variable vector $\boldsymbol{y}_t = [r_t, \boldsymbol{x}_t]'$ contains mid-quote returns (r_t), and trade and limit order variables $\boldsymbol{x}_t = \left[Trades^{same}, Trades^{change}, Submit^{improve}, Submit^{BBO}, Submit^{Non-BBO}, Cancel^{worsen}, Cancel^{BBO}, Cancel^{Non-BBO}\right]'$. The number of lags ($p$) is selected based on the Schwarz Information Criterion (SIC) with a maximum lag of 10.[7] $\boldsymbol{A}$ is a 9×9 matrix of structural parameters measuring the contemporaneous relationship between the endogenous variables. Due to the mechanics of the LOB, mid-quote returns can be moved by *Trades – change price* ($Trades^{change}$), *improving submission* ($Submit^{improve}$), and *worsening cancellation* ($Cancel^{worsen}$) contemporaneously, but not vice versa. Below, we define our $\boldsymbol{A}$ matrix in equation (1), allowing for the contemporaneous interactions described:

$$\boldsymbol{A} = \begin{bmatrix} 1 & \boldsymbol{C} \\ \mathbf{0}_{8\times1} & \boldsymbol{I}_{8\times8} \end{bmatrix}_{9\times9}, \tag{2}$$

where $\boldsymbol{C} = \begin{bmatrix} 0 & -a_{13} & -a_{14} & 0 & 0 & -a_{17} & 0 & 0 \end{bmatrix}$, $\mathbf{0}_{8\times1}$ is a 8×1 vector of zeros, and $\boldsymbol{I}_{8\times8}$ is a 8×8 identity matrix.

We measure the permanent price impacts following a 1-unit shock on either a trade or a limit order using impulse response (IRF) analysis. Notice a 1-unit shock is equivalent to a 1-million-dollar shock due to the scaling of the variables in million dollars. Specifically, we calculate the cumulative IRF corresponding to the mid-quote return equation. We truncate the impulse response up to 150 events after a shock and a confidence interval is computed by bootstrapping with 1,000 replications.[8]

[7] The maximum lag of 10 is imposed to reduce the computational burden. The proportions of trading days with lag orders less than 10 are 82.26% (95.92%), 43.82% (95.38%), and 78.76% (96.74%) at day (night) trading session in the corn, soybean, and wheat markets, respectively.

[8] The truncation level was determined in a preliminary analysis to ensure that all IRFs have stabilized at this point. Our bootstrapping is as follows. First, a random sample is drawn from the estimated model

Following Hasbrouck (1991) and Chaboud, Hjalmarsson, and Zikes (2021), we calculate the information share (IS) of each event by decomposing the variance of the mid-quote returns. The IS measures the proportion of the permanent price component that can be explained by the different elements in $\boldsymbol{y}_t = [r_t, \boldsymbol{x}_t]'$. Notice that the IS of r_t in $\boldsymbol{y}_t$ measures the role of the autoregressive component of the mid-quote returns on the efficient price variance. As discussed in Chaboud, Hjalmarsson, and Zikes (2021), ISs reflect the relative ex-ante variances of the IRFs described above. To calculate ISs, we express the stationary SVAR model as an infinite Wold moving-average (Wold-MA) process as follows:

$$\boldsymbol{y}_t = \boldsymbol{\Phi}_0 \boldsymbol{\epsilon}_t + \boldsymbol{\Phi}_1 \boldsymbol{\epsilon}_{t-1} + \boldsymbol{\Phi}_2 \boldsymbol{\epsilon}_{t-2} + \cdots , \tag{3}$$

Where the 9×9 $\boldsymbol{\Phi}$ matrices are MA terms. Following Beveridge and Nelson (1981), equation (3) can be decomposed as

$$\boldsymbol{y}_t = \widetilde{\boldsymbol{\Phi}}_1 (1) \boldsymbol{\epsilon}_t + \eta_t, \tag{4}$$

where $\widetilde{\boldsymbol{\Phi}}_1 (1) = \sum_{i=0}^{\infty} \boldsymbol{\Phi}_i$ is the long-run MA matrix. In our empirical application, we use $\widetilde{\boldsymbol{\Phi}}_1 (1) = \sum_{i=0}^{150} \boldsymbol{\Phi}_i$ where 150 has been previously identified as the number of events that ensures the mid-quote return has stabilized after a shock. In terms of the mid-quote return equation, $\widetilde{\boldsymbol{\Phi}}_1 (1) \boldsymbol{\epsilon}_t$ measures the permanent (efficient) price movements derived from the permanent random walk of the price process, while η_t are the returns generated by the transitory pricing errors. The variance of the permanent component of $\boldsymbol{y}_t$ is

$$\boldsymbol{\Omega} = \widetilde{\boldsymbol{\Phi}}_1 (1) \widetilde{\boldsymbol{\Phi}}_1 (1)', \tag{5}$$

and the permanent mid-quote return variance is given by the first diagonal element of $\boldsymbol{\Omega}$, i.e., $\omega_{11} = \widetilde{\Phi}_{11} (1)^2 + \widetilde{\Phi}_{12} (1)^2 + \cdots + \widetilde{\Phi}_{1k} (1)^2$, where $\widetilde{\Phi}_{1k}$ is the kth element in the first row

residuals with replacement. Second, new endogenous variable samples are reconstructed through the random sample and estimated parameters. Third, we re-estimate the SVAR model on the reconstructed endogenous variable samples and compute the cumulative IRF. The process is repeated 1,000 times and we then use the 2.5%-97.5% percentiles of bootstrapped cumulative IRFs as the 95% confidence interval.

of $\widetilde{\mathbf{\Phi}}_1(1)$, with $k = 1, \dots, 9$. The information share (IS) of the ith variable is defined as the contribution of variable i to the permanent mid-quote return variance, i.e.,

$$IS_i = \frac{\widetilde{\Phi}_{1i}(1)^2}{\sum_{j=1}^{k} \widetilde{\Phi}_{1j}(1)^2} = \frac{\widetilde{\Phi}_{1i}(1)^2}{\omega_{11}}. \tag{6}$$

The estimated transitory pricing error (noise), denoted as s_t, is derived as follows. We use the VMA representation in equation (3) to generate $\widetilde{\mathbf{\Phi}}_1(1)$, which is assumed to be constant within each day. For each observation t within a day, we generate 1,000 random shocks $\boldsymbol{\epsilon}_t \sim i.i.d.(\mathbf{0}, \boldsymbol{I})$ and use equation (4) to derive a sample of 1,000 noise observations (η_t) by keeping $\boldsymbol{y}_t$ constant. We use the sample average of η_t as the transitory pricing error s_t associated to the observed mid-quote returns (r_t). We model how trade and limit order variables affect the transitory pricing errors through the following regression estimated in each market:

$$\begin{aligned} s_t = & \alpha_0 + \alpha_1 s_{t-1} + \alpha_2 \mid Trades_t^{same} \mid + \alpha_3 \mid Trades_t^{change} \mid + \alpha_4 \mid Submit_t^{improve} \mid + \alpha_5 \mid Submit_t^{BBO} \mid + \\ & \alpha_6 \mid Submit_t^{Non-BBO} \mid + \alpha_7 \mid Cancel_t^{worsen} \mid + \alpha_8 \mid Cancel_t^{BBO} \mid + \alpha_9 \mid Cancel_t^{Non-BBO} \mid + e_t, \end{aligned} \tag{7}$$

where $\mid \cdot \mid$ denotes the absolute values of trades and limit orders, which assumes symmetric effects of buy and sell-initiated trades and changes in the bid and ask sides of the LOB. Using OLS, we estimate the regression for every trading day for each market and we report the median estimated coefficients and the proportion of statistically significant coefficients at the 5% level over the entire sample period.

In Table 5 we offer summary statistics of the variables in vector $\boldsymbol{y}_t$ by reporting the average of the daily proportions of each variable, both in number of events and contract values for the day (Panel A) and night (Panel B) trading sessions. We also report the contemporaneous impacts of each variable on mid-quote returns. For the day trading session and the three markets studied, trades represent around 2%-3% both in terms of total market events and their dollar values, with dollar value shares being usually above event time shares.

Most trades do not move the BBO, and those that move it represent less than 0.30% (0.75%) of total events (dollar value). Limit orders that move the BBO are also rare events and range between 0.1%-1.0% of total events and their dollar values. Most market activity corresponds to limit orders priced at the BBO or behind the BBO. Notice the relevance of cancellations both at and behind the BBO which represent between 16.90% and 31.26% of total events, with their dollar values ranging between 12.43% and 25.92%, respectively. Submissions at and behind the BBO represent 17.09%-34.49% of market events. Overnight market activity yields similar results, with submissions and cancellations behind the BBO being relatively more relevant than during the day trading session. Our results are qualitatively similar to Brogaard, Hendershott, and Riordan (2019), who suggest market events that move the BBO are rare in the TSX.

The median contemporaneous price impacts generated by trades that move the BBO during the day trading sessions are 3.32 bps (0.12 cents/bushel based on daily sample median prices, hereafter), 1.40 bps (0.13 cents/bushel) and 2.45 bps (0.13 cents/bushel). In the corn, soybean and wheat markets, respectively. These returns are similar to those triggered by limit orders that move the BBO, ranging from 1.40 to 3.32 bps across markets. Limit orders and trades priced at or behind the BBO have a null contemporaneous impact on mid-quote returns by definition. Similar contemporaneous price impacts can be observed in the night trading session.

3.3.1 Permanent price impacts

As discussed, permanent price impacts of trades and limit orders are calculated as the cumulative impulse responses of mid-quote returns up to 150 events derived from the SVAR models estimated for each day, and for the two continuous trading sessions. We report the descriptive statistics for the day trading session in Panel A of Table 6. The '% sig.' column shows the percent of sample days where price responses are statistically significant according to our bootstrap analysis. Market activity that moves the BBO generates statistically significant permanent responses in virtually all (100%) sample days, with the exception of worsening cancellations in the corn market, where around 89% of responses are statistically significant. Activity priced at or behind the BBO shows a wider range of statistical significance across markets (from 16.94% to 100%) and generates permanent price impacts generally below 1 basis point.

Permanent price impacts are consistent with the contemporaneous impacts on the mid-quote returns reported in Table 5. Median values suggest that a 1-million-dollar trade moving the BBO changes the corn and soybean mid-quote returns by 3.08 bps (0.12 cents/bushel) and 2.00 bps (0.18 cents/bushel), respectively. A 1-million-dollar submission moving the BBO results in median permanent corn and soybean price impacts of 1.99 bps (0.07 cents/bushel) and 1.58 bps (0.14 cents/bushel), respectively, whereas a 1-million-dollar cancellation moving the BBO causes permanent price shocks of 3.73 bps (0.14 cents/bushel) and 2.42 bps (0.22 cents/bushel), respectively. Results in the less liquid wheat market show relatively larger permanent price impacts. Trades that improve the BBO result in a 8.09 bps (0.41 cents) median permanent price impact, whereas aggressive cancellations and submissions cause median permanent price impacts of 4.93 bps (0.25 cents/bushel) and 6.94 bps (0.35 cents/bushel), respectively.

Consistent with price discovery requiring some time to complete and initial market underreaction, permanent price impacts could be larger than temporary price impacts except for the corn market. In the corn market however, the initial price impact of aggressive trades and submissions reverses over time. Compared to the corn and soybean markets, permanent price impacts in the less liquid wheat market are substantially larger than their contemporaneous counterparts for aggressive trades and limit orders. These results are consistent with differences in liquidity across markets. Abundant liquidity in the corn market may initially result in price overshooting before timely reaching the new equilibrium. In contrast, the light liquidity in the wheat market may prevent prices from quickly reaching their new equilibrium.

The night trading session results are presented in Panel B of Table 6 and are consistent with reduced liquidity during the night. Most 1-million-dollar events moving the BBO result in much larger permanent price impacts than during the day trading session, especially in the corn and wheat markets, where median price impacts across events can reach up to 9.82 bps (0.37 cents/bushel) and 14.19 bps (0.72 cents/bushel), respectively, with soybean median permanent price impacts across events reaching a maximum of 4.17 bps (0.37 cents/bushel).

3.3.2 Information shares

We report summary statistics of daily information shares (ISs) for the day trading session in Panel A of Table 7.[9] Results are highly consistent with the permanent price impacts reported in the previous section, with larger price impacts eliciting larger variability in the permanent price component. According to median values, while trades moving the BBO contribute by about 27%-30% to corn and soybean price discovery, they represent around 42% of the wheat price discovery. Limit order submissions or cancellations moving the BBO jointly represent around 56% of the corn and soybean price discovery, and about 50% of the wheat price discovery. Hence, at least half of the price discovery in grain futures markets can be attributed to aggressive limit orders. Wilcoxon signed-rank test results indicate that limit order joint contribution to the permanent price movement is larger than trades' contribution in all markets at 1% significance level. Our results are consistent with Pascual and Pascual-Fuster (2014), who suggest that limit orders are more informative about the permanent price component than trades. Notice that the ISs displayed by aggressive cancellations are substantially larger than those of aggressive submissions. These differences are statistically significant at the 1% level in all markets according to the Wilcoxon signed-rank test. This may indicate that traders cancel the most attractive market quotes to avoid being adversely selected by informed traders, which reduces transitory pricing errors and enhances pricing efficiency. In contrast, other trades and limit orders at or behind the BBO have a marginal

[9] Notice that the shares do not add to 100% as the IS of mid-quote returns autoregressive pattern is not reported in the table.

impact on the permanent price change, with their joint IS being smaller than 2% in corn and soybean markets and around 4% in the wheat market. This suggests that limit orders that do not move the BBO are less likely to incorporate new information to the permanent price as they have low execution probabilities compared to the aggressive limit orders.

Similar patterns can also be found in the night trading session shown in Panel B of Table 6. Cancellations moving the BBO have slightly higher ISs overnight than in the day trading session in all markets. Similar to day trading session, overnight limit orders are jointly more informative than trades at 1% significance level according to the Wilcoxon signed-rank tests. Tests also show the ISs of submissions moving the BBO are significantly different from those of cancellations moving the BBO at 1% level in all markets.

Our results are qualitatively similar to Brogaard, Hendershott, and Riordan (2019) and Chaboud, Hjalmarsson, and Zikes (2021). Brogaard, Hendershott, and Riordan (2019) measure the average permanent price impacts of different market events in the TSX 60 stock market. They identify permanent price impacts of trades separately for high-frequency traders (HFTs) and non-HFT traders who trade, on average, 1-million-dollar and 0.35-million-dollar worth of stocks on a daily basis. Similar to our results, they find limit orders priced at or behind the BBO to be more frequent than trades and limit orders moving the BBO. They identify price impacts of trades, submissions and cancellations moving the BBO to be on the order of 3.0-3.2 bps, 1.1-1.6 bps and 2.0-2.2 bps, respectively. Non-aggressive trades have price impacts between 0.1 and 1.0 bps and limit orders priced at or behind the BBO have price impacts up to 0.2 bps. Their variance decomposition results in IS values qualitatively similar to ours, with non-aggressive limit orders generating ISs mostly below 0.2% and up to 1.5%. Trades and limit orders moving the BBO cause most of the permanent price variance, with IS values between 5.2% and 19.6%. Focusing on the foreign currency markets in the Electronic Broking Services (EBS) platform, Chaboud, Hjalmarsson, and Zikes (2021) identify trades contributing about 32% to price discovery in recent years. Limit orders moving the BBO have price discovery shares between 5% and 17%, while limit orders priced at BBO have an IS of about 5%.

3.3.3 Price discovery around the USDA WASDE announcement

Like other financial markets (Chordia, Green, and Kottimukkalur 2018), traders in agricultural commodity markets change their behavior around public information releases, resulting in a spike in trading volume and realized volatility (e.g., Huang, Serra, and Garcia 2022). As shown in Fleming, Mizrach, and Nguyen (2018) for U.S. Treasury markets, this may result in changes in the informativeness of trades and limit orders. The World Agricultural Supply and Demand Estimates (WASDE) reports released by the United States Department of Agriculture (USDA) are a major public information source in agricultural futures markets, which we use to study how trades and limit orders contribute to price discovery around public information events. The WASDE reports are released monthly at 11:00 Central Time during the day trading session, which allows us to study the process of price discovery in real-time. Following Fleming, Mizrach, and Nguyen (2018), we estimate a SVAR for each announcement day using market events occurred during the time interval of 15, 30, 60, and 90 minutes before, during and after the WASDE announcements. Different window lengths allow us to assess how the value of information is assimilated over time (Hasbrouck 1991) as traders interpret the implications of public news. Also, this empirical setting allows us to explore how heightened uncertainty leading up to the report release changes trader behavior. We compare permanent price impacts and ISs on announcement days with their non-announcement counterparts measured through SVAR models estimated using the five days preceding and following the announcements. These models are estimated using the same intraday time interval as for non-announcement days to control for time-of-day effects and market conditions. Our sample includes 17 announcement days and 170 non-announcement days for every market. We estimate a SVAR model using observations within each window.[10]

The results are presented in Figures 1 and 2 where the upper (lower) panel shows the

[10]A few limit order activities are extremely tranquil with almost all zero values in some windows, our SVAR model cannot be estimated in three (one) non-announcement days in the corn (soybean) market.

difference between median permanent price impacts (information shares) on announcement and non-announcement days. Figure 1 focuses on aggressive trades and limit orders, which contribute the most to price discovery, and trades priced at the BBO. Figure 2 focuses on non-aggressive limit orders. The horizontal axis indicates the minutes before (negative numbers) and after (positive numbers) the announcements. For permanent price impacts, the median is calculated based on the statistically significant IRFs (5% level), with non-significant IRFs being assigned a value of zero. We find the uncertainty prior to the announcement causes a change in trading strategy, with the most aggressive limit orders, especially aggressive cancellations, and aggressive trades triggering larger price impacts (up to 2 bps) than on non-announcement days. As the announcement approaches, differences in median price impacts decline for both aggressive trades and limit orders, with the latter becoming less relevant than on non-announcement days. In contrast, non-aggressive trades become almost as relevant as aggressive trades. This is consistent with Figure F1 in Appendix F that shows trade messages in total are more frequent than aggressive limit order messages on announcement days. BBO-level liquidity submissions and cancellations (Figure 2) generally have an increased role in price discovery relative to non-announcement days, especially after the release, though the magnitudes of price impacts are not as large as trades and aggressive limit orders, especially in corn and soybean markets. This is consistent with resilient liquidity provision coming into the market during relevant price changes (He, Serra, and Garcia 2021), and with increased risk of adverse selection, which changes liquidity providers' strategies to more conservative approaches. Notice that price impacts of submissions and cancellations priced behind the BBO remain virtually unchanged. Figure F1 in Appendix F shows that during the announcement non-aggressive limit orders are at least 10 times more frequent than trades and aggressive limit orders, which suggests conservative liquidity provision is prevailing, facilitating a tight bid-ask spread on the announcement days.[11] Price

[11] A wider bid-ask spread occurs right after the announcement with the incorporation of new information and is tightened quickly. We calculate the median bid-ask spread per 1-min bin using a 90-min window before and after the announcements. Our results (not reported) show that the 1-min median bid-ask is indeed 1 tick size (0.25 cents in all markets).

impacts at announcement days do not return to the non-announcement benchmark within the 90-minute interval. Our results add to previous research on USDA WASDE reports by showing, for the first time, how different limit orders and trades incorporate information during public releases of information. These studies generally find that price discovery, measured as realized volatility, to be complete after one hour following the announcement (e.g., Bian et al. 2022). Our research suggests that changes in trader behavior last longer, as the market does not return to benchmark levels during at least 90 minutes after announcement.

We now turn the discussion to changes in information shares on announcement days. Relative to non-announcement days, cancellations that move the BBO experience a large increase in information shares in the soybean (up to 20%) and wheat (up to 10%) markets, but not in the most liquid corn market. Consistent with permanent price impacts, the most aggressive limit orders reduce their relevance after the announcement, with aggressive trades increasing their price discovery shares up to 33%. Non-aggressive trades' information shares stay relatively above, but very close to non-announcement days. While after the announcement, the price discovery role of aggressive liquidity diminishes, the role of passive liquidity increases.[12] In the case of soybean, for example, information shares driven by submissions and cancellations both at BBO, increase up to 0.33% and 0.22%, respectively. As expected, and consistent with permanent price impacts, limit orders priced behind the BBO still have marginal roles in price discovery. Similar to permanent price impacts, information shares after announcement relative to non-announcement days do not return to the non-announcement benchmark within 90 minutes.

In summary, our results indicate that traders adjust their trading schedules ahead of news arrival. Fleming, Mizrach, and Nguyen (2018) find a similar pattern in the U.S. Treasury market for Federal Open Market Committee (FOMC) announcements. However, our results extend Fleming, Mizrach, and Nguyen (2018) by separating limit orders into differ-

[12] We test whether the differences of median information shares between announcement and non-announcements are statistically different using the Wilcoxon signed rank test. Our results (not reported) show that the post window information shares of aggressive and non-aggressive trades are statistically greater on announcement days than those at non-announcement days at the 1% level.

ent categories and showing their different roles in price discovery. Our results are consistent with liquidity providers learning the news gradually and avoiding adverse selection by either canceling liquidity or submitting liquidity at or behind the BBO. Moreover, and especially relevant after the announcement, trades contribute to the price discovery more than aggressive limit orders compared to same time interval on non-announcement days, which suggests that trades are strongly involved in the race to capture the value of public information. While this finding is consistent with Huang, Serra and Garcia (2022), it is different from Fleming, Mizrach, and Nguyen (2018) who find the informativeness of trades does not increase as much for post-FOMC announcement periods. These differences may be due either to differences in modeling approach or different trader behavior across different markets.

3.4 Transitory pricing errors

In this subsection we present the results of our transitory pricing error analysis. We consider two different model specifications denoted as models (1) and (2). In model (1) we regress transitory pricing errors against their first lag, which essentially captures the autoregressive component of transitory pricing errors. Model (2) extends model (1) by adding all trade and limit order variables as in equation (7). We use Newey-West standard errors to assess statistical significance. While these regressions do not have a causal interpretation, they show which factors are statistically significantly correlated with transitory pricing errors.

Median parameter estimates and the percent of days where parameters are statistically significant are presented in Table 8. Consistent with previous literature (e.g., Hansen and Lunde 2006), our results indicate that the autoregressive component of transitory pricing errors is statistically significant in at least 90% of the sample days. Non-aggressive limit orders are weakly correlated with transitory pricing errors as their coefficients are close to zero, have mixed signs and are only statistically significant in a marginal portion of the sample period (around 5% of the days across markets). Trades priced at the BBO are only significant in around 5%-7% of the sample days. Median parameter values are positive for soybean and wheat, suggesting that trades priced at the BBO are associated to increased transitory pricing errors. In contrast, trades at the BBO are negatively correlated with pricing errors in the most liquid corn market. Aggressive trades and limit orders are statistically significant in a larger proportion of sample days (from 12%-19% for submissions; 15%-22% for trades; and 26%-28% for cancellations moving the BBO). An aggressive 1-million-dollar trade is associated with a 0.017 and 0.052 bps increase in transitory pricing errors in soybean and wheat markets, respectively and with a trivial increase in pricing errors in the most liquid corn market. This is consistent with the corn market being highly liquid and resilient (He, Serra, Garcia 2021), which reduces liquidity constraints preventing the market price from reaching a new equilibrium. The correlation between an aggressive 1-million-dollar limit order submission and transitory pricing errors in corn, soybean, and wheat markets is -0.003, -0.016, and -0.084 bps, respectively. Notice that aggressive order submissions contribute to tighten the quoted spread, with wider spreads being associated to pricing errors through lower liquidity (e.g., Putniņš 2013). A 1-million-dollar aggressive cancellation, resulting in a widening of the quoted spread, is associated to increased pricing errors on the order of 0.053 (0.149) bps in the soybean (wheat) market price. However, aggressive cancellations are negatively correlated with transitory pricing errors in the most liquid corn market (0.073 bps) which is consistent with the previous argument on liquidity and resiliency in this market.[13] Results for the night trading session are presented in Table G1 of Appendix G and show some differences with the day trading session.

4 Conclusions

Electronic trading platforms allow traders to update their orders in real time, which has resulted in a high level of limit order submissions, followed by fast revisions and cancella-

[13]We investigate if worsening cancellations are followed by improving submissions (as this would tighten the quoted spread). We calculate the proportion of subsequent (defined as 1 event time later) improving submissions over the total worsening cancellations in each trading day. For corn, the average across the whole sample is 18%, for soybean 11%, while for wheat 8%. This indicates that the corn market tightens the spread relatively faster than the other two markets.

tions. Electronic trading has also blurred the traditional distinction between informed and uninformed traders (Eisler, Bouchaud, and Kockelkoren 2012). In the current environment, informed traders provide liquidity through limit orders rather than merely consuming liquidity through market orders. Not surprisingly, previous research has shown that price discovery is not restricted to trades, as limit orders can also reveal information (Fleming, Mizrach, and Nguyen 2018; Brogaard, Hendershott, and Riordan 2019; Chaboud, Hjalmarsson, and Zikes 2021). This is the first study that investigates the dynamics of limit orders, and their role in price discovery in the futures markets. We focus on CME Globex corn, soybean and wheat futures markets observed from January 7, 2019, to June 26, 2020. Our results suggest that around 75%-79% of the limit orders submitted are finally cancelled, which contrasts with a much smaller proportion of these orders getting executed (25%-28%) or revised (7%-8%). Most submissions, executions, revisions, and deletions occur during the opening and closing of the day trading session, and aggressive limit orders are more likely to be executed than less aggressive ones. Latency of limit orders is low, with half of the limit orders being deleted, revised or executed within 5 to 12 seconds after their placement across markets. This positions human traders at a clear disadvantage in the new market environment.

This is the first study that investigates the dynamics of limit orders, and their role in price discovery in the agricultural futures markets. We focus on CME Globex corn, soybean and wheat futures markets observed from January 7, 2019, to June 26, 2020. Our results suggest that around 75%-79% of the limit orders submitted are finally cancelled, which contrasts with a much smaller proportion of these orders getting executed (25%-28%) or revised (7%-8%). Most submissions, executions, revisions, and deletions occur during the opening and closing of the day trading session, and aggressive limit orders are more likely to be executed than less aggressive ones. Latency of limit orders is low, with half of the limit orders being deleted, revised or executed within 5 to 12 seconds after their placement across markets. This positions human traders at a clear disadvantage in the new market environment.

We follow Chaboud, Hjalmarsson, and Zikes (2021)'s framework and use a structural

VAR model that explores the price discovery role of different orders classified by their aggressiveness. We document how these different orders contribute to permanent (efficient) price movements and transitory pricing errors (noises). We find that aggressive limit orders dominate price discovery statistically, while trades contribute less than half to overall price discovery across the different markets. Among limit orders, price discovery essentially comes from submissions that tighten the quoted spread and cancellations that widen the spread. These two order types jointly represent less than 1.5% of overall market messages. A 1-million-dollar limit order either improving or worsening the spread has a median permanent price impact of 1.6-3.7 bps in the corn and soybean markets, which compares to the 2.0-3.1 bps permanent price impact of a one-million-dollar aggressive trade. In the less liquid wheat market, price impacts are larger, in the range between 4.9 and 8.1 bps. In terms of information shares, cancellations that change the midpoint price contribute the most to price discovery, with shares ranging between 33%-45% across markets, followed by aggressive trades and submissions whose price discovery shares range between 28%-42% and 12%-16%, respectively. Non-aggressive trades representing around 2% of market events, have relatively small price discovery shares (2%-3%). Non-aggressive limit orders represent 95% of total market events but have a marginal role in price discovery, with information shares being less than 1% in all markets. Our results are largely consistent with Brogaard, Hendershott, and Riordan (2019) and Chaboud, Hjalmarsson, and Zikes (2021) and suggest that limit orders are at least as informative as trades, with the most aggressive limit orders carrying most of this information.

We also assess how price discovery evolves around the USDA WASDE announcements. Our results show that traders change their trading strategy, especially aggressive limit orders, prior to the arrival of announcements. Aggressive trades show a significantly increased role in price discovery (up to 33%) following the announcements while aggressive limit orders show a diminishing role. Limit orders priced at BBO also contribute more to the price discovery but with trivial magnitudes of price impacts (less than 1.5 bps) and information shares (up to 1.2%). Similarly, limit orders behind the BBO still have a marginal role in price discovery around the announcements.

Aggressive trades and limit orders have the largest correlation with transitory pricing errors. Submissions that tighten the spread are negatively correlated with price errors in all markets, which is consistent with previous literature attributing a large proportion of transitory pricing errors (noises) to the bid-ask spread and illiquidity. Cancellations that increase the spread and aggressive trades are negatively correlated to pricing errors in the most liquid corn market but positively correlated with pricing errors in the soybean and wheat markets.

We depart from previous research studying the informativeness of volume-weighted midpoint prices at different depths of the LOB in futures markets (Arzandeh and Frank 2019). Consistent with the mechanics of the LOB, this research shows that these midpoint prices at different LOB depths are highly correlated, display a common stochastic trend assumed to represent the efficient market price, and are informative, even if they are deep down the book. Instead, we focus on how market and limit order submissions, revisions, and cancellations classified by their aggressiveness, contribute to price discovery. Our results suggest that only a small proportion of market activities impounds new information into the price, with activities far down the book being hardly informative.

Our findings are compatible with informed traders pursuing execution through aggressive limit orders to earn the quoted spread instead of immediate trades. Our results are also consistent with more uninformed liquidity providers being willing to provide liquidity either at or behind the BBO in the new market environment due to the transparency of the LOB, their ability to monitor the market in real time and to cancel their orders at any time.

Information on trader IDs would further allow identifying what is the role of different trader types on price discovery in our markets, such as in Brogaard, Hendershott, and Riordan (2019). Our results suggest differences between the most and least liquid markets. From this perspective, it would be informative to consider livestock markets, which are among the least liquid wheat markets in agricultural commodities, for comparison purposes. An analysis of the distributional impacts of changes in liquidity provision after the introduction of electronic trading in CME futures markets is another avenue of further research.

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Table 1: Limit order activities.

This table reports summary statistics of limit order activities in the CME corn, soybean, and wheat futures markets. The three different markets are organized by columns. Panel A reports the proportions of limit order executions, deletions, and revisions defined as the number of limit orders executed, deleted, and revised over the total number of limit orders submitted, respectively, during the continuous trading sessions. The three order activity categories are not mutually exclusive as a limit order may be both revised and executed for example. Hence, the sum across the three categories may not necessarily be 100%. Panel B shows the proportions of limit order executions, deletions, and revisions by order aggressiveness during the continuous trading sessions. Two aggressiveness levels are distinguished, *BBO* and *Non-BBO*. *BBO* (*Non-BBO*) represents limit orders submitted at (behind) the best bid/ask quote. Proportion of limit order submissions is defined as the number of limit orders submitted at each order aggressiveness level over the total number of limit orders. Proportions of limit order executions, deletions, and revisions are defined as the number of limit orders executed, deleted, and revised for each order aggressiveness level over the total number of limit orders submitted at that specific aggressiveness level, respectively. Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day trading sessions and 368 night trading sessions.

	Corn					Soybean					Wheat				
	Mean	Std	Min	Med	Max	Mean	Std	Min	Med	Max	Mean	Std	Min	Med	Max
Panel A: Order activity.															
Execution rate (%)	27.82	3.39	18.98	27.70	36.31	24.45	2.98	13.19	24.59	32.13	27.77	3.39	15.39	28.02	35.63
Revision rate (%)	7.91	1.60	3.63	7.72	17.29	6.83	1.30	3.90	6.61	15.52	7.42	1.34	3.29	7.27	12.67
Deletion rate (%)	78.05	3.10	70.81	78.30	86.57	78.73	2.67	71.53	78.63	88.17	75.29	2.99	68.19	75.18	86.00
Panel B: Order activity by aggressiveness.															
Submission (*BBO*, %)	71.01	4.68	55.57	71.39	83.39	72.54	3.23	58.76	72.71	81.13	67.15	4.66	56.63	67.21	80.73
Submission (*Non-BBO*, %)	28.99	4.68	16.61	28.61	44.43	27.46	3.23	18.87	27.29	41.24	32.85	4.66	19.27	32.79	43.37
Execution (*BBO*, %)	35.19	5.09	19.06	34.70	47.54	29.95	3.89	15.16	30.02	40.89	36.33	3.61	23.81	36.70	44.77
Execution (*Non-BBO*, %)	10.28	2.09	5.38	10.02	22.74	10.07	1.65	5.67	9.97	16.01	10.51	2.55	4.12	10.46	17.62
Deletion (*BBO*, %)	73.07	4.68	61.02	73.37	87.62	74.22	3.49	64.85	74.26	86.65	67.95	3.28	60.03	67.60	78.81
Deletion (*Non-BBO*, %)	89.68	1.94	82.65	89.74	94.45	90.47	1.61	85.08	90.56	94.68	90.06	2.36	83.28	90.14	96.00
Revision (*BBO*, %)	6.78	1.74	2.58	6.52	16.65	5.18	1.47	2.23	4.90	15.71	4.59	1.00	2.33	4.43	7.84
Revision (*Non-BBO*, %)	10.64	2.87	5.30	10.17	34.63	11.14	1.88	6.64	11.13	16.73	13.36	2.98	5.33	13.66	22.53

Table 2: Limit order executions after revisions and before cancellations.

This table displays the percentage of limit order submissions that are executed after revision or before cancellation during the two continuous (day and night) trading sessions in the CME corn, soybean, and wheat futures markets. The three different markets are organized by columns. Statistics for the continuous trading sessions are based on limit orders submitted during the continuous trading sessions. Executions after revisions represent the percent of limit orders that are executed after revision relative to the total number of limit orders that are revised during the continuous trading sessions. Executions before deletions represent the percentage of limit orders that are executed before cancellation relative to the total number of limit orders that are finally cancelled. *Total* denotes all submitted limit orders. *BBO* (*Non-BBO*) represents limit orders submitted at (behind) the best bid/ask quotes. The equal means Welch t-test between *BBO* and *Non-BBO* is conducted. *** denotes statistical significance at 1% level. Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day and 368 night trading sessions.

		Corn			Soybean			Wheat		
		Total	*BBO*	*Non-BBO*	*Total*	*BBO*	*Non-BBO*	*Total*	*BBO*	*Non-BBO*
Executions after revisions	Mean	41.94%	48.73%	33.11%	37.33%	43.36%	31.45%	41.87%	66.12%	25.34%
	Std. Dev	7.38%	10.41%	7.67%	7.27%	10.77%	6.62%	6.86%	8.73%	6.91%
	Min.	18.72%	15.37%	13.56%	11.53%	9.59%	13.67%	23.56%	41.66%	9.14%
	Median	42.51%	49.25%	32.75%	37.89%	43.26%	31.84%	42.31%	67.93%	24.10%
	Max.	62.10%	73.67%	50.72%	56.44%	67.88%	54.75%	60.50%	82.45%	48.06%
	Diff.		t-stat.	23.30***		t-stat.	18.17***		t-stat.	70.63***
Executions before deletions	Mean	8.34%	11.42%	2.37%	4.33%	5.67%	1.44%	4.36%	6.34%	1.32%
	Std. Dev	1.39%	1.99%	0.66%	0.79%	1.07%	0.33%	0.91%	1.11%	0.45%
	Min.	4.99%	6.50%	1.21%	1.77%	2.09%	0.66%	1.70%	2.56%	0.35%
	Median	8.32%	11.38%	2.33%	4.43%	5.76%	1.41%	4.34%	6.36%	1.26%
	Max.	12.70%	17.67%	8.46%	6.47%	8.85%	2.73%	6.93%	9.17%	3.16%
	Diff.		t-stat.	83.30***		t-stat.	72.67***		t-stat.	81.14***

Table 3: Limit order activity latency during continuous trading sessions.

This table reports the latency of limit order executions (Panel A), cancellations (Panel B), and revisions (Panel C) during the two continuous (day and night) trading sessions in CME corn, soybean, and wheat futures markets. The three different markets are organized by columns. Latency is defined as the elapsed time between limit order placement and 1st execution, deletion, and 1st revision, respectively. '–' indicates the two order activities have identical timestamps. 's', 'ms', 'μs', and 'ns' represent second, millisecond, microsecond, and nanosecond, respectively. *Total* denotes all submitted limit orders. *BBO* (*Non-BBO*) represents limit orders submitted at (behind) the best bid/ask quotes. CME continuous trading sessions include night trading and day trading sessions. Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day trading sessions and 368 night trading sessions.

	Corn			Soybean			Wheat		
	Total	*BBO*	*Non-BBO*	*Total*	*BBO*	*Non-BBO*	*Total*	*BBO*	*Non-BBO*
Panel A: Execution latency–submission to the 1st execution.									
Mean	506.51s	155.68s	3369.26s	293.74s	94.92s	1860.00s	326.93s	99.24s	1959.42s
Std. Dev	3154.06s	1042.88s	8547.12s	2197.17s	765.88s	5955.93s	2352.48s	776.64s	6152.50s
Min.	–	–	–	–	–	–	–	–	–
P25	0.81s	0.50s	62.94s	0.20s	0.08s	25.11s	0.31s	0.12s	28.41s
Median	11.53s	7.93s	330.88s	5.46s	3.76s	125.60s	7.54s	5.10s	133.53s
Panel B: Deletion latency–submission to deletion.									
Mean	935.67s	149.75s	2468.55s	446.88s	83.96s	1235.38s	598.70s	117.37s	1324.76s
Std. Dev	4818.60s	1243.50s	7869.94s	3077.50s	850.16s	5250.69s	3598.60s	1013.00s	5482.64s
Min.	238.42ns	238.42ns	0.16μs	–	238.42ns	–	–	–	–
P25	0.09s	0.02s	1.86s	0.02s	4.87ms	1.39s	0.10s	0.01s	1.77s
Median	4.33s	1.71s	38.87s	2.00s	0.87s	16.75s	4.74s	1.65s	21.91s
Panel C: Revision latency–submission to the 1st revision.									
Mean	711.39s	131.59s	1585.32s	343.88s	74.41s	680.49s	413.79s	101.62s	633.26s
Std. Dev	3778.42s	1135.67s	5707.96s	2425.09s	804.31s	3495.02s	2672.37s	904.20s	3386.88s
Min.	238.42ns	238.42ns	0.15μs	238.42ns	238.42ns	2.86μs	238.42ns	238.42ns	4.29μs
P25	0.19s	5.92ms	5.02s	0.01s	2.45ms	1.07s	0.81s	0.51s	1.00s
Median	8.29s	2.03s	52.55s	2.92s	0.60s	11.09s	8.01s	6.06s	9.90s

Table 4: Summary of the order categories.

Aggressiveness of event	Variable name	Description
Move the BBO	*Trades – change price* ($Trades^{change}$)	Buy-initiated (+1) or sell-initiated (−1) trades that deplete full liquidity at BBO and move the mid-quote price.
	Improving Submission ($Submit^{improve}$)	Limit order placements either increasing the best bid price (+1) or decreasing the best ask price (−1).
	Worsening cancellation ($Cancel^{worsen}$)	Limit order cancellations either decreasing the best bid (−1) price or increasing the best ask (+1) price.
At the BBO	*Trades – same price* ($Trades^{same}$)	Buy-initiated (+1) or sell-initiated (−1) trades that do not deplete full liquidity at BBO and do not move the midpoint price.
	Submission at BBO($Submit^{BBO}$)	Limit orders adding liquidity at the current best bid price (+1) or the current best ask price (−1).
	Cancellation at BBO ($Cancel^{BBO}$)	Limit orders reducing liquidity at the current best bid price (−1) or the current best ask price (+1).
Behind the BBO	*Submission at Non-BBO* ($Submit^{Non-BBO}$)	Limit orders adding liquidity below the current best bid price (+1) or above the current best ask price (−1).
	Cancellation at Non-BBO ($Cancel^{Non-BBO}$)	Limit orders reducing liquidity below the current best bid price (−1) or above the current best ask price (+1).

Table 5: Summary statistics of messages.

This table reports the average proportion of trade and limit order messages expressed in number of events and dollar values in a day trading session (Panel A) and night trading session (Panel B) across all trading days in the sample in CME corn, soybean, and wheat futures markets. The three different markets are organized by columns. Event time proportions are measured as the average message ratio of each variable over the total number of messages across all trading days in the sample. Dollar value proportions are measured as the average ratio of the sum (in absolute million dollar values) of each variable relative to the total absolute dollar values of all variables across all trading days in the sample. Contemporaneous price impacts to mid-quote returns (bps) is measured as the immediate price impacts (median absolute bps.) generated by each variable. *Trades – change price* represents trades that deplete full liquidity at the BBO, *Trades – same price* captures trades that do not deplete full liquidity at the BBO. *Improving submission* represents limit order placements that tighten the quoted spread, *Submission at BBO* represents limit order placements that add liquidity at the current best bid/ask price. *Submission at Non-BBO* represents limit order placements that add liquidity below the current best bid/ask price. *Worsening cancellation* represents limit order cancellations that widen quoted spread, *Cancellation at BBO* represents limit order cancellations that reduce liquidity at the current best bid/ask price. *Cancellation at Non-BBO* represents limit order cancellations that reduce liquidity below the current best bid/ask price. Our revision messages are decomposed into corresponding cancellation and (re)submission messages. Implied order messages are also included. Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day trading sessions and 368 night trading sessions.

	Corn			Soybean			Wheat		
	# event	$ values	Contemporaneous price impacts	# event	$ values	Contemporaneous price impacts	# event	$ values	Contemporaneous price impacts
Panel A: Day trading session.									
Trades – change price	0.16%	0.40%	3.32	0.24%	0.50%	1.40	0.30%	0.75%	2.45
Trades – same price	2.48%	2.18%		1.96%	2.47%		2.17%	2.89%	
Improving submission	0.37%	0.43%	3.32	0.75%	0.71%	1.40	0.90%	1.01%	2.45
Submission at BBO	22.46%	18.68%		21.50%	16.83%		17.09%	13.06%	
Submission at Non-BBO	29.29%	37.10%		33.04%	38.72%		34.49%	43.57%	
Worsening cancellation	0.14%	0.10%	3.32	0.29%	0.29%	1.40	0.35%	0.36%	2.45
Cancellation at BBO	21.67%	16.79%		21.69%	15.94%		16.90%	12.43%	
Cancellation at Non-BBO	27.16%	24.30%		29.19%	24.59%		31.26%	25.92%	
Avg. event time per day	378,121			589,257			359,047		
Panel B: Night trading session.									
Trades – change price	0.20%	0.43%	3.32	0.33%	0.74%	1.40	0.31%	0.62%	2.45
Trades – same price	2.29%	2.29%		2.19%	2.72%		2.10%	2.23%	
Improving submission	0.51%	0.68%	3.32	1.07%	1.19%	1.40	1.06%	1.19%	2.45
Submission at BBO	17.37%	15.13%		16.22%	12.62%		13.03%	9.84%	
Submission at Non-BBO	34.06%	40.53%		37.17%	43.12%		37.89%	45.33%	
Worsening cancellation	0.22%	0.20%	3.32	0.48%	0.41%	1.40	0.51%	0.47%	2.45
Cancellation at BBO	16.65%	13.60%		16.15%	11.88%		12.77%	9.32%	
Cancellation at Non-BBO	32.15%	27.14%		33.38%	27.32%		35.20%	31.01%	
Avg. event time per day	113,852			163,714			113,971		

Table 6: Permanent price impacts to mid-quote returns.

This table reports the summary statistics of daily price impacts (bps.) of trades and limit order flows during the day trading session (Panel A), and night trading session (Panel B) across all trading days in our sample in CME corn, soybean, and wheat futures markets, respectively. The three different markets are organized by columns. Price impacts are calculated as the cumulative impulse responses of mid-quote returns to trades and limit order flows up to 150 events. All results are obtained based on the estimated SVAR model

$$\boldsymbol{A}\boldsymbol{y}_t = \sum_{i=1}^{p} \boldsymbol{B}_i \boldsymbol{y}_{t-i} + \boldsymbol{\epsilon}_t,$$

where $\boldsymbol{y}_t = \left[r_t, Trades_t^{same}, Trades_t^{change}, Submit_t^{improve}, Submit_t^{BBO}, Submit_t^{Non-BBO}, Cancel_t^{worsen}, Cancel_t^{BBO}, Cancel_t^{Non-BBO}\right]'$ and $\boldsymbol{A}$ matrix is detailed in equation (2). r_t denotes log mid-quote returns. $Trades_t^{change}$ represents trades that deplete full liquidity at the BBO and $Trades_t^{same}$ represents trades that do not deplete full liquidity at the BBO. All trades variables are signed $+1$ for buy-initiated trades and -1 for sell-initiated trades. $Submit_t^{improve}$, $Submit_t^{BBO}$, and $Submit_t^{Non-BBO}$ denote limit orders that tighten the quoted spread, add liquidity at the BBO, and add liquidity behind the BBO, all in million dollar values, respectively. $Cancel_t^{worsen}$, $Cancel_t^{BBO}$, and $Cancel_t^{Non-BBO}$ denote limit orders that widen the quoted spread, reduce the liquidity at BBO, and reduce the liquidity behind BBO, all in million dollar values, respectively. All submission variables are signed $+1$ for bids and -1 for offers while all cancellation variables are signed -1 for bids and $+1$ for offers. We calculate the proportion of statistically significant price impacts across all trading days in our sample based on the 95% confidence interval by bootstrapping with 1,000 replications and results are shown in column "% sig.". Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day trading sessions and 368 night trading sessions.

	Corn (bps.)				Soybean (bps.)				Wheat (bps.)			
	Mean	Std.	Med	% sig.	Mean	Std.	Med	% sig.	Mean	Std.	Med	% sig.
Panel A: Day trading session.												
Trades – change price	3.23	1.39	3.08	100.00%	2.12	0.64	2.00	100.00%	8.23	2.46	8.09	99.73%
Trades – same price	0.71	0.37	0.64	100.00%	0.59	0.23	0.53	100.00%	1.99	0.85	1.95	99.46%
Improving submission	2.14	1.00	1.99	99.46%	1.66	0.64	1.58	100.00%	5.29	2.55	4.93	98.92%
Submission at BBO	0.13	0.13	0.09	98.92%	0.23	0.15	0.19	100.00%	1.15	0.67	1.01	100.00%
Submission at Non-BBO	-0.02	0.01	-0.01	56.18%	-0.01	0.01	-0.01	53.23%	-0.05	0.03	-0.04	25.81%
Worsening cancellation	4.14	2.65	3.73	89.25%	2.61	1.09	2.42	98.39%	7.52	3.21	6.94	97.58%
Cancellation at BBO	0.03	0.05	0.01	16.94%	0.08	0.09	0.05	43.01%	0.56	0.38	0.48	79.03%
Cancellation at Non-BBO	0.06	0.06	0.04	87.63%	0.08	0.06	0.08	53.23%	0.25	0.13	0.22	80.11%
Panel B: Night trading session.												
Trades – change price	7.78	4.89	6.35	98.39%	2.85	1.00	2.72	100.00%	14.19	5.45	13.33	99.46%
Trades – same price	1.00	0.64	0.81	89.52%	0.54	0.27	0.49	98.39%	2.66	1.38	2.40	96.77%
Improving submission	5.32	3.93	4.31	98.66%	1.56	0.75	1.49	100.00%	8.52	5.00	7.69	100.00%
Submission at BBO	0.25	0.27	0.15	74.19%	0.29	0.13	0.28	100.00%	1.67	1.01	1.52	98.92%
Submission at Non-BBO	-0.02	0.02	-0.01	5.11%	-0.01	0.01	-0.01	69.35%	0.01	0.05	0.01	2.96%
Worsening cancellation	9.82	7.68	7.97	89.78%	4.17	2.05	4.05	100.00%	13.14	7.16	12.46	96.24%
Cancellation at BBO	0.18	0.17	0.12	52.42%	0.16	0.07	0.15	92.47%	1.02	0.62	0.87	78.76%
Cancellation at Non-BBO	0.10	0.09	0.09	52.42%	0.10	0.04	0.09	95.97%	0.33	0.20	0.30	66.40%

Table 7: Information shares.

This table reports summary statistics of the daily information shares during the day trading session (Panel A), and night trading session (Panel B) across all trading days in our sample in CME corn, soybean, and wheat futures markets. The three different markets are organized by columns. Information shares are calculated based on the estimated SVAR model

$$\boldsymbol{A}\boldsymbol{y}_t = \sum_{i=1}^{p} \boldsymbol{B}_i \boldsymbol{y}_{t-i} + \boldsymbol{\epsilon}_t,$$

where $\boldsymbol{y}_t = \Big[r_t, Trades_t^{same}, Trades_t^{change}, Submit_t^{improve}, Submit_t^{BBO}, Submit_t^{Non-BBO}, Cancel_t^{worsen}, Cancel_t^{BBO}, Cancel_t^{Non-BBO}\Big]'$ and $\boldsymbol{A}$ matrix is detailed in equation (2). r_t denotes log mid-quote returns. $Trades_t^{change}$ represents trades that deplete full liquidity at the BBO and $Trades_t^{same}$ represents trades that do not deplete full liquidity at the BBO. All trades variables are signed $+1$ for buy-initiated trades while -1 for sell-initiated trades. $Submit_t^{improve}$, $Submit_t^{BBO}$, and $Submit_t^{Non-BBO}$ denote limit orders that tighten the quoted spread, add liquidity at the BBO, and add liquidity behind the BBO, all in million dollar values, respectively. $Cancel_t^{worsen}$, $Cancel_t^{BBO}$, and $Cancel_t^{Non-BBO}$ denote limit orders that widen the quoted spread, reduce the liquidity at BBO, and reduce the liquidity behind BBO, all in million dollar values, respectively. All submission variables are signed $+1$ for bids and -1 for offers while all cancellation variables are signed -1 for bids and $+1$ for offers. We assess whether the median aggregated information shares of improving submission and worsening cancellation are statistically equal to those of trades – change price using the Wilcoxon signed rank test with p-values shown in row "Limit total vs. Trades". The same test is used to examine whether the distributions of information shares of improving submissions are statistically different from those of worsening cancellations with p-values shown in row "Improve vs. Worsen". Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day trading sessions and 368 night trading sessions.

	Corn (%)			Soybean (%)			Wheat (%)		
	Mean	Std.	Med	Mean	Std.	Med	Mean	Std.	Med
Panel A: Day trading session.									
Trades – change price	31.68	17.23	29.71	29.13	12.29	27.48	42.62	15.18	41.80
Trades – same price	1.91	2.02	1.14	2.31	1.55	1.94	2.81	2.03	2.31
Improving submission	14.88	10.57	12.10	18.24	10.54	16.36	18.08	10.73	16.36
Submission at BBO	0.09	0.14	0.03	0.41	0.49	0.25	0.99	1.00	0.71
Submission at Non-BBO	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Worsening cancellation	43.95	22.74	44.63	40.47	15.76	39.49	34.19	14.94	33.22
Cancellation at BBO	0.01	0.02	0.00	0.07	0.14	0.01	0.24	0.28	0.15
Cancellation at Non-BBO	0.02	0.03	0.00	0.06	0.07	0.04	0.05	0.05	0.03
Limit total vs. Trades	<0.001			<0.001			<0.001		
Improve vs. Worsen	<0.001			<0.001			<0.001		
Panel B: Night trading session.									
Trades – change price	33.96	20.76	30.21	33.59	17.77	32.58	43.89	20.92	39.55
Trades – same price	0.99	1.64	0.45	1.32	1.29	0.90	1.87	1.93	1.26
Improving submission	16.76	15.22	12.38	13.17	10.45	10.65	16.54	12.8	13.47
Submission at BBO	0.08	0.20	0.02	0.48	0.48	0.33	0.74	0.81	0.46
Submission at Non-BBO	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Worsening cancellation	46.28	23.18	47.51	45.41	20.5	45.65	36.23	19.66	34.5
Cancellation at BBO	0.03	0.06	0.01	0.21	0.25	0.12	0.28	0.33	0.18
Cancellation at Non-BBO	0.01	0.03	0.00	0.04	0.04	0.03	0.03	0.04	0.02
Limit order vs. Trades	<0.001			<0.001			<0.001		
Improve vs. Worsen	<0.001			<0.001			<0.001		

Table 8: Transitory pricing errors (noises) during the day trading session: Trades and limit orders.

This table reports the regression results of transitory pricing errors (noises) on all trades and limit order variables during the day trading session in our sample in CME corn, soybean, and wheat futures markets, respectively. The three different markets are organized by columns. The transitory pricing errors are extracted from the VMA representation of our structural VAR model. Our regression specifications are as follows

$$
\begin{aligned}
s_t = &\alpha_0 + \alpha_1 s_{t-1} + \alpha_2 \mid Trades_t^{same} \mid + \alpha_3 \mid Trades_t^{change} \mid + \alpha_4 \mid Submit_t^{improve} \mid + \alpha_5 \mid Submit_t^{BBO} \mid + \alpha_6 \mid Submit_t^{Non-BBO} \mid + \\
&\alpha_7 \mid Cancel_t^{worsen} \mid + \alpha_8 \mid Cancel_t^{BBO} \mid + \alpha_9 \mid Cancel_t^{Non-BBO} \mid + e_t,
\end{aligned}
$$

where s_t is the transitory pricing errors at event time t and s_{t-1} is its first-lag value. $\mid \cdot \mid$ denotes absolute values of independent variables. $Trades_t^{change}$ represents trades that deplete full liquidity at the BBO and $Trades_t^{same}$ represents trades that do not deplete full liquidity at the BBO. $Submit_t^{improve}$, $Submit_t^{BBO}$, and $Submit_t^{Non-BBO}$ denote limit orders that tighten the quoted spread, add liquidity at the BBO, and add liquidity behind the BBO, all in million dollar values, respectively. $Cancel_t^{worsen}$, $Cancel_t^{BBO}$, and $Cancel_t^{Non-BBO}$ denote limit orders that widen the quoted spread, reduce the liquidity at BBO, and reduce the liquidity behind BBO, all in million dollar values, respectively. Newey-West standard errors are reported in model (2). We estimate the model in each trading day. We report the median estimated coefficients and the proportion of statistically significant coefficients at the 5% level in parentheses over the entire sample period. 'Avg. event time' denotes the average number of events (observations) per regression, while 'Avg. Adj. R^2' is the adjusted R^2 averaged across all regressions. Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day trading sessions and 368 night trading sessions.

	Corn		Soybean		Wheat	
	(1)	(2)	(1)	(2)	(1)	(2)
s_{t-1}	-0.014	-0.015	-0.015	-0.015	0.008	0.008
	(89.95%)	(92.93%)	(94.57%)	(95.65%)	(75.00%)	(91.03%)
$\mid Trades_t^{same} \mid$		-0.004		0.003		0.003
		(5.71%)		(4.62%)		(6.52%)
$\mid Trades_t^{change} \mid$		0.000		0.017		0.052
		(18.75%)		(22.01%)		(15.22%)
$\mid Submit_t^{improve} \mid$		-0.003		-0.016		-0.084
		(12.23%)		(16.85%)		(19.02%)
$\mid Submit_t^{BBO} \mid$		-0.001		0.002		-0.002
		(2.45%)		(7.61%)		(3.80%)
$\mid Submit_t^{Non-BBO} \mid$		0.000		-0.001		-0.004
		(4.08%)		(4.35%)		(4.89%)
$\mid Cancel_t^{worse} \mid$		-0.073		0.053		0.149
		(28.26%)		(27.99%)		(25.82%)
$\mid Cancel_t^{BBO} \mid$		0.000		0.000		-0.010
		(5.71%)		(4.62%)		(4.89%)
$\mid Cancel_t^{Non-BBO} \mid$		0.001		-0.001		0.006
		(4.89%)		(5.43%)		(5.43%)
Intercept	0.000	0.000	0.000	0.000	0.001	0.000
	(4.89%)	(4.89%)	(6.52%)	(4.89%)	(4.35%)	(5.16%)
Avg. event time	378,121	378,121	589,257	589,257	359,047	359,047
Avg. Adj. R^2	0.0011	0.0012	0.0009	0.0009	0.0001	0.0002

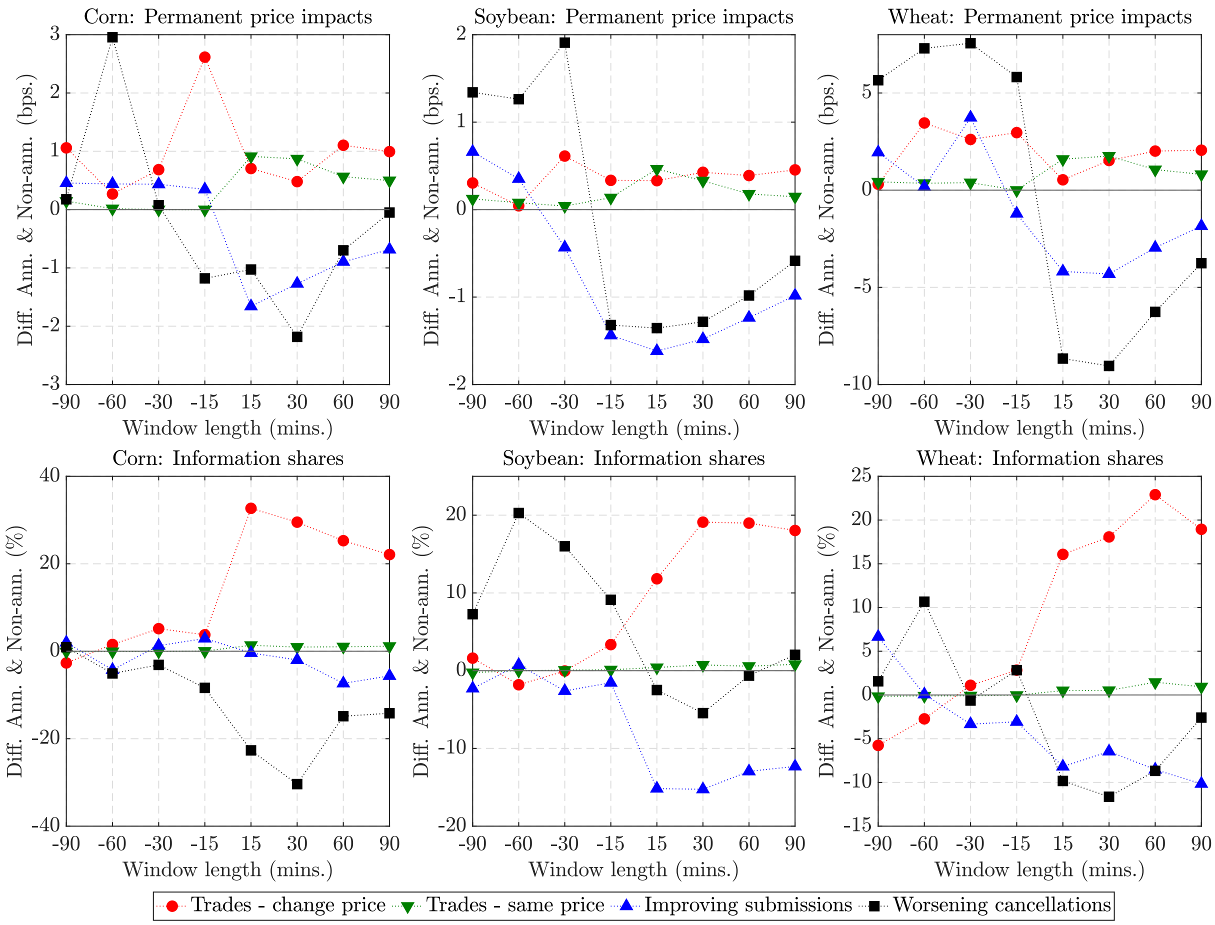

Figure 1: Permanent price impacts and information shares around the USDA WASDE announcements: Trades and aggressive limit orders.

This figure displays the permanent price impacts and information shares of trades and aggressive limit orders derived using data in four different time intervals: 90, 60, 30, and 15 minutes before, during, and after the USDA WASDE announcements. These are compared to results derived from the same time intervals on the five non-announcement days preceding and following each announcement day. The USDA WASDE report is released monthly at 11:00 Central Time. The upper panel shows the differences in median permanent price impacts between announcement and non-announcement days, expressed in basis points. The lower panel shows the differences in median information shares between announcement and non-announcement days, expressed in percentages. Permanent price impacts and information shares are calculated based on the estimated structural VAR model in each window. Permanent price impacts are derived from IRFs, with non-significant values being assigned a value of zero. Our sample period spans from January 7, 2019 to June 26, 2020, comprising 17 announcement days and 170 non-announcement days.

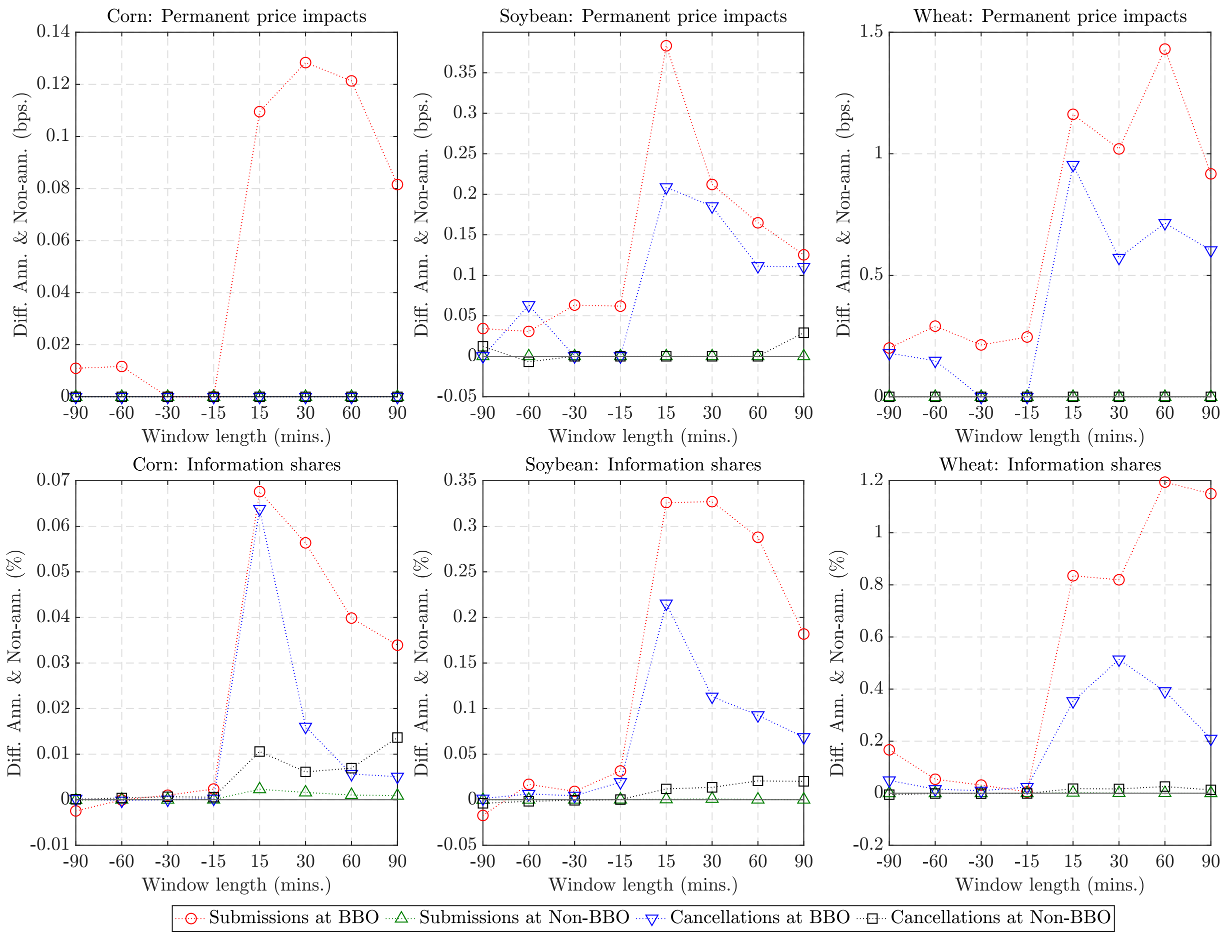

Figure 2: Permanent price impacts and information shares around the USDA WASDE announcements: Non-aggressive limit orders.

This figure displays the permanent price impacts and information shares of non-aggressive limit orders derived using data in four different time intervals: 90, 60, 30, and 15 minutes before, during, and after the USDA WASDE announcements. These are compared to results derived from the same time intervals on the five non-announcement days preceding and following each announcement day. The USDA WASDE report is released monthly at 11:00 Central Time. The upper panel shows the differences in median permanent price impacts between announcement and non-announcement days, expressed in basis points. The lower panel shows the differences in median information shares between announcement and non-announcement days, expressed in percentages. Permanent price impacts and information shares are calculated based on the estimated structural VAR model in each window. Permanent price impacts are derived from IRFs, with non-significant values being assigned a value of zero. Our sample period spans from January 7, 2019 to June 26, 2020, comprising 17 announcement days and 170 non-announcement days.

Appendix

A CME Globex sessions and trading hours

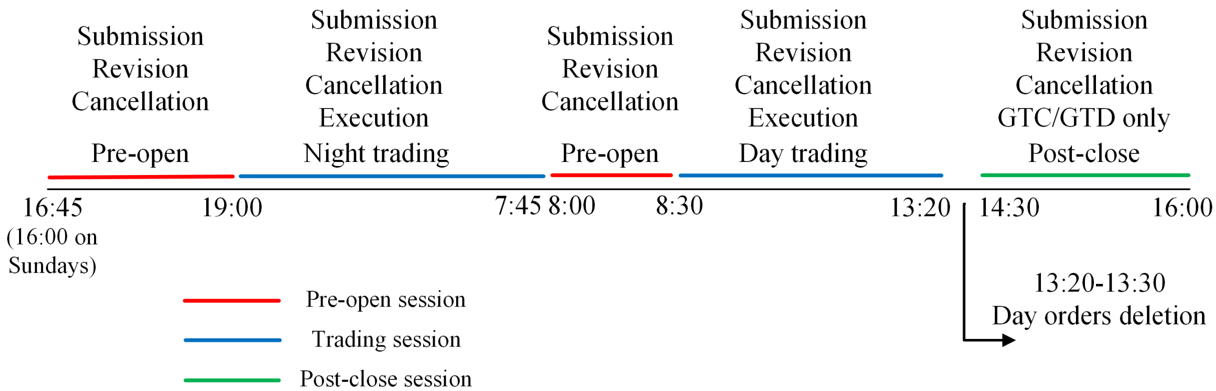

Figure A1: CME Globex sessions and trading hours.

This figure displays the CME Globex sessions and hours over a trading day. All time is U.S. Central Time (CT). The pre-open session starts at 16:00 on Sundays. Batch auctions are held during pre-open and post-close sessions. Only Good-till-cancel (GTC) or Good-till-day (GTD) orders are allowed to participate in post-close sessions. The day trading session is from 8:30 to 13:20 CT and the night session from 19:00 to 7:45 CT. Generally, in our sample markets, CME holds batch auction sessions during the continuous trading sessions on national holidays. CME assumes all limit orders automatically expire after the day trading session closes, unless they are flagged as GTC and GTD. Details on order types can be found at https://www.cmegroup.com/confluence/display/EPICSANDBOX/Order+Types+for+Futures+and+Options.

B Price, realized volatility, and trading volume

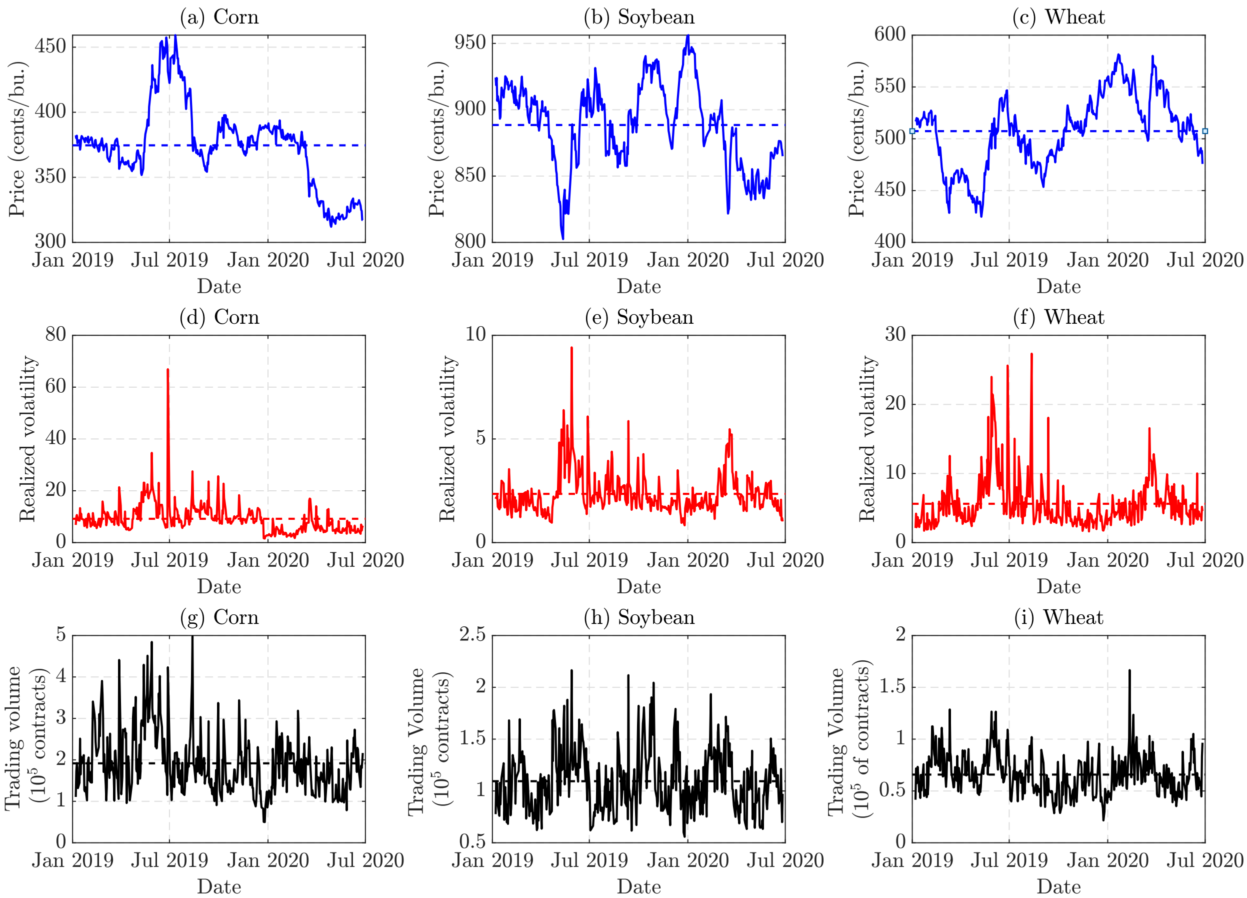

Figure B1: Price, realized volatility, and trading volume in CME corn, soybean, and wheat markets.

This figure displays the daily settlement prices, realized volatility, and trading volumes in CME corn, soybean and SRW wheat futures markets. The three different markets are organized by columns. Dashed lines represent the mean over the sample period. All settlement prices are quoted in U.S. cents per bushel. Realized volatility is defined as the sum of squared returns in a trading day, i.e., $\sum_{t=1}^{T} r_t^2$, where $r_t = \log(p_t) - \log(p_{t-1})$. p_t are intraday trade prices and r_t are intraday trade price returns. $t = 1, \ldots, T$ represents the number of trades within in a trading day. Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 trading days. Source: Prices and trading volumes are from Bloomberg terminal and trade data are from CME. Our sample spans from January 7, 2019 to June 26, 2020.

C Messages during continuous trading sessions

Table C1: Message distribution during continuous trading sessions.

This table displays summary statistics for the proportion (in percentage) of different types of messages relative to the total messages for continuous (day and night) trading sessions. Panels A, B and C present details for corn, soybean and wheat, respectively. Submission indicates outright (customer) limit order submitted to markets. Execution represents all matched outright limit orders. Revision represents limit order modifications initiated by traders that modify the quoted price and/or quoted quantity. Deletion represents the deletion of the whole limit order initiated by traders. Our sample spans from January 7, 2019 to June 26, 2020.

Type	Mean	Std. Dev	Min.	P25	Median	P75	Max
Panel A: Corn futures market.							
Submission	26.47%	2.28%	20.13%	24.99%	26.41%	27.88%	33.57%
Execution	33.56%	4.39%	15.69%	30.82%	33.55%	36.52%	44.37%
Revision	12.83%	4.32%	5.44%	9.93%	11.70%	14.93%	34.92%
Deletion	27.14%	2.20%	19.66%	25.89%	27.15%	28.40%	33.85%
Panel B: Soybean futures market.							
Submission	28.60%	2.01%	21.39%	27.27%	28.70%	30.15%	33.25%
Execution	22.07%	2.99%	11.99%	20.31%	22.00%	23.99%	30.11%
Revision	22.50%	4.78%	10.14%	18.93%	22.27%	25.42%	39.84%
Deletion	26.83%	2.29%	18.66%	25.16%	26.91%	28.55%	32.17%
Panel C: Wheat futures market.							
Submission	30.13%	2.02%	24.65%	28.71%	29.97%	31.29%	36.28%
Execution	28.42%	3.46%	17.49%	26.22%	28.61%	30.77%	38.86%
Revision	13.05%	3.65%	5.79%	10.79%	12.77%	14.78%	32.65%
Deletion	28.39%	2.26%	21.50%	26.80%	28.24%	29.74%	35.59%

D Limit order submissions, executions, deletions, and revisions

D.1 Session distributions

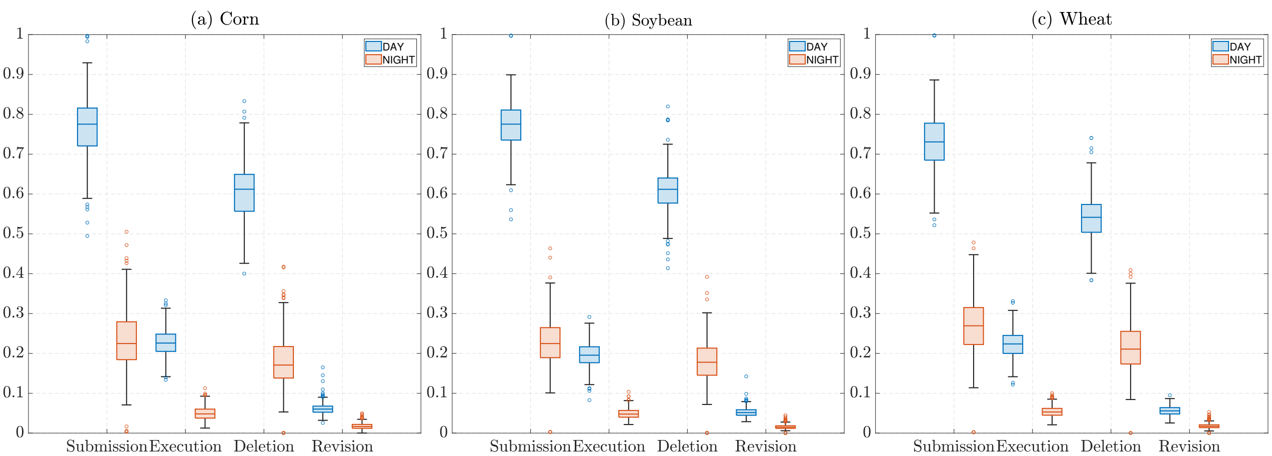

Figure D1: Distribution of limit order submissions, executions, deletions, and revisions across day and night trading sessions.

This figure displays the boxplots showing the distribution of limit order submissions, executions, deletions, and revisions across day and night trading sessions for the sample period in CME corn, soybean, and wheat futures markets, respectively. The three different markets are organized by columns. Proportions of limit order submissions, executions, deletions, and revisions are defined as the number of limit orders submitted, executed, deleted, and revised within each session over the total number of limit orders submitted across the two sessions, respectively. Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day trading sessions and 368 night trading sessions.

D.2 Time distributions

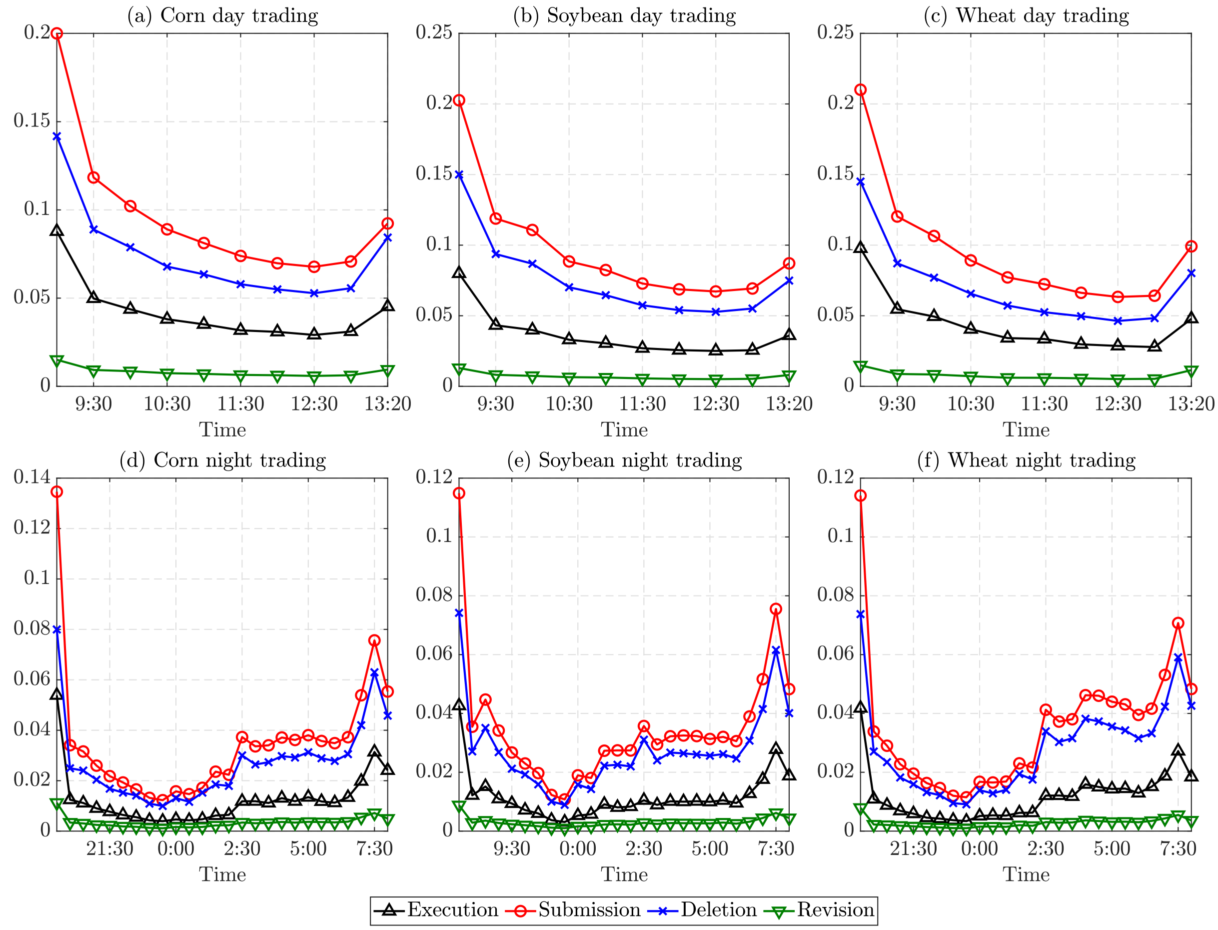

Figure D2: Distribution of limit order submissions, executions, deletions, and revisions within the day and night trading sessions.

This figure displays the distribution of limit order submissions, executions, deletions, and revisions by 30-minute intervals through the whole continuous (day and night) trading sessions in CME corn, soybean, and wheat futures markets. The upper panel represents day trading sessions and the lower panel night trading sessions. The three different markets are organized in columns. The proportion of limit order submissions, executions, deletions, and revisions are measured as the number of limit orders submitted, executed, deleted, and revised in each 30-min intervals over the total number of limit orders submitted for the whole trading session, respectively. Median values for each 30-min interval across all trading days in the sample are shown in the figure. All time is the U.S. Central Time. Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day trading sessions and 368 night trading sessions.

E Limit order duration

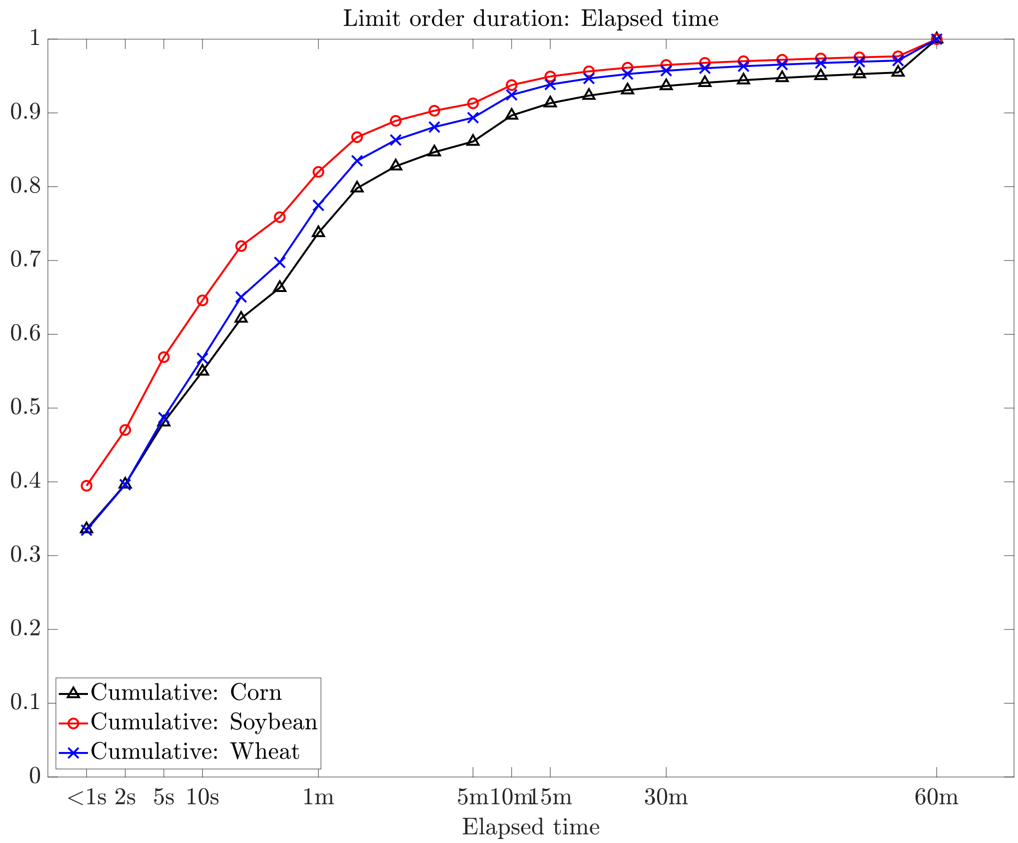

Figure E1: Cumulative distributions of limit order duration.

This figure displays the cumulative distributions of limit order duration during continuous trading sessions in CME corn, soybean, and wheat futures markets, respectively. The duration is truncated to 60 minutes to enhance visibility. The limit order duration is defined as the elapsed time between order placement and order conclusion. CME continuous trading sessions include both day trading and night trading sessions. Our sample spans from January 7, 2019 to June 26, 2020.

F Messages around the USDA WASDE announcements

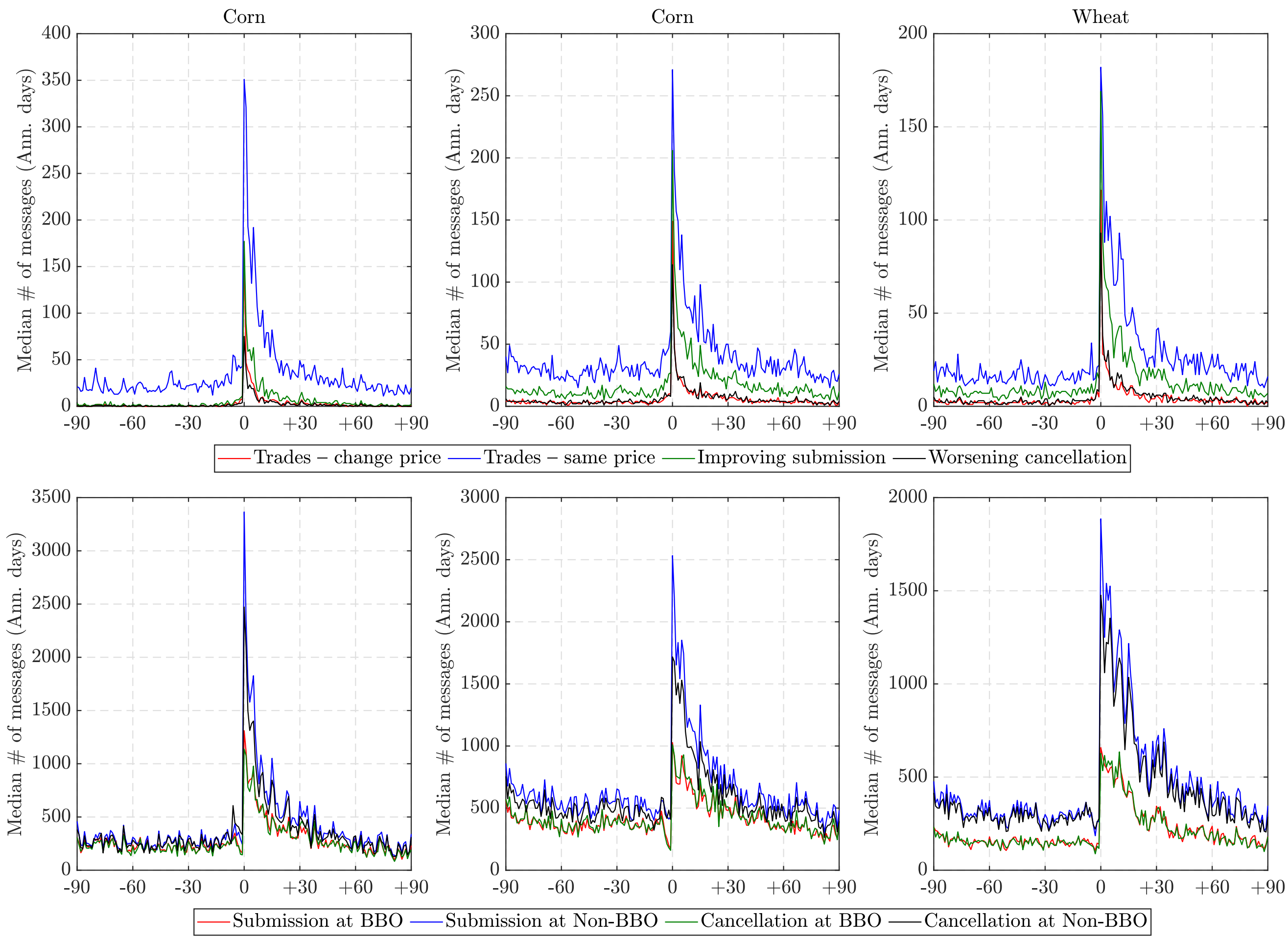

Figure F1: Messages around the USDA WASDE announcements.

This figure displays the number of messages from 90 minutes before (negative numbers) to 90 minutes after (positive numbers) the USDA announcement. USDA WASDE report is released monthly at 11:00 Central Time. The upper panel shows the median number of trades and aggressive limit order messages per 1-minute bin across announcement days. The lower panel shows the median number of non-aggressive limit order messages per 1-minute bin across announcement days.

G Transitory pricing errors (noises) during the night trading session

In Table G1, we report the regression results for transitory pricing error during the night trading sessions. The magnitude of the effects in the night trading session where liquidity is reduced, is generally larger than the day trading session, especially for aggressive trades and limit orders. Differently from the day trading session, aggressive liquidity submissions are positively correlated with transitory pricing errors in corn and soybean markets, while the effect is still negative in the wheat market. Liquidity cancellations that move the BBO reduce pricing errors in soybean and wheat markets, while the opposite is true in corn market. The results show that the effect of aggressive limit orders may be conditional on the overall liquidity condition.

Table G1: Transitory pricing errors (noises) during the night trading session: Trades and limit orders

This table reports the regression results of transitory pricing errors (noises) on all trades and limit order variables during the night trading session in our sample in CME corn, soybean, and wheat futures markets, respectively. The three different markets are organized by columns. The transitory pricing errors are extracted from the VMA representation of our structural VAR model. Our regression specifications are as follows

$$s_t = \alpha_0 + \alpha_1 s_{t-1} + \alpha_2 \mid Trades_t^{same} \mid + \alpha_3 \mid Trades_t^{change} \mid + \alpha_4 \mid Submit_t^{improve} \mid + \alpha_5 \mid Submit_t^{BBO} \mid + \alpha_6 \mid Submit_t^{Non-BBO} \mid + \alpha_7 \mid Cancel_t^{worsen} \mid + \alpha_8 \mid Cancel_t^{BBO} \mid + \alpha_9 \mid Cancel_t^{Non-BBO} \mid + e_t,$$

where s_t is the transitory pricing errors at event time t and s_{t-1} is its first-lag value. $\mid \cdot \mid$ denotes absolute values of independent variables. $Trades_t^{change}$ represents trades that deplete full liquidity at the BBO and $Trades_t^{same}$ represents trades that do not deplete full liquidity at the BBO. $Submit_t^{improve}$, $Submit_t^{BBO}$, and $Submit_t^{Non-BBO}$ denote limit orders that tighten the quoted spread, add liquidity at the BBO, and add liquidity behind the BBO, all in million dollar values, respectively. $Cancel_t^{worsen}$, $Cancel_t^{BBO}$, and $Cancel_t^{Non-BBO}$ denote limit orders that widen the quoted spread, reduce the liquidity at BBO, and reduce the liquidity behind BBO, all in million dollar values, respectively. Newey-West standard errors are reported in model (2). We estimate the model in each trading day. We report the median estimated coefficients and the proportion of statistically significant coefficients at the 5% level in parentheses over the entire sample period. 'Avg. event time' denotes the average number of events (observations) per regression, while 'Avg. Adj. R^2' is the adjusted R^2 averaged across all regressions. Our sample spans from January 7, 2019 to June 26, 2020, comprising 372 day trading sessions and 368 night trading sessions.

	Corn		Soybean		Wheat	
	(1)	(2)	(1)	(2)	(1)	(2)
s_{t-1}	0.001	0.001	0.005	0.005	0.006	0.006
	(43.21%)	(72.28%)	(78.26%)	(83.15%)	(48.64%)	(87.50%)
$\mid Trades_t^{same} \mid$		-0.007		-0.006		-0.007
		(7.61%)		(7.34%)		(4.08%)
$\mid Trades_t^{change} \mid$		0.116		0.037		0.018
		(24.46%)		(23.37%)		(13.86%)
$\mid Submit_t^{improve} \mid$		0.016		0.083		-0.070
		(16.58%)		(20.11%)		(11.41%)
$\mid Submit_t^{BBO} \mid$		-0.001		0.010		-0.064
		(3.53%)		(5.43%)		(4.89%)
$\mid Submit_t^{Non-BBO} \mid$		0.004		0.000		-0.002
		(5.71%)		(6.25%)		(7.34%)
$\mid Cancel_t^{worse} \mid$		0.202		-0.196		-0.366
		(20.38%)		(21.47%)		(16.58%)
$\mid Cancel_t^{BBO} \mid$		-0.001		0.010		-0.017
		(5.71%)		(4.89%)		(4.62%)
$\mid Cancel_t^{Non-BBO} \mid$		-0.003		0.004		0.024
		(5.43%)		(4.08%)		(5.71%)
Intercept	-0.001	0.000	0.000	-0.001	-0.001	0.000
	(5.43%)	(5.43%)	(9.78%)	(6.25%)	(7.07%)	(6.52%)
Avg. event time	113,852	113,852	163,714	163,714	113,971	113,971
Avg. Adj. R^2	0.0002	0.0003	0.0005	0.0005	0.0001	0.0001