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Intraday liquidity in soybean complex futures markets

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Abstract

We examine persistence and cross-market liquidity spillovers in the Chicago Mercantile Exchange soybean complex futures markets. A multidimensional liquidity measure is derived from the limit-order-book, and a Vector Heterogeneous Autoregressive model estimates high-resoluted liquidity from 30 s to one trading day. We find traders' order placement influenced by the liquidity of related markets. Liquidity persistence and positive liquidity spillovers mainly occur within 30 s, whereas spillovers for longer horizons are mostly negative. Findings are important for hedgers that hedge the crush and traders who wish to capitalize on the short-term deviation of price relationships.

KEYWORDS

commodity markets, futures markets, limit-order-book, liquidity spillovers

JEL CLASSIFICATION

G13, C22, Q14

1 | INTRODUCTION

Liquid markets have low trading costs, a large number of participants with no market power, and negligible price effects of trades (Hasbrouck, 2007). Liquidity plays a substantial role in derivative pricing (Acharya & Pedersen, 2005; Amihud et al., 2005) and hedging effectiveness (Mello & Parsons, 2000; Pennings & Meulenberg, 1997; Roll et al., 2007), making it a core element of well-functioning markets.

Given the strong connection between financial markets, the academic literature has studied liquidity relationships across different assets and markets. Various studies have analyzed liquidity commonalities, defined as common determinants of liquidity that lead to its comovement across different markets (Brockman & Chung, 2002; Chordia et al., 2000, 2001; Hasbrouck, 2001; Karolyi et al., 2012; Mancini et al., 2013; Rösch & Kaserer, 2013). Commonalities could result from market-wide liquidity reductions or general trading patterns changes. Other studies analyzed liquidity spillovers, defined as the propagation of liquidity shocks from one asset to another (e.g., Cespa & Foucault, 2014; Chordia et al., 2011), which may occur next to liquidity persistence of the asset itself. Liquidity conveys information; a change in the liquidity of one asset can make its priceless/more informative for other assets, potentially inducing changes in other assets' liquidity (Cespa & Foucault, 2014).

Kyle and Xiong (2001) stated that liquidity suppliers have limited resources; hence, adverse shocks may enhance liquidity spillovers. Spillovers are relevant to the soybean complex futures markets in which spread trading is a common strategy. With this strategy, buying and selling of three different contracts happen simultaneously to hedge the crushing process or to speculate on potential profits. The hedging effectiveness determined by the covariance of prices of the three markets is partly driven by liquidity. Zhang and Ding (2018) investigated the role of liquidity spillovers in the comovement of commodity price changes and their volatilities, finding that liquidity is the common causal factor for price and price-volatility comovement. In addition, liquidity dynamics may signal systemic intraday events in financial markets, for example, the 2010 Flash Crash (Kirilenko et al., 2017). Liquidity costs also influence the performance of hedging and the profits from speculation.

Kang et al. (2020) explained that insurance and liquidity are two independent premia offered as a reward to investors in commodity markets. Speculators may earn an insurance premium to compensate for the risk taken from hedgers. Meanwhile, hedgers may earn a premium by providing liquidity to speculators. The liquidity premium is higher in illiquid and short-term markets, particularly in bear markets (Cho et al., 2019). Through its premium, liquidity can influence the return on speculation or hedging performance.

Recent developments in financial markets changed the behavior and analysis of liquidity. Electronic trading increases the speed and handling of information, with orders that are processed lightning fast (Hirsch et al., 2019). Liquidity relations among markets have changed as a result, with shifts in liquidity occurring within extremely short periods (Hasbrouck, 2018).

Most of the literature on liquidity commonalities and spillovers in high-frequency trading focuses on stock markets and equity derivatives. We analyze intraday liquidity spillovers using high-frequency limit-order-book (LOB) data from the Chicago Mercantile Exchange (CME) soybean crush complex futures markets. Agricultural commodity futures markets are interesting study objects due to their unique financial relevance as an asset class and their important role in providing a hedging mechanism. Moreover, various commodity futures markets are physically related, for example, the markets for soybeans, soy meal, and soy oil, which raises several interesting questions: For example, does liquidity spill over into such markets in a relatively short time? (e.g., within seconds), and if so, are there differences across different time frames? Does the nature of spillovers differ between markets? What is the nature of liquidity persistence within markets? Are there differences in liquidity persistence and spillovers between Regular Trading Hours (RTHs) and Extended Trading Hours (ETHs) trade or within a year as suggested by Sørensen (2002)?

This study examines intraday liquidity relations among futures markets in the soybean crush complex. More specifically, we explore the reaction span, persistence, and liquidity spillovers over time using a Vector Heterogeneous Autoregressive (VHAR) model. To do so, the null hypothesis that cross-market liquidity spillovers are zero is tested. If confirmed, one may conclude that traders' strategies of order placements are not based on liquidity in closely related markets. Another research objective is to examine differences between liquidity spillovers during RTH and ETH and within the year. Electronic trading opened up the possibility for 24-h trading. Due to traders' diverse strategies and activities, there may be liquidity differences between day and night trading sessions (Aidov & Daigler, 2015; Barclay & Hendershott, 2004). Moreover, liquidity persistence and spillovers may differ within the year.

To capture multiple dimensions of liquidity, a comprehensive order-weighted average liquidity measure is obtained by calculating the cost-of-round-trip (CRT) trade of a certain dollar value (Irvine et al., 2000). Liquidity relations may exist at different time frames, for instance, within seconds, but also within hours or even days, limiting the suitability of standard time-series techniques. To study the dynamics of liquidity in different commodity markets at different time frames, a Heterogeneous Autoregressive (HAR) model as proposed by Corsi (2009) is adjusted to a multivariate (VHAR) setting, in line with Bubák et al. (2011). To analyze liquidity spillovers, we estimate intraday liquidity levels, in line with Hasbrouck (2019), who used a VHAR model to conduct price discovery analyses on high-frequency US equity market data. The advantage of the VHAR over other autoregressive models is its lag structure. The VHAR estimation captures the effects of different lagged liquidities on current liquidity, enabling us to capture trading heterogeneity (Corsi, 2009).

This study contributes to the literature in several ways. First, we analyze multidimensional liquidity in a high-frequency framework with data derived from all—rather than top-of-the-book—LOB snapshots of commodity futures contracts. Second, whereas most scholars use larger intervals, we examine direct intraday liquidity persistence and cross-market liquidity spillovers of related commodity futures markets. Third, within-year and trading-hours effects on liquidity spillovers are assessed by creating subsamples of specific periods, as well as subsamples of RTH and ETH.

The remainder of the paper is structured as follows. Section 2 provides a literature review of liquidity and its measurement. Section 3 describes the data and methodology, and Section 4 outlines the results. Section 5 presents conclusions and discussion.

2 | LIQUIDITY AND ITS MEASUREMENT

Liquidity determines the ability to trade in the market and consists of four dimensions: immediacy, resilience, width, and depth (Hasbrouck, 2007). Immediacy is the speed at which a certain number of assets can be sold or bought. Resilience refers to the recovery time and price path due to order imbalances (Pennings et al., 1998). Width identifies the spread between the best bid and ask price and accounts for the cost of a transaction. Market depth refers to the number of securities tradeable at a certain price and hence the ability to sustain a certain price level after relatively large market orders are placed.

The most common liquidity measures in the literature are either order-based or trade-based. Trade-based liquidity measures cover trading volume, trading value, the number of trades, and turnover ratios, that is, the number of futures traded in a particular time window. Trade-based measures require an actual trade to have taken place; as such, they are ex post measures offering a lagged estimate (indicator) of liquidity. LOBs, on the other hand, are ex ante measures of liquidity since they use the inventory of open orders in the market. Liquidity is often measured via proxies rather than direct measures based on the liquidity dimensions because comprehensive liquidity data—that is, the LOB—are harder to obtain. LOB-based electronic markets are a relatively recent development.

Many researchers have used the bid–ask spread as a liquidity proxy (Brogaard et al., 2019; Foucault et al., 2013; Shang et al., 2018). Ex post assessments of liquidity usually measure the rise (fall) of the market price due to a certain number of incoming buying (selling) orders, quantified by the price-impact function, which measures the depth dimension of liquidity (Frank & Garcia, 2011; Hasbrouck, 2004). Weber and Rosenow (2005) extended the price-impact function with information from the LOB, enabling them to capture more information about market depth. Other scholars who focus on the depth dimension have based their liquidity measures on quoted depth (Chordia et al., 2001; Coppejans et al., 2002; Kirilenko et al., 2017). Alongside these one-dimensional liquidity measures, Hautsch and Huang (2012) proposed an impulse-response function that captures both the short-term price effects of a limit order (i.e., the width, depth, and immediacy dimension) and its long-term price impact (i.e., resilience). Moreover, Aitken and Comerton-Forde (2003) proposed a liquidity measure based on the bid–ask spread, order depth, and probability of executing orders in the LOB. This measure shows low liquidity if the probability of execution of orders relatively remote from the midquote price is high.

Irvine et al. (2000) designed a CRT liquidity measure that captures the width, immediacy, and depth dimension of liquidity, which does not depend on actual trades and is usable in an intraday framework. The CRT calculates the costs involved in simultaneously buying and selling an equal monetary amount V and hence adheres to Kyle's notion of execution costs (Kyle, 1985). On both the bid and ask sides, an average contract or asset price can be calculated for executing that certain monetary amount V; the difference between the two is the liquidity spread. Irvine et al. (2000) found evidence that the CRT is a strong proxy for liquidity with two major advantages: First, it maps ex ante liquidity, unlike ex post measures, like general liquidity measures that use volume measures. Second, the CRT approach calculates liquidity based on width (the actual bid–ask spread)—and depth (adverse price movements [APMs] resulting from orders that exceed the bid–ask size). According to Hachmeister (2007), this combination of assessing width and depth reinforces the immediacy of the measure. Rösch and Kaserer (2013) used a CRT-based liquidity measure on an electronic order-driven market system, finding commonality among individual stock liquidity and market liquidity that increases substantially in times of financial turmoil.

Cao et al. (2009) found that a liquidity measure calculated within a CRT framework had additional value over other liquidity measures. Moreover, Ernst et al. (2012) found that the CRT was the most accurate of the liquidity measures using LOB data, and liquidity measures based on LOB data outperformed non-LOB liquidity measures.

3 | DATA AND METHODOLOGY

3.1 | Data

We obtained data from the CME for soybean, soy meal, and soy oil futures (CME Group, 2015). The data include all market messages between January 2015 and December 2015 required to recreate the first 10 levels of the LOB in the CME Market Depth 3.0 (MDP) format with millisecond precision. The sample covers a year in an already mature electronic market and a stable underlying soybean market; this strengthens the generalizability of our findings. The LOB messages follow the FIX protocol (FIXtrading, 2020). Two trading sessions are distinguished for each day: RTHs and ETHs. ETH sessions start the previous day at 19:00 and close at 07:45. RTH sessions start at 08:30 and close at 13:20.[1] The data contain multiple contracts. The roll-over date to the next contract takes place on the first trading day of the month in which the current contract matures.[2] The roll-over date roughly coincides with the notice-day and indicates a shift of trading from the expiring to the next contract. After the notice-day, a decline in liquidity can be associated with traders' avoidance to run the risk of being forced into physical delivery while the contracts are still being traded. Market depth is significantly lower in the preharvest period, which may be related to the old-crop–new-crop cycle.

According to Arzandeh and Frank (2019), the average price duration of soybean contracts is around 7.6 s. Arzandeh and Frank (2019) based these price durations on CME LOB data from November 23, 2015, until March 31, 2016. The 7.6 s interval is used to determine optimal spacing to obtain sufficient information and avoid excessive noise in the analysis. On the basis of Arzandeh and Frank (2019), our data are also snapshots of LOBs with intervals of 7.5 s. Studies on more liquid markets, such as the E-mini S&P500, rely on higher frequencies (i.e., 1-s intervals; Cao et al., 2009; Hasbrouck, 2019).

3.2 | Construction of the liquidity measure

As discussed in Section 2, the CRT measure combines multiple liquidity dimensions into one scalar and resembles the liquidity costs of trading. In the CRT framework, a dollar amount V must be determined to estimate the costs incurred when simultaneously selling and buying this amount V—that is, the costs incurred when "making a round-trip" in the amount of V; hence the name CRT. The relevant information is obtained from the LOB. The liquidity measure is an order-size-dependent, volume-weighted spread based on the round-trip costs of volume V. On the basis of Rösch and Kaserer (2013), the following equation is specified:

$$L_t(V) = \frac{\frac{1}{n}\left(\sum_i ask_{i,t} n_{i,t} - \sum_j bid_{j,t} n_{j,t}\right)}{P_{\mathrm{mid},t}} * 10{,}000, \tag{1}$$

whereby $L_t(V)$ represents the liquidity at time t for the CRT of dollar amount V, $ask_{i,t}$ and $bid_{j,t}$ denote the ask and bid prices at time t at levels i and $j = (1, ..., 10)$, where the level is the distance between the midquote price ($P_{\mathrm{mid},t}$) and the LOB level. Furthermore, $n_{i,t}$ and $n_{j,t}$ are the numbers of specific ask and bid levels to fulfill the amount V, which is represented by the sums $\sum_i ask_{i,t} n_{i,t}$ and $\sum_j bid_{j,t} n_{j,t}$. The difference between $\sum_i ask_{i,t} n_{i,t}$ and $\sum_j bid_{j,t} n_{j,t}$ is the absolute spread based on the execution of the amount of V on both the bid and ask sides. This is normalized by dividing it by n, which is the number of orders at the midquote price to fulfill V, and by the midquote price. Finally, the amount is multiplied by 10,000 to obtain the liquidity in basis points.[3] Following Gomber et al. (2015) and Hachmeister (2007), the CRT liquidity measure can be divided into three equations: the quoted bid–ask spread and two equations of the APM covering the bid and the ask side:

$$APM_{A,t}(V) = \frac{\overline{P}_{A,t}(V) - ask_{1,t}}{P_{\mathrm{mid},t}} * 10{,}000 \tag{2}$$

and

$$APM_{B,t}(V) = \frac{bid_{1,t} - \overline{P}_{B,t}(V)}{P_{\mathrm{mid},t}} * 10{,}000, \tag{3}$$

[1]Trading hours are in US Central Time.

[2]The roll-over date is the point in time when we switch from the front contract to the next one (Carchano & Pardo, 2009). To avoid higher liquidity costs or increased price volatility that often occurs close to the expiration of the contracts, we roll the contracts before they become illiquid, thus about 2 weeks before the day when trading ends, which usually matches the first calendar day of the expiration month. This is consistent with procedures from the literature (i.e., Aidov & Daigler, 2015; Arzandeh & Frank, 2019; Cho et al., 2019).

[3]One basis point (bp) equals one-hundredth of 1%.

where $\bar{P}_{A,t}(V)$ and $\bar{P}_{B,t}(V)$ are the quantity-weighted average execution prices for volume V on the ask and the bid side, respectively. The difference between the average execution price of dollar volume V and the first bid or ask is the exact adverse price change due to depth risk. An example of a CRT liquidity measure calculation is provided in the appendix.

A dollar amount of V that equals the complete order book value at time t is preferable since it will provide the most comprehensive information. If V exactly equals the total dollar volume on the bid and ask side in the LOB, one can calculate the mean price of all orders at different levels in the LOB on both the ask and the bid side and hence calculate the spread between those two different average bid and ask prices. Setting the dollar volume V is important as the order size grid is not similar in different markets (Gomber et al., 2015). Irvine et al. (2000) use size ranges to determine the dollar volumes V while other researchers like Hachmeister (2007) use fixed sizes. We set unique dollar volumes for the three markets based on fixed LOB distribution data as our study assesses three different markets with dissimilar underlying products, contract sizes, and sizes.

On the basis of the whole sample, four different Vs are implemented to ensure sufficient liquidity information from the LOB and that the information resembles the total liquidity costs. First, the 0.1 percentile V in terms of dollar volume is identified for all snapshots of the LOB at the end of a 7.5-s interval. By doing this, we ensure that at least 99.9% of the snapshots we analyze is larger in size than the volume V. Second, two Vs are calculated by taking the value of the 25th and 75th percentile of all order books. Finally, the average dollar volume of all LOBs is used as the last V. The different dollar volumes calculated for all markets based on the four cut-offs are shown in Table 1.

The 0.1% dollar volumes relate to the orders closest to the midquote price. In contrast, the 75% volume also includes orders deeper in the order book, explaining why a larger share leads to a less than proportionate volume increase. The differences in volumes among the three commodities are due to different units (see note below Table 1 for units). These four different dollar values of V are used to calculate the APMs on both the bid and ask sides, from which the liquidity scalars are derived. So, we use fixed values of V throughout our analysis calculated at each 7.5-s interval. Finally, the arithmetic mean of the eight different liquidity scalars is calculated and used as the liquidity measure in the analyses to generate one single metric that combines the liquidity with respect to the multiple dollar volumes used. The different units of the volumes in Table 1 are not a problem in the empirical analysis since the liquidity measure defined in Equation (1) is expressed in basis points.

Table 2 displays the covariance matrices for the APMs from all three markets. From this table, we can derive that the APMs that utilize a relatively large share of the LOB is, to a large extent, correlated, which is in line with our expectations. Although we see a correlation among the APMs based on the mean order book size and 75th percentile, we include these volumes to cover the distribution of the order book in the best possible way. Note that the APMs are zero, and the CRT liquidity measure equals the quoted spread if V does not exceed the first-level dollar-depth levels on both sides—that is, the dollar amount of all orders at the first bid and ask. In that case, liquidity only consists of width as there is no, or hardly any, depth risk. Furthermore, if V exceeds the total dollar volume of the LOB, the average execution price (either bid, ask, or both) equals the average price in the total order book. This treatment of relative illiquid intervals might bias the liquidity calculation. However, coverage of the tails of the order book by including Vs that are larger than the order book at time t is preferred over avoiding these potential biases during illiquid intervals.

Basic statistics, including the average values for the calculated CRT, are given in Table 3. From this table, we obtain three different insights in the numbers of bid and ask orders. First, the numbers of orders on the first 10 levels in the LOB are consistently smaller on the ask side compared with the bid side. Second, the numbers of orders for all three markets are skewed to the right. Third, the distributions of the numbers of orders are consistently leptokurtic, which means that the probability of a low or high number of orders (market depth) relative to the median is large. During certain short time periods, market depth is either very large or very low, which potentially indicates that liquidity

TABLE 1 Dollar volumes utilized as input for the calculation of the cost-of-round-trip (CRT) liquidity measure

	Dollar volumes			
	0.1%	**25%**	**Mean**	**75%**
Soybeans ($)	16,720	115,624	264,740	351,138
Soy meal ($)	31,216	232,555	457,044	579,097
Soy oil ($)	50,409	243,835	456,854	587,042

Note: Soybeans are based on volume multiplied US dollars and cents per bushel, soy meal is based on volume multiplied by US dollars and cents per short ton, and soy oil is based on volume multiplied by US dollars and cents per pound.

TABLE 2 Correlation matrix of Average Price Movements (APM) based on the cost-of-round-trip liquidity measure in soybean, soy oil, and soy meal futures markets

	APM bid ($Q = 0.001$)	**APM bid ($Q = 0.250$)**	**APM bid ($Q = \text{mean}$)**	**APM bid ($Q = 0.750$)**	**APM ask ($Q = 0.001$)**	**APM ask ($Q = 0.250$)**	**APM ask ($Q = \text{mean}$)**	**APM ask ($Q = 0.750$)**
Soybean covariance matrix								
APM bid ($Q = 0.001$)	1.00	0.54	0.65	0.51	0.54	0.29	0.35	0.27
APM bid ($Q = 0.250$)		1.00	0.91	0.99	0.37	0.42	0.41	0.41
APM bid ($Q = \text{mean}$)			1.00	0.87	0.42	0.38	0.41	0.36
APM bid ($Q = 0.750$)				1.00	0.35	0.41	0.39	0.40
APM ask ($Q = 0.001$)					1.00	0.70	0.77	0.69
APM ask ($Q = 0.250$)						1.00	0.95	0.99
APM ask ($Q = \text{mean}$)							1.00	0.93
APM ask ($Q = 0.750$)								1.00
Soy meal covariance matrix								
APM bid ($Q = 0.001$)	1.00	0.82	0.87	0.82	0.52	0.62	0.63	0.63
APM bid ($Q = 0.250$)		1.00	0.96	0.99	0.42	0.57	0.57	0.57
APM bid ($Q = \text{mean}$)			1.00	0.95	0.42	0.57	0.58	0.58
APM bid ($Q = 0.750$)				1.00	0.42	0.57	0.57	0.58
APM ask ($Q = 0.001$)					1.00	0.85	0.88	0.84
APM ask ($Q = 0.250$)						1.00	0.97	0.99
APM ask ($Q = \text{mean}$)							1.00	0.96
APM ask ($Q= 0.750$)								1.00
Soy oil covariance matrix								
APM bid ($Q = 0.001$)	1.00	0.95	0.98	0.94	0.02	0.01	0.02	0.01
APM bid ($Q = 0.250$)		1.00	0.97	0.99	0.06	0.07	0.06	0.07
APM bid ($Q = \text{mean}$)			1.00	0.97	0.03	0.03	0.03	0.03
APM bid ($Q = 0.750$)				1.00	0.06	0.08	0.06	0.08
APM ask ($Q = 0.001$)					1.00	0.56	0.77	0.53
APM ask ($Q = 0.250$)						1.00	0.78	0.99
APM ask ($Q = \text{mean}$)							1.00	0.74
APM ask ($Q = 0.750$)								1.00

Note: Q(0.01, 0.25, mean, 0.75), respectively, denote the Average Price Movement (APM) based on the 0.1 percentile, 25th percentile, mean, and 75th percentile of the total Dollar Volume sizes of the limit-order-books (LOBs) in each market.

TABLE 3 Summary statistics for soybean, soy oil, and soy meal futures markets

	Orders			
	Bid	**Ask**	**Price**	**CRT liquidity measure**
Soybean				
Mean	257.606	255.697	946.188	9.173
Median	188.000	193.000	960.000	8.953
Standard deviation	237.472	221.062	53.938	3.443
Minimum	9.000	10.000	844.500	1.442
Maximum	5617.000	6300.000	1060.75	235.554
Kurtosis	21.375	21.710	1.846	74.010
Skewness	3.112	2.864	−0.099	5.193
Observations	1,924,483	1,924,483	1,924,483	1,924,483
Soy oil				
Mean	141.087	132.184	3056.314	12.537
Median	111.000	107.000	3105.000	11.002
Standard deviation	111.605	92.055	217.990	11.288
Minimum	2.000	10.000	253.800	1.468
Maximum	5941.000	2502.000	3528.000	319.880
Kurtosis	64.642	19.373	2.044	124.401
Skewness	4.415	2.770	−0.374	9.483
Observations	1,924,483	1,924,483	1,924,483	1,924,483
Soy meal				
Mean	139.950	120.530	3202.943	13.609
Median	102.000	98.000	3190.000	11.858
Standard deviation	132.699	84.400	213.792	9.062
Minimum	10.000	9.000	266.500	1.862
Maximum	4629.000	1702.000	3862.000	277.907
Kurtosis	34.815	11.858	2.810	34.671
Skewness	4.034	2.007	0.071	4.893
Observations	1,924,483	1,924,483	1,924,483	1,924,483

Note: Orders are differentiated between bid and ask orders on the first 10 levels in the limit-order-book (LOB).

Abbreviation: CRT, cost-of-round-trip.

attracts liquidity. On the basis of the standard deviations and kurtosis values from the basic statistics of the price variable, we can conclude that the soybean market faces less price volatility than the soy oil and soy meal markets. The relatively low mean CRT liquidity measure value (9.173) for the soybean markets compared with the soy oil (12.537) and soy meal (13.609) mean values constitute the aforementioned lower price volatility in the soybean market. Please note that a larger CRT liquidity measure value constitutes lower liquidity. The total number of observations is 1,924,483.

Figure 1 represents histograms of the illiquidities of the three markets. Figure 1 shows that the soybean market generally has lower CRT liquidity outcomes with thinner tails than the soy meal and soy oil markets. This implies that the aforementioned soybean market has more consistent and relatively high liquidity than the other soy-based markets. The number of observations varies across these markets. As a consequence and by necessity, the model is based on the lowest number of market observations, as it can only incorporate periods in which snapshots of *all* markets were available, that is, were nonzero. Thus, if a particular market lacked a session or if it was filtered out,

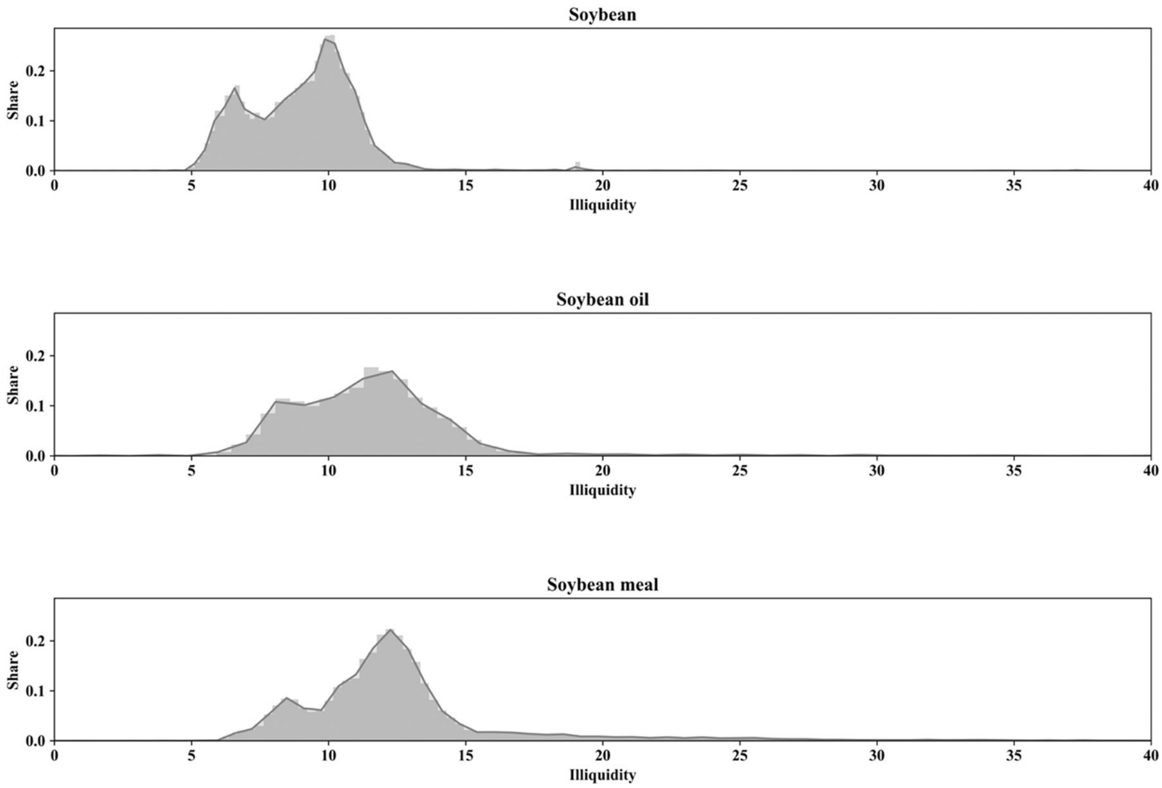

FIGURE 1 CRT liquidity measure for soybean, soy oil, and soy meal. Histograms show the distribution of the cost-of-round-trip (CRT) liquidity measure in the soybean, soy oil, and soy meal futures markets.

this session had to be deleted for all markets. During certain periods, the volatility of liquidity seems relatively high, for instance, during the preharvest months of July and August, when there is generally not much trade (USDA, 2020).

3.3 | Spillovers analysis using a VHAR model

The empirical literature suggests that price and liquidity shocks in futures markets are short-lived. Findings by Kirilenko et al. (2017) in the E-mini S&P 500 stock index futures market suggest that traders react to liquidity shocks within approximately 4 min. On the basis of the liquidity changes after the announcement of USDA reports, Lehecka et al. (2014) found that the incorporation of information takes about 10 min in the corn futures market. Kauffman (2013) reported that post-announcement volatility in corn futures markets does not last longer than 30–60 min. On the basis of these findings, this study examines the fundamentals of liquidity dynamics by using several aggregated lag structures. To cover immediate effects, the first lag window used is 30 s. A second lag of 5 min is in place to capture the typical liquidity shock response in line with Kirilenko et al. (2017). The third and fourth lag windows are set at 30 and 60 min to study traders' typical maximum reaction span. The longest lag window applied is 290 min, the equivalent of one RTH trading session. These lags capture the presence of different trading objectives and preferences among traders. Position traders would be mainly interested in execution risk at the daily frequency. Market makers, and scalpers/daily traders, would track liquidity throughout the day. Meanwhile, high-frequency traders would focus on liquidity in the short term. We calculate these lags for each commodity. To avoid begin-of-day and end-of-day effects, the first and last 15 min of each session are deleted.

A VHAR model is an adequate method to measure liquidity relations among different futures markets at different lag structures as defined above. The HAR model introduced by Corsi (2009) captures different lag effects based on moving averages retrieved from various time windows. In a high-frequency data setting, this avoids using an extremely large number of lags required in traditional VAR models. Therefore, a HAR is a simple yet effective tool to aggregate lags and to help yield robust dynamic components (Corsi, 2009). Bubák et al. (2011) and Souček and Todorova (2013) implemented the HAR model in a multivariate setting as VHAR models to study realized volatility spillovers in different markets. More recently, a VHAR model has also been used to estimate association in levels. Hasbrouck (2019) investigated price discovery (quotes) from a data set using timestamps accurate to nanoseconds.

Following the VHAR specification by Hasbrouck (2019) for analyzing the effects of liquidity persistence and spillovers at different time lags, the following trivariate model is written for three commodities i (soybean, soymeal, and soy oil) at the five different time lags discussed above, that is, 30 s, 5, 30, 60, and 290 min. With time measured in periods of 7.5 s, this corresponds to lags of 4, 40, 240, 480, and 2320 periods:

$$L_{i,t} = \beta_{i0} + \sum_{i=1}^{3} \beta_{i1}\overline{L}_{i,t-1|t-4} + \sum_{i=1}^{3} \beta_{i2}\overline{L}_{i,t-1|t-40} + \sum_{i=1}^{3} \beta_{i3}\overline{L}_{i,t-1|t-240} + \sum_{i=1}^{3} \beta_{i4}\overline{L}_{i,t-1|t-480} + \sum_{i=1}^{3} \beta_{i5}\overline{L}_{i,t-1|t-2320} + \varepsilon_{i,t}, \tag{4}$$

where $\overline{L}_{i,t-1|t-s}$ is a moving average liquidity from period $t-1$ till $t-s$ for commodity i, with $s \in [4, 40, 240, 480, 2320]$. In Equation (4), the liquidity of commodity i at period t $(L_{i,t})$ depends on a constant (β_{i0}), five moving averages of own liquidity, and moving averages over the same time periods for the other two commodities.

To control for possible correlations in liquidities among markets, the VHAR model is also estimated using orthogonalized liquidities as a robustness check (Bubák et al., 2011). First, to get rid of any correlations, any lagged liquidity is regressed on the lagged liquidities from the other commodities:

$$\overline{L}_{i,t-1|t-s} = \gamma_{i0} + \gamma_{i1}\overline{L}_{j,t-1|t-s} + \gamma_{i2}\overline{L}_{k,t-1|t-s} + \omega_{i,t-1|t-s}. \tag{5}$$

In this equation, the residual $\omega_{i,t-1|t-s}$ denotes the variation in liquidity of commodity i unexplained by the liquidity of commodities j and k for the moving average over period $t-1$ till $t-s$. The ultimate orthogonalized version of the model is specified as

$$\begin{aligned} L_{i,t} = {} & \beta_{i0} + \beta_{i1}\overline{L}_{i,t-1|t-4} + \beta_{i2}\overline{L}_{i,t-1|t-40} + \beta_{i3}\overline{L}_{i,t-1|t-240} + \beta_{i4}\overline{L}_{i,t-1|t-480} + \beta_{i5}\overline{L}_{i,t-1|t-2320} \\ & + \beta_{j1}\omega_{j,t-1|t-4} + \beta_{j2}\omega_{j,t-1|t-40} + \beta_{j3}\omega_{j,t-1|t-240} + \beta_{j4}\omega_{j,t-1|t-480} + \beta_{j5}\omega_{j,t-1|t-2320} \\ & + \beta_{k1}\omega_{k,t-1|t-4} + \beta_{k2}\omega_{k,t-1|t-40} + \beta_{k3}\omega_{k,t-1|t-240} + \beta_{k4}\omega_{k,t-1|t-480} + \beta_{k5}\omega_{k,t-1|t-2320} + \varepsilon_{i,t}. \end{aligned} \tag{6}$$

Dickey–Fuller tests suggest that the series of the liquidity measures are stationary. The Ljung-Box test, which checks the liquidity of all three commodities for autocorrelation, shows significant autocorrelation of the first 40 lags at a 1% confidence level. Both sets of results can be found in the appendix. The presence of autocorrelation and a high level of kurtosis make the VHAR an appropriate tool to analyze liquidity spillovers (Corsi, 2009).

4 | RESULTS

This section discusses the results of the VHAR analyses on the main model, for the subsamples of RTHs, ETHs, and "preharvest period." Finally, robustness checks are discussed.

4.1 | Results of the main model

Table 4 shows the regression results of the three trivariate models with moving average lag structures of 30 s, 5, 30, 60, and 290 min. Several observations can be made. First, all three commodities own lagged liquidity terms have a statistically significant positive effect on liquidity at period t. In other words, past liquidity has a persistent effect on current liquidity throughout the day. However, the size of the effect declines for longer lag structures, with the impact of a 1 bp change in liquidity within the preceding 30 s being the strongest, varying from 0.839 bps liquidity change for soymeal to 0.873 bps for soy oil, and the effect of 1 bp averaged over a trading day being rather small, varying from 0.002 bps for soymeal to 0.014 bps for soybeans. Even the effect averages over the preceding 5 min are already smaller than 0.1 bps, that is, 0.092 for soy meal down to 0.047 for soy oil. Thus, liquidity shocks prevail within a short time

TABLE 4 Regression results full sample

	Soybeans	Soy meal	Soy oil
Liq_beans_0.5	0.8646***	0.0242***	0.0078***
	(0.0006)	(0.0013)	(0.0021)
Liq_beans _5	0.0515***	−0.0062***	−0.0003
	(0.0009)	(0.0018)	(0.0031)
Liq_beans _30	0.0464***	0.0017	0.0067
	(0.0015)	(0.0031)	(0.0052)
Liq_beans _60	0.0174***	−0.0147***	−0.0069
	(0.0015)	(0.0031)	(0.0053)
Liq_beans _290	0.0142***	−0.0020	−0.0043
	(0.0008)	(0.0016)	(0.0027)
Liq_meal_0.5	0.0030***	0.8386***	0.0149***
	(0.0003)	(0.0007)	(0.0011)
Liq_meal_5	0.0021***	0.0920***	0.0084***
	(0.0005)	(0.0010)	(0.0016)
Liq_meal_30	0.0005	0.0502***	0.0011
	(0.0007)	(0.0015)	(0.0025)
Liq_meal_60	−0.0013**	0.0115***	−0.0160***
	(0.0007)	(0.0014)	(0.0024)
Liq_meal_290	−0.0037***	0.0023***	−0.0025**
	(0.0003)	(0.0006)	(0.0010)
Liq_oil_0.5	0.0015***	0.0032***	0.8731***
	(0.0002)	(0.0004)	(0.0006)
Liq_oil_5	0.0001	0.0037***	0.0474***
	(0.0002)	(0.0005)	(0.0009)
Liq_oil_30	−0.0003	−0.0021**	0.0361***
	(0.0004)	(0.0008)	(0.0014)
Liq_oil_60	−0.0019***	−0.0015*	0.0280***
	(0.0004)	(0.0009)	(0.0014)
Liq_oil_290	0.0009***	−0.0022***	0.0045***
	(0.0002)	(0.0005)	(0.0008)
Intercept	0.0408***	0.0324***	0.0327***
	(0.0030)	(0.0062)	(0.0105)
Observations	1,924,483	1,924,483	1,924,483
R^2	0.8907	0.9337	0.8776
F test	1.046e + 06	1.807e + 06	920,235

Note: Standard errors in parentheses.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

frame of half a minute and rapidly diminish in the time frames afterward. This may be due to high-resolution algorithmic trading; the number of orders is changed based on the activity in that market at a high frequency.

Many cross-market liquidity relations are statistically significant. Liquidity in all markets is positively related to 30-s liquidity in the other markets, showing consistent liquidity spillovers in the short run. However, considering liquidity spillovers from 30 min we observe that all terms have statistically insignificant parameters, except for the 30-min spillover from soy oil to soymeal. At the other end, we see that the longest lags of 60 and 290 min often have a statistically significant relation with current liquidity. Still, these terms are all but one negative. Those observations show interesting dynamics in the soybean complex. The 30-s positive cross-market spillovers are potentially caused by traders attracted to the increased activity in the soybean complex. However, in the longer time spans, a positive liquidity persistence spiral comes at the expense of liquidity in the other markets within the soybean complex. This constitutes two different trading dynamics: (i) traders increase/decrease activity in markets with similar fundamentals once liquidity increases/decreases in the short term, and (ii) traders within the soybean complex distribute their market positions, taking into account the liquidity at the expense of the other two markets in the longer term.

Several Granger causality tests are performed on subsets of parameters to test the overall relations. In all cases, a subset of liquidity terms from another commodity help explain the evolution of liquidity in a certain market, so we cannot conclude that one commodity is leading liquidity in others. Liquidity in all markets seems to be interrelated throughout the trading day (Table 5).

4.2 | RTH and ETH

The Globex trading hours can be divided into two sessions: RTHs and ETHs. During RTH, the trading volumes are significantly higher than during ETH. Chow tests were performed to assess whether this variation in trade activity affects liquidity dynamics and to evaluate potential differences between the two samples. The Chow test indicates a structural difference between the two subsamples for all three commodities with F test values of 1076 for soybeans, 783 for soymeal, and 243 for soil oil, respectively. Tables 6 and 7 contain the regression results of the RTH and ETH sessions. What immediately stands out is that the own 30-s liquidity persistence effects are smaller, and the 5- and 30-min own lags are larger in the RTH subsample than the ETH sample. In addition, the liquidity spillover effects from other commodity markets are also larger during RTH and more prevalent. Whereas, during RTH there is a statistically significant 30-s positive spillover from soybean liquidity to soy oil, this effect is absent during ETH. Thus, during day trading, liquidity seems driven more by other markets' liquidity positions compared with night trading.

4.3 | Preharvest subsample

Table 8 displays the results of the subsample analysis using data for July, August, and September. This period is characterized as relatively illiquid and unstable as yields can be influenced by exogenous factors, such as the weather.

TABLE 5 Granger causality F tests on liquidity spillovers

	Soybeans	Soy meal	Soy oil
All Liq_meal & Liq_oil	108.72***		
All Liq_meal	150.83***		
All Liq_oil	36.24***		
All Liq_beans & Liq_oil		115.92***	
All Liq_beans		116.38***	
All Liq_oil		103.89***	
All Liq_beans & Liq_meal			114.90***
All Liq_beans			8.93***
All Liq_meal			185.82***

***$p < 0.01$.

TABLE 6 Regression results of sample with Regular Trading Hours (RTHs) sessions

	Soybeans	Soy meal	Soy oil
Liq_beans_0.5	0.6843***	0.0730***	0.0365***
	(0.0017)	(0.0037)	(0.0039)
Liq_beans _5	0.1740***	−0.0242***	−0.0092
	(0.0028)	(0.0062)	(0.0066)
Liq_beans _30	0.1227***	−0.0284**	−0.0127
	(0.0051)	(0.0112)	(0.0120)
Liq_beans _60	−0.0027	−0.0058	−0.0106
	(0.0048)	(0.0106)	(0.0113)
Liq_beans _290	0.0067***	−0.0091*	0.0029
	(0.0022)	(0.0049)	(0.0052)
Liq_meal_0.5	0.0129***	0.6956***	0.0300***
	(0.0008)	(0.0017)	(0.0019)
Liq_meal_5	−0.0011	0.2383***	0.0446***
	(0.0012)	(0.0026)	(0.0028)
Liq_meal_30	0.0072***	0.0467***	−0.0623***
	(0.0019)	(0.0041)	(0.0044)
Liq_meal_60	−0.0141***	0.0081**	−0.0046
	(0.0018)	(0.0039)	(0.0041)
Liq_meal_290	−0.0019**	−0.0016	−0.0006
	(0.0008)	(0.0019)	(0.0020)
Liq_oil_0.5	0.0048***	0.0072***	0.7573***
	(0.0006)	(0.0014)	(0.0015)
Liq_oil_5	0.0030***	0.0286***	0.1241***
	(0.0010)	(0.0023)	(0.0024)
Liq_oil_30	−0.0163***	−0.0237***	0.0845***
	(0.0019)	(0.0041)	(0.0044)
Liq_oil_60	0.0075***	−0.0063	0.0243***
	(0.0018)	(0.0039)	(0.0042)
Liq_oil_290	0.0002	−0.0005	−0.0077***
	(0.0008)	(0.0017)	(0.0018)
Intercept	0.0801***	0.0500***	0.0449**
	(0.0076)	(0.0167)	(0.0178)
Observations	503,602	503,602	503,602
R^2	0.7940	0.9040	0.8713
F test	129,387	315,988	227,381

Note: Standard errors in parentheses.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

TABLE 7 Regression results of sample with Extended Trading Hour (ETH) sessions

	Soybeans	Soy meal	Soy oil
Liq_beans_0.5	0.8966***	0.0178***	0.0041
	(0.0007)	(0.0013)	(0.0025)
Liq_beans _5	0.0254***	−0.0051***	0.0006
	(0.0009)	(0.0018)	(0.0036)
Liq_beans _30	0.0410***	0.0034	0.0087
	(0.0015)	(0.0031)	(0.0059)
Liq_beans _60	0.0170***	−0.0136***	−0.0067
	(0.0016)	(0.0032)	(0.0062)
Liq_beans _290	0.0133***	−0.0003	−0.0058*
	(0.0008)	(0.0017)	(0.0033)
Liq_meal_0.5	0.0017***	0.8721***	0.0128***
	(0.0004)	(0.0007)	(0.0014)
Liq_meal_5	0.0021***	0.0552***	0.0022
	(0.0005)	(0.0010)	(0.0020)
Liq_meal_30	−0.0012	0.0490***	0.0072**
	(0.0008)	(0.0016)	(0.0031)
Liq_meal_60	0.0012	0.0157***	−0.0153***
	(0.0008)	(0.0015)	(0.0030)
Liq_meal_290	−0.0031***	0.0039***	−0.0007
	(0.0003)	(0.0007)	(0.0013)
Liq_oil_0.5	0.0014***	0.0030***	0.8830***
	(0.0002)	(0.0003)	(0.0007)
Liq_oil_5	−0.0001	0.0016***	0.0391***
	(0.0003)	(0.0005)	(0.0010)
Liq_oil_30	0.0001	−0.0011	0.0347***
	(0.0004)	(0.0008)	(0.0016)
Liq_oil_60	−0.0018***	−0.0008	0.0268***
	(0.0004)	(0.0008)	(0.0016)
Liq_oil_290	0.0008***	−0.0020***	0.0058***
	(0.0002)	(0.0005)	(0.0009)
Intercept	0.0529***	0.0280***	0.0439***
	(0.0040)	(0.0080)	(0.0155)
Observations	1,420,881	1,420,881	1,420,881
R^2	0.8903	0.9406	0.8754
F test	768659	1.500e + 06	665780

Note: Standard errors in parentheses.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

TABLE 8 Regression results of preharvest period sample (July, August, and September)

	Soybeans	Soy meal	Soy oil
Liq_beans_0.5	0.8516***	0.0165***	0.0124***
	(0.0012)	(0.0023)	(0.0047)
Liq_beans _5	0.0459***	−0.0142***	−0.0014
	(0.0019)	(0.0035)	(0.0070)
Liq_beans _30	0.0469***	0.0039	0.0057
	(0.0034)	(0.0063)	(0.0127)
Liq_beans _60	0.0172***	−0.0055	0.0102
	(0.0037)	(0.0069)	(0.0139)
Liq_beans _290	0.0260***	0.0051	−0.0128
	(0.0022)	(0.0042)	(0.0084)
Liq_meal_0.5	0.0004	0.8435***	0.0084***
	(0.0007)	(0.0013)	(0.0026)
Liq_meal_5	0.0008	0.0688***	−0.0019
	(0.0010)	(0.0019)	(0.0038)
Liq_meal_30	−0.0025	0.0497***	0.0134**
	(0.0017)	(0.0031)	(0.0063)
Liq_meal_60	0.0036**	0.0265***	−0.0208***
	(0.0017)	(0.0031)	(0.0062)
Liq_meal_290	−0.0012	0.0060***	0.0075***
	(0.0008)	(0.0014)	(0.0028)
Liq_oil_0.5	0.0009***	0.0017***	0.8541***
	(0.0003)	(0.0006)	(0.0012)
Liq_oil_5	0.0005	0.0020**	0.0529***
	(0.0005)	(0.0009)	(0.0018)
Liq_oil_30	0.0002	−0.0014	0.0350***
	(0.0008)	(0.0016)	(0.0031)
Liq_oil_60	−0.0022**	−0.0016	0.0436***
	(0.0009)	(0.0016)	(0.0033)
Liq_oil_290	0.0020***	−0.0005	−0.0005
	(0.0005)	(0.0009)	(0.0018)
Intercept	0.0794***	0.0334*	−0.0422
	(0.0108)	(0.0202)	(0.0405)
Observations	485,681	485,681	485,681
R^2	0.7855	0.8901	0.8214
F test	118,572	262,345	148,951

Note: Standard errors in parentheses.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

However, the own liquidity persistence effects and the liquidity spillover effects from other commodities are remarkably similar to the effects found in the full sample. The persistence coefficients hardly differ. The liquidity spillover effects are in some cases weaker (e.g., soy oil on soymeal and soymeal on soybeans). Still, despite these differences in significance and signs of individual coefficients, subsets of Wald tests show that liquidity spillover effects from all commodities to other commodities exist just like in the full sample.

4.4 | Robustness checks

Three alternative approaches were taken to assess the robustness of the results. Details can be found in the appendix. Overall, it can be concluded that the original spillover and persistence estimates are robust.

First, as described in the methodology section, an orthogonalized model was used to control for potential correlation among the liquidity scalars (Table A2). Controlling for potential correlation has minimal effects on the parameter estimates, revealing only minor changes in the magnitudes of the liquidity persistence. In contrast, the cross-market spillovers are virtually identical in the default and the orthogonalized models. The only difference observed is that orthogonalized soybean liquidity has more statistically significant effects on soy oil than in the default model, although these effects are all rather small. These results further substantiate the finding that cross-market liquidity relations indeed exist and are not the effect of an unobserved external driver.

Second, the bid–ask spread was used as an alternative measure for liquidity (Table A3). Although the bid–ask spread is widely accepted as a liquidity measure, it only comprises a single dimension of liquidity, namely, width, contrary to the multidimensional CRT liquidity measure used in this study. Indeed, using the bid–ask spread as an alternative measure yields slightly different spillover effects than the CRT method. The own 30-s persistence effects are somewhat smaller, whereas the other liquidity persistence effects are larger. The Wald statistics, however, continue to show consistent and robust cross-market spillover effects, while the decrease in explanatory value (R^2) is not surprising: Whereas the inclusion of multiple dimensions in the CRT liquidity measure may reveal mutually reinforcing effects towards relative uniformity, such effects would not be noticed by the one-dimensional bid–ask spread measure. The usage of the bid–ask spread as a liquidity measure further confirms the existence of cross-market liquidity spillovers.

Third, two alternative CRT measures based on (i) the 0.1 percentile of trade volume (so trades close to the midquote price; Table A4) and (ii) the 0.1 percentile and the average trade volume are used to assess the sensitivity of chosen volume (Table A5). Using the 0.1 percentile of trade volume yields slightly different results, with the 30-s persistence effect somewhat smaller for soybeans and to a lesser extent for soy oil, but not for soymeal. The effects of the moving averages over a longer time horizon are somewhat stronger for beans. Regarding spillovers, we find more significant effects of soybeans on soy oil, whereas the spillover effects of meal on beans are less strong. However, overall the picture is rather similar as well as the overall model fit with similar R^2 values. The results based on a CRT based on the 0.1 percentile and average trade volume are very similar to our original results. Overall, both results suggest rather robust liquidity persistence and cross-market effects.

5 | CONCLUSIONS AND DISCUSSION

We use the information of the full LOB of the futures markets of the soybean crush complex (soybean, soymeal, and soy oil). Our analyses show significant intraday liquidity persistence and cross-market liquidity associations. This result indicates that in the soybean futures complex, traders' strategy of order placements is partly based on committed liquidity in closely related markets. The findings are important for hedgers that hedge the crush and traders that wish to capitalize on short-term deviation of the price relationship (cointegrated) structure (Marowka et al., 2020).

Lag windows of 30 s, 5, 30, 60, and 290 min (one trading day) were used to aggregate liquidity in the three markets to study the span of the liquidity persistence and cross-market liquidity relations. The sample was divided into subsamples to assess potential differences in the magnitude of liquidity spillovers during RTHs and ETHs and during preharvest and non-preharvest months.

Short-term liquidity positive autocorrelation is strongest and persistent within a 30-s span. Consistent across the markets, liquidity autocorrelation is positive but gradually decreases during the day. In other words, past liquidity has a persistent effect on current liquidity throughout the day. However, the size of the effect declines for longer lag structures. Cross-market liquidity spillover effects show the same consistency as 30-s liquidity persistence relations, although this does not hold for cross-market spillovers in time frames larger than 30-s. Within the 5-min cross-market effect, we generally see either a positive or no effect, except for the beans to meal spillover. In contrast, the lags of 60 and 290 min do have a statistically significant relation with current liquidity but these terms are all but one negative. It seems that high-frequency traders tend to base their trading strategies. Thus their order decisions, mainly on the first 30 s lagged developments in a particular market and gradually less over larger time spans, while shocks in other markets are mainly incorporated over a 30-s time window. The overall conclusion is that the liquidity in the soybean crush markets positively influences liquidity in a time window of 30-s. In contrast to the shorter spanned cross-market effects, the 60- and 290-min lags are generally negative.

Accounting for the strong and significant positive coefficients of the liquidity persistence effects, it seems that, in a daily window, traders tend to prefer to place orders in markets with higher liquidity. If liquidity was relatively high on the previous day in one market, the current liquidity of that market tends to be high as well, while the previous day's liquidity of one market has consistently negative effects on the liquidity of other markets. In other words, in the time span of more than 60 min, traders tend to be active in markets where liquidity has been relatively high at the expense of other markets, which is called a "flight-to-liquidity" (Rösch & Kaserer, 2013; Vayanos, 2004). This effect holds for all markets, except for beans to oil. These dynamics can affect the hedging effectiveness (Pennings & Meulenberg, 1997) and the liquidity premia for hedgers and speculators (Cho et al., 2019), thus affecting trading behavior.

This study finds evidence that liquidity relations in RTH sessions deviate from those in ETH sessions: liquidity persistence relations tend to be more pronounced during ETH. At the same time, cross-markets seem to be more outstanding in RTH, which may suggest intramarket herd behavior. A general increase in trading could explain this phenomenon in that it implies a greater presence of similar trading strategies. During night trading, the liquidity persistence effects tend to be more pronounced, implying algorithmic trading with strategies based on the liquidity persistence market circumstances. It is also clear that liquidity relations hardly deviate during the preharvest months. This indicates that this period within general volatile markets due to the supply nature of the underlying commodity does not affect the interdependencies of these markets.

The results of this study are robust for a different liquidity measure (bid–ask spread), potential correlation among liquidity estimations of different markets, and the effect of the realized price variance in the different lag structures on liquidity. However, there are certain drawbacks to using LOB data and the VHAR approach: First, LOB data do not always reflect all committed liquidity. As mentioned before, iceberg orders and dark trading may affect liquidity while remaining unaccounted for in the CRT liquidity calculation. Second, the time periods used—of 7.5 s, based on the average price duration—are only a proxy for "liquidity duration." Third, heterogeneous trading behavior may deviate from the chosen lag windows. The evidence for highly resoluted liquidity spillovers (i.e., occurring faster than 30 s) could spark interesting follow-up research. Fourth, the CRT liquidity measure does not comprise the resiliency dimension of liquidity. Finally, as the data set spans only 1 year (2015), external validity might be compromised if any external factors particularly influenced traders' behavior during that year.

Further research can examine the drivers behind particular liquidity transmissions and the seasonal effects. Research into liquidity spillovers in the family of grain contracts (corn, wheat, and soy) would be an interesting start; it could provide insights into how the degree of similarity among commodities affects the intensity of cross-market liquidity spillovers. Furthermore, applying the VHAR method using more granular time intervals would be interesting to explore liquidity spillovers in a very high-resoluted environment and reveal algorithmic trading effects. In addition, with the proper data (i.e., commodity futures trading commission), researchers could label the type of traders per order, identifying who provides liquidity.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Chicago Mercantile Exchange. Restrictions apply to the availability of these data, which were used under license for this study. The data are available from the authors with the permission of the Chicago Mercantile Exchange.

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APPENDIX A

To illustrate the liquidity measure, assume a liquidity scalar based on one dollar volume V that equals the dollar volume size of the 0.01 percentile of the dollar volumes of all markets. Furthermore, in a certain time frame, the 0.01 percentile market has a market depth of \$15,000, and hence the first V equals \$15,000. The liquidity scalar of the volume class of \$15,000 needs to be calculated with an LOB as given in Figure A1. As can be seen in Figure A1, the quoted bid–ask spread is calculated first to capture the market's width ($Ask_1 - Bid_1/midquote$). In Figure A1, the relative bid–ask spread is $((416.5 - 416.0)/416.25)$, which equals a percentage spread of 0.12%, or 12 bps. Furthermore, the average order price is calculated for the execution of a \$15,000 order on both the ask and bid sides. In the LOB of Figure A1, the execution of a V of \$15,000 requires orders further in the LOB than the quoted depth. On the bid side, this means that the calculation of the average bid price $\bar{P}_{B,t}(V)$ accounts for orders up to the third level. Using Equations (2) and (3), the difference between the average price of the executed amount V and the best bid and ask price, divided by the midquote price, reflects the APM. In the example of Figure A1, the APM of the bid price is $(416.00 - 415.3974 = 0.6026)$, which equals the relative value of $(\frac{0.6026}{416.25} = 14.5\,\text{bps})$. By summing the bid–ask spread and the relative APMs of the ask and bid sides, the liquidity metric is calculated for each snapshot, which equals a liquidity scalar of 64.0 bps in this example, that is, for this V (Tables A1–A5).

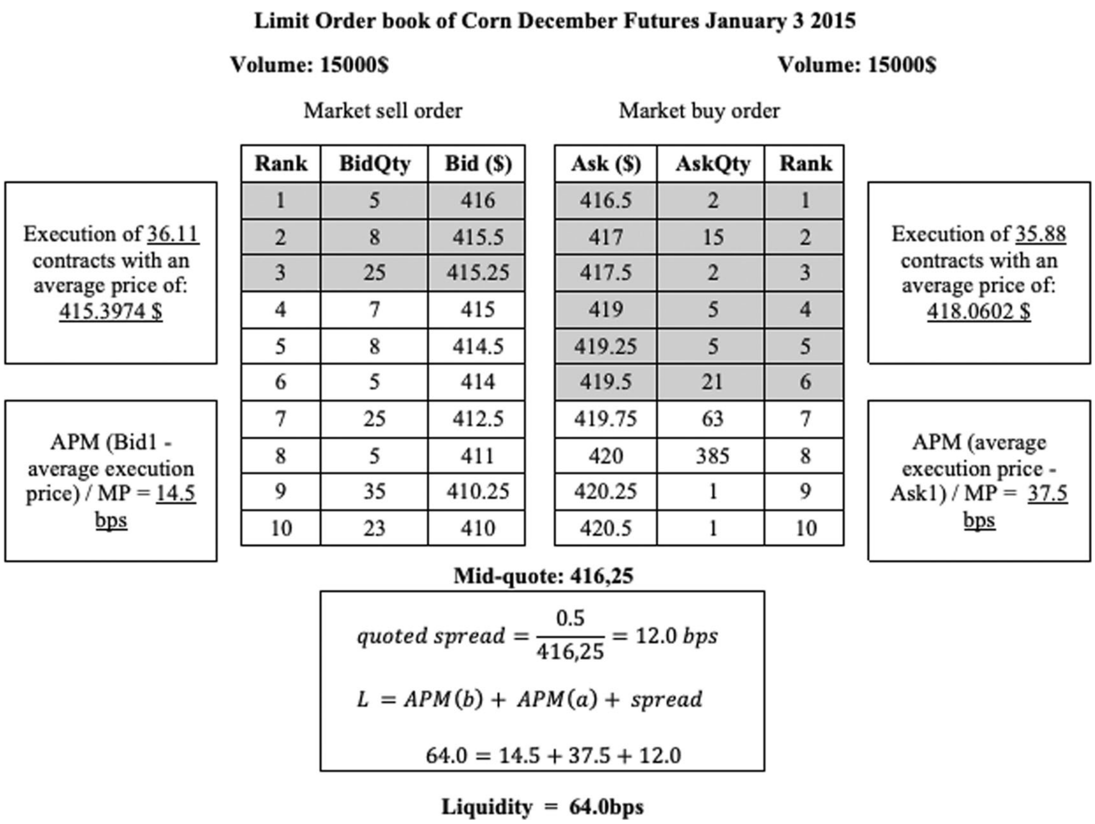

FIGURE A1 Example of a cost-of-round-trip liquidity measure calculation. APM, adverse price movement; MP, midquote price

TABLE A1 Results of ADF and Ljung-Box tests

	Soybean	Soy oil	Soy meal
ADF	−72.757	−66.045	−46.399
	(0.000)	(0.000)	(0.000)
Ljung-Box	51,426,000	53,187,000	59,857,000
	(0.000)	(0.000)	(0.000)

Note: The *p*-values are given in parentheses.

Abbreviation: ADF, Dickey–Fuller test.

TABLE A2 Regression results orthogonalized cross-commodity liquidities

	Soybeans	Soy meal	Soy oil
Liq_beans_0.5	0.8699***	0.0255***	0.0251***
	(0.0007)	(0.0013)	(0.0027)
Liq_beans _5	0.0546***	−0.0051***	0.0095**
	(0.0011)	(0.0018)	(0.0040)
Liq_beans _30	0.0468***	0.0011	0.0095
	(0.0017)	(0.0031)	(0.0066)
Liq_beans _60	0.0127***	−0.0153***	−0.0292***
	(0.0016)	(0.0032)	(0.0065)
Liq_beans _290	0.0093***	−0.0027*	−0.0084***
	(0.0007)	(0.0016)	(0.0030)
Liq_meal_0.5	0.0047***	0.8448***	0.0188***
	(0.0004)	(0.0007)	(0.0014)
Liq_meal_5	0.0028***	0.0933***	0.0099***
	(0.0006)	(0.0010)	(0.0020)
Liq_meal_30	0.0004	0.0491***	0.0027
	(0.0010)	(0.0015)	(0.0031)
Liq_meal_60	−0.0035***	0.0076***	−0.0212***
	(0.0009)	(0.0013)	(0.0028)
Liq_meal_290	−0.0045***	0.0003	−0.0040***
	(0.0004)	(0.0005)	(0.0011)
Liq_oil_0.5	0.0030***	0.0040***	0.8798***
	(0.0002)	(0.0004)	(0.0008)
Liq_oil_5	0.0011***	0.0036***	0.0513***
	(0.0004)	(0.0005)	(0.0011)
Liq_oil_30	−0.0002	−0.0021**	0.0375***
	(0.0006)	(0.0008)	(0.0018)
Liq_oil_60	−0.0034***	−0.0020**	0.0178***
	(0.0006)	(0.0009)	(0.0017)
Liq_oil_290	−0.0012***	−0.0023***	0.0023***
	(0.0003)	(0.0005)	(0.0007)
Intercept	0.0608***	0.0672***	0.1409***
	(0.0031)	(0.0035)	(0.0056)
Observations	1,924,483	1,924,483	1,924,483
R^2	0.8907	0.9337	0.8776
F test	1.046e + 06	1.807e + 06	920,235

Note: Liquidities of other commodities are orthogonalized values. Standard errors in parentheses.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

TABLE A3 Regression results using bid–ask spread as liquidity measure

	Soybeans	Soy meal	Soy oil
BAS_beans_0.5	0.6947***	0.0166***	0.0022
	(0.0008)	(0.0051)	(0.0048)
BAS_beans _5	0.1123***	0.0165*	0.0117
	(0.0015)	(0.0091)	(0.0084)
BAS_beans _30	0.0797***	−0.0278	0.0422**
	(0.0031)	(0.0191)	(0.0177)
BAS_beans _60	0.0410***	0.0207	−0.0874***
	(0.0035)	(0.0214)	(0.0199)
BAS_beans _290	0.0536***	0.0392***	0.0633***
	(0.0022)	(0.0136)	(0.0126)
BAS_meal_0.5	0.0008***	0.7758***	0.0002
	(0.0001)	(0.0007)	(0.0007)
BAS_meal_5	−0.0001	0.0980***	0.0014
	(0.0002)	(0.0012)	(0.0011)
BAS_meal_30	−0.0000	0.0698***	0.0107***
	(0.0004)	(0.0022)	(0.0020)
BAS_meal_60	0.0008**	0.0230***	−0.0085***
	(0.0004)	(0.0022)	(0.0021)
BAS_meal_290	−0.0003	0.0200***	−0.0037***
	(0.0002)	(0.0013)	(0.0012)
BAS_oil_0.5	0.0008***	0.0008	0.7123***
	(0.0001)	(0.0009)	(0.0008)
BAS_oil_5	−0.0007***	−0.0104***	0.0691***
	(0.0003)	(0.0016)	(0.0015)
BAS_oil_30	−0.0028***	0.0054	0.1070***
	(0.0006)	(0.0035)	(0.0033)
BAS_oil_60	0.0034***	0.0176***	0.0714***
	(0.0006)	(0.0038)	(0.0035)
BAS_oil_290	−0.0002	−0.0051**	0.0146***
	(0.0003)	(0.0021)	(0.0020)
Intercept	−0.0049***	0.0131***	−0.0374***
	(0.0005)	(0.0033)	(0.0031)
Observations	1,924,483	1,924,483	1,924,483
R^2	0.5467	0.7447	0.5154
F test	154,729	374,147	136,431

Note: Standard errors in parentheses.

Abbreviation: BAS, bid–ask spread.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

TABLE A4 Regression results using CRT based on 0.1% percentile of trade volume

	Soybeans	Soy meal	Soy oil
Liq_beans_0.5	0.7885***	0.0140***	0.0178***
	(0.0007)	(0.0011)	(0.0017)
Liq_beans _5	0.1085***	−0.0022	0.0115***
	(0.0011)	(0.0017)	(0.0026)
Liq_beans _30	0.0447***	0.0032	−0.0192***
	(0.0020)	(0.0030)	(0.0045)
Liq_beans _60	0.0361***	−0.0191***	0.0026
	(0.0020)	(0.0031)	(0.0047)
Liq_beans _290	0.0149***	0.0083***	−0.0078***
	(0.0010)	(0.0016)	(0.0023)
Liq_meal_0.5	0.0061***	0.8292***	0.0178***
	(0.0004)	(0.0007)	(0.0010)
Liq_meal_5	−0.0008	0.1078***	0.0205***
	(0.0006)	(0.0010)	(0.0015)
Liq_meal_30	−0.0013	0.0494***	−0.0117***
	(0.0010)	(0.0015)	(0.0022)
Liq_meal_60	−0.0017*	0.0015	−0.0104***
	(0.0009)	(0.0014)	(0.0021)
Liq_meal_290	−0.0007	0.0072***	−0.0127***
	(0.0004)	(0.0007)	(0.0010)
Liq_oil_0.5	0.0036***	0.0047***	0.8199***
	(0.0003)	(0.0004)	(0.0007)
Liq_oil_5	0.0015***	0.0075***	0.0768***
	(0.0004)	(0.0007)	(0.0010)
Liq_oil_30	0.0003	−0.0015	0.0688***
	(0.0008)	(0.0012)	(0.0018)
Liq_oil_60	−0.0037***	−0.0008	0.0143***
	(0.0008)	(0.0012)	(0.0018)
Liq_oil_290	−0.0021***	−0.0090***	0.0117***
	(0.0004)	(0.0006)	(0.0009)
Intercept	0.0222***	0.0111***	0.0121***
	(0.0017)	(0.0027)	(0.0040)
Observations	1,924,483	1,924,483	1,924,483
R^2	0.8387	0.9459	0.8967
F test	667,106	2.245e + 06	1.113e + 06

Note: Standard errors in parentheses.

Abbreviation: CRT, cost-of-round-trip.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

TABLE A5 Regression results using CRT based on 0.1% percentile and average of trade volume

	Soybeans	Soy meal	Soy oil
Liq_beans_0.5	0.8544***	0.0250***	0.0119***
	(0.0006)	(0.0013)	(0.0022)
Liq_beans _5	0.0621***	−0.0078***	−0.0009
	(0.0009)	(0.0019)	(0.0031)
Liq_beans _30	0.0442***	0.0028	0.0021
	(0.0015)	(0.0031)	(0.0052)
Liq_beans _60	0.0201***	−0.0169***	−0.0061
	(0.0016)	(0.0032)	(0.0053)
Liq_beans _290	0.0134***	−0.0000	−0.0030
	(0.0008)	(0.0016)	(0.0027)
Liq_meal_0.5	0.0034***	0.8345***	0.0166***
	(0.0003)	(0.0007)	(0.0011)
Liq_meal_5	0.0019***	0.0997***	0.0093***
	(0.0005)	(0.0010)	(0.0016)
Liq_meal_30	−0.0001	0.0490***	0.0002
	(0.0007)	(0.0015)	(0.0025)
Liq_meal_60	−0.0013*	0.0094***	−0.0167***
	(0.0007)	(0.0014)	(0.0023)
Liq_meal_290	−0.0033***	0.0021***	−0.0037***
	(0.0003)	(0.0006)	(0.0010)
Liq_oil_0.5	0.0016***	0.0036***	0.8684***
	(0.0002)	(0.0004)	(0.0006)
Liq_oil_5	0.0001	0.0042***	0.0511***
	(0.0003)	(0.0005)	(0.0009)
Liq_oil_30	0.0001	−0.0025***	0.0383***
	(0.0004)	(0.0009)	(0.0014)
Liq_oil_60	−0.0024***	−0.0015*	0.0266***
	(0.0004)	(0.0009)	(0.0015)
Liq_oil_290	0.0009***	−0.0026***	0.0048***
	(0.0002)	(0.0005)	(0.0008)
Intercept	0.0347***	0.0259***	0.0192**
	(0.0026)	(0.0052)	(0.0088)
Observations	1,924,483	1,924,483	1,924,483
R^2	0.8890	0.9395	0.8844
F test	1.027e + 06	1.991e + 06	981,710

Note: Standard errors in parentheses.

Abbreviation: CRT, cost-of-round-trip.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.